AFFECTIVE BODY LANGUAGE OF HUMANOID ROBOTS

PERCEPTION AND EFFECTS IN HUMAN ROBOT INTERACTION

Proefschrift

ter verkrijging van de graad van doctor
aan de Technische Universiteit Delft,
op gezag van de Rector Magnificus prof. ir. K. C. A. M. Luyben,
voorzitter van het College voor Promoties,
in het openbaar te verdedigen op
maandag 14 december 2015 om 12:30 uur

Door

Junchao XU

Bachelor of Engineering
in Measuring Control Technology & Instruments
from Southeast University, China
geboren te Nanjing, China

This dissertation has been approved by the

promotor: Prof. dr. M. A. Neerincx

copromotor: Dr. K. V. Hindriks
copromotor: Dr. D. J. Broekens

Composition of the doctoral committee:

Rector Magnificus	chairman
Prof. dr. M. A. Neerincx,	Delft University of Technology
Dr. K. V. Hindriks,	Delft University of Technology
Dr. D. J. Broekens,	Delft University of Technology

Independent members:

Prof. dr. P. Jonker,	Delft University of Technology
Prof. dr. T. Belpaeme,	University of Plymouth, United Kingdom
Prof. dr. V. Evers,	University of Twente, Netherlands
Prof. dr. A. Paiva,	University of Lisbon, Portugal
Prof. dr. M. Reinders,	Delft University of Technology, reserve member

The research reported in this thesis has been supported by Chinese Scholarship Council (No. 2010609043). The research has also been carried out under the auspices of SIKS, the Dutch Research School for Information and Knowledge Systems (SIKS Dissertation Series No. 2015-35).

ISBN/EAN: 978-94-6186-575-5

An electronic version of this dissertation is available at
http://repository.tudelft.nl/.

Contents

1

Introduction

A robot companion in a home environment needs to 'do the right things',
i.e. it has to be useful and perform tasks around the house,
but it also has to 'do the things right',
i.e. in a manner that is believable and acceptable to humans.

—Kerstin Dautenhahn [1]

1

1.1. SOCIAL ROBOTICS AND HUMAN ROBOT INTERACTION

ROBOTS are likely to become an integral part of our daily lives in the near future. Scenarios in which robots share the same work space and usually cooperate with humans are increasingly emerging (see [2] for an overview). For example, robots are used for the purposes of elderly care [3, 4], rehabilitation and health care [5–7], education [8, 9], entertainment [10–12], personal companion [13–16], guide [17–20], and receptionist [21, 22]. It is inevitable for a robot in such scenarios to interact with humans. Social abilities are essential for such a robot to coexist with humans in harmony and to be efficient in cooperation with humans.

In general, robots with social abilities are called *social robots (SR)* or *socially intelligent robots*. Several definitions of social robots have been proposed and fundamental aspects of social robots are identified [1, 23–27]. Different from traditional intelligent robots, which are designed to deal with objects, social robots are designed to interact, collaborate, and "live" together with humans within environments designed for humans. A particular research field on the interaction between robots and humans is called *human robot interaction (HRI)*. Dautenhahn described HRI as "*a highly interdisciplinary area, at the intersection of robotics, engineering, computer science, psychology, linguistics, ethology and other disciplines, investigating social behavior, communication and intelligence in natural and artificial systems*" [1]. HRI addresses not only the development of the robot abilities (a robot-centered view) but also the effects of the robot behavior on humans and the responses elicited in humans during an interaction (a human-centered view). The work presented in this thesis includes the modelling and evaluation of the robot social behavior, and also how people perceive and react to the robot behavior and its effects on humans in an interaction. Our work thus contains both a robot-centered view and a human-centered view of designing social robots. More specifically, we design body language of humanoid robots by means of modulating functional behaviors to express robot mood.

One major goal of designing social robots is to make a robot no longer considered only as tools or machines but more as partners [28, 29]. To this end, a social robot has to behave in a proper way, while interacting with humans, that is accepted by humans and thus is favorable for maintaining a good relationship with humans. One major way of improving the acceptance of social robots is to enable the robots to interact with humans in a "natural" way. That is, a social robot should appear and behave in a way that humans can perceive, understand, and respond to the robot in a manner similar to what they do to other humans [24, 26]. For example, a social robot may converse with humans using natural language; may use expressions to indicate the robot internal affective states; and may use gaze to indicate the focus of the robot's attention, etc. Humans are able to interact with such a robot using their social skills developed in daily human-human interactions. Hence, robots with "natural" interaction capabilities are able to communicate with humans efficiently and intuitively, are also perceived more lifelike and believable, and are more acceptable to users [1, 24, 25, 30].

1.2. AFFECTIVE EXPRESSION IN SOCIAL ROBOTS

THE expression of affect (e.g., emotion and mood) has been recognized as a key social ability of social robots [24, 26, 31–33]. This section explains the motivation for developing affective expression for social robots. Before we introduce affective expression, we first briefly introduce the concept of affect. Affect is an umbrella term in psychology that presents the experience of feelings, emotions, or moods. In this thesis, affect refers to emotion and mood. Distinctions between affect, emotion, and mood are explained in [34–38]. Here, we highlight the distinctions between mood and emotion that are related to expression: an *emotion* is a short-term, intense affective state, associated with specific expressive behaviors; a *mood* is a long-term, diffuse affective state, without such specific behaviors. Mood emphasizes a stable affective context, while emotion emphasizes affective responses to events.

The main reasons to endow social robots with the ability of expressing affects are that

- Affective expression is an important element of interacting with humans socially;
- Affective expression indicates the internal states of robots and makes them more predictable;
- Affective expression improves life-like quality of robots;
- Affective expression has (positive) effects on users.

First, a social robot can use expression to interact with humans in a social manner. For example, a receptionist robot may display a smile to welcome a guest warmly; an empathic companion robot may display sadness when the user is sad. Second, expression of affect also helps humans to understand the internal states of a robot, e.g., emotions, moods, beliefs, rationale, motives, and intentions [24, 32]. From these internal states, humans can understand better the robot's decision and current actions, and can predict its next move. The predictability is important for the acceptance of the robot, as predictable robots are often perceived as trustworthy and reliable [24].

Third, expression of affect makes a robot less like a machine but be more life-like and believable [24, 39]. Expression of affect is essential to the believability of a robot [39]. Expression of affect makes humans to believe, at least speculate, that a robot actually has affective states and is capable to perceive the environment: the change of expression indicates the change of the robots' internal affective states; to have different affective states a robot must be able to perceive and feel the changes of the environment. Expression of affect also makes a robot more anthropomorphic [40]. Humans have the tendency to treat an inanimate object as a living creature, and attribute the social properties and abilities that humans or animals have, such as personality, attention, thinking, or showing emotions, to the inanimate object [41]. Expression of affect, as a typical social ability of humans, potentially increases the level of the anthropomorphism and hence contribute the social acceptance of a robot [40]. An example of anthropomorphic and believable robot is the Kismet robot [24, 25]. Humans tend to anthropomorphize such a robot and interact with it in a manner that they use to interact with other humans and "living" creatures (e.g., pets).

Finally, affective expression can have positive effects on humans during an interaction. The effects include the way of interacting with a robot [42], the attitude towards a robot/agent [4, 43–45], the effectiveness of assistive tasks [46], user behavior [7, 47], and user task performance [48].

1.2.1. DEVELOPING AFFECTIVE EXPRESSIONS VIA ROBOT BODY LANGUAGE

We are in particular interested in designing robot body language of humanoid robots[1]. More specifically, we focus on how a social robot should behave to express mood through body language. The motivation of working on mood and using body language to express mood is explained in this section. We first demonstrate the importance of robot body language for expressing affect. Then we explain the challenges of designing robot body language that can be used in HRI scenarios and introduce our solution.

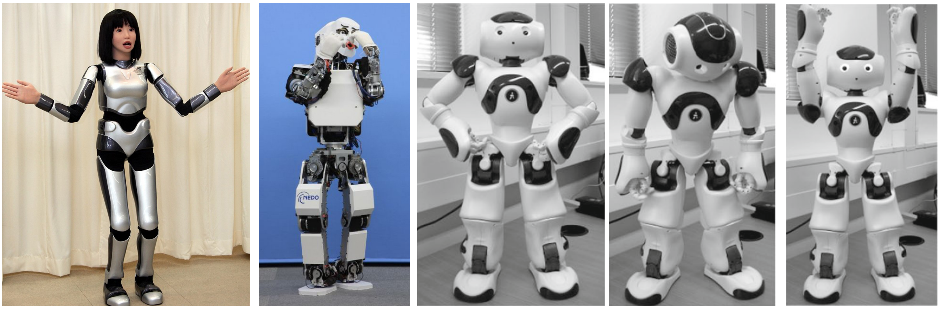
1.2.2. MOTIVATION FOR DEVELOPING ROBOT BODY LANGUAGE

Humans communicate with each other not only verbally (i.e., via speech and texts), but also nonverbally: they hear the tone and volume, and they see facial expressions, gaze directions, hand gestures, postures, and movements, from which they interpret the body and mental states and thoughts of others. Studies have shown the importance of nonverbal expression in human-human communication. For example, Mehrabian found that humans communicate their feelings and attitudes largely by nonverbal behavior [49, 50].

Body language is an important channel of nonverbal expression. Body language is also a major modality that conveys information through the human visual perception system. It has been shown that gestures are frequently used to convey information in conversations and speech [51, 52]. Body language may also improve the overall effectiveness of communication when combined with other communication modalities. For example, Kret et al. studied humans' recognition and response to isolated facial and bodily expressions as well as face-body compounds [53]. The results showed that the recognition of the expression was improved when congruent facial and bodily expressions were shown, compared to isolated facial or bodily expressions.

Robots can also use body language in communication with humans. Studies have begun to focus on the design of robot body language and several studies showed the importance of body language in human-robot interaction. Humans have developed sophisticated skills to interpret behavioral cues from other humans. Those skills can be used to interpret the behavioral cues displayed by robots. Experimental studies on robot bodily expressions showed that people can recognize these expressions (e.g., [54–57]), which indicates bodily expression is an effective communication channel of affect. We believe that robot body language is essential to natural human robot interaction since it provides another channel for humans to apply the same skills of understanding other humans to understanding robots. Moreover, it has been shown that bodily expression improves humans' recognition of robots' emotion ([54, 55]). Body language also has been shown to increases the efficiency of human-robot task performance and robustness [58]. Practically, for robots that lack sophisticated facial features (e.g., NAO, QRIO, and ASIMO) bodily expression is an important nonverbal communication modality.

[1] We will use expressive/affective body language and bodily expression exchangeably throughout the thesis.



(a) HRP4 surprise (b) Kobian fear (c) NAO angry (d) NAO sad (e) NAO happy

Figure 1.1: Examples of bodily emotion expression of humanoid robots

1.2.3. CHALLENGES OF EXPRESSING AFFECT VIA BODY LANGUAGE IN INTERACTIONS

Researchers in the field of social robots have carried out extensive work on bodily emotion expressions. Our idea of developing body language for expressing mood stemmed from the challenges we encountered when we attempted to use the bodily emotion expressions in human robot interaction scenarios. We discuss related work on robot bodily emotion expression in this section and explain the challenges and our idea.

One way of constructing bodily emotion expression is "mimicking" humans' behaviors (static postures and dynamic movements). These bodily expressions are typically designed as explicit body actions. For example, raising both hands shows happiness [54, 59]; stretching arms shows surprise [60]; arms akimbo shows anger [55, 59]; covering eyes by hands shows fear [56]. Figure 1.1 illustrates some examples of these expressions. These body actions are deliberately designed to express emotions but do not have other functions such as fulfilling a task. We call them body-action based expression in the reminder of the chapter.

A long term goal is to be able to embed bodily expression in a seamless way in any robot behaviors. In daily activities, a robot needs to perform certain behaviors to fulfil tasks or interact with humans. For example, a robot receptionist may deliver drinks to guests; a robot guide may point to the direction that visitors ask about. In these cases, it would be good if the robot can show a slightly positive expression at the same time. It is a challenge, however, to apply the aforementioned body-action based expressions to interaction scenarios as such. First, the body actions dedicated to expressing affect may interrupt functional actions, typically when these actions occupy the same effectors or the effectors required collide with each other. In the above example, a robot cannot express happiness by raising both hands while pointing to the direction or carrying drinks. Thus, the bodily expression cannot be performed simultaneously as task related behaviors. This situation is illustrated in Figure 1.2(c). Second, these body actions used for expressing emotion rise and dissipate quickly; they do not extend over time. For example, the expression of happiness with hand raising takes only a few seconds to complete, and then the hands will return to neutral positions. As a result, robots' affects are not visible in between expressions or during a task execution, as shown in (Figure 1.2(a)). The aim of this thesis is to develop mood expression that can indicate robots' affect consecutively

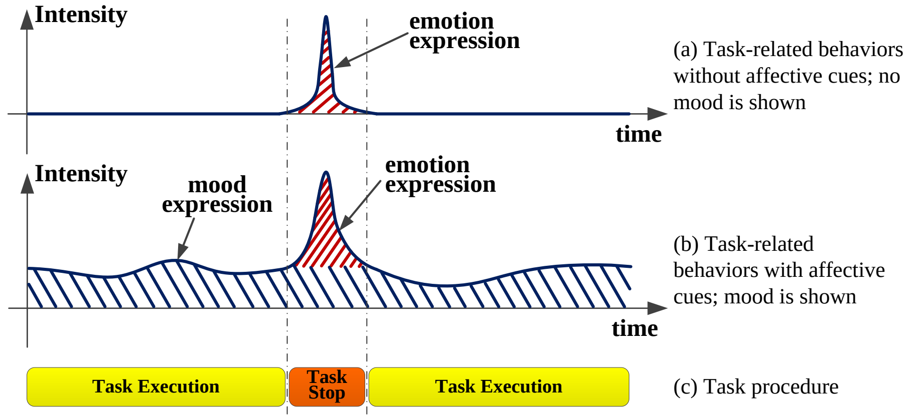


Figure 1.2: Integration of bodily expression with task-related behaviors

and simultaneously with tasks, as shown in (Figure 1.2(b)). The issue of invisible robot affect becomes more obvious for scenarios in which robots need to perform task-related actions constantly.

1.3. Expressing Mood through Behavior Modulation

To enable robots to express affect during task execution, we integrate bodily expression of mood with functional behaviors. To this end, we propose a parameterized behavior model in which behavior parameters control the spatial and temporal extent of a behavior. Modulating these parameters can generate variations of the same behavior. Put differently, modulating these parameters provide affective behavioral cues in the behavior. Thus, moods can be expressed using the same behavior executed in different "styles", rather than additional body actions used to show emotions. Applying the parameterized behavior model to functional behaviors thus can express robot mood continuously over time, even when the robot is executing a task.

Here, we explain why we call the bodily expression by means of behavior modulation mood expression. The distinction between emotion and mood is explained in Section 1.2. First, the expression by means of behavior modulation extends over time and thus is suitable to express long-term affect. We aim to design a generic model that can be applied to a broad range of robot behaviors. By applying the model to multiple behaviors (including task-related behaviors) in a series, the robot mood can be expressed in a more or less continuous fashion and extend over time. Second, the expression by means of behavior modulation does not show a particular action tendency. What behaviors should be performed at a particular moment is determined according to the task requirements, but not to the desire of showing mood. Mood expression only changes the "styles" of the behaviors. Third, the expression by means of behavior modulation is implicit and less intense. The expression relies on the affective cues generated by behavior modulation. We keep the interference caused by the parameter modulation of a behavior with the behavior functions as minimum as possible. The primary function of a behavior is still to fulfill a task, while the mood expression is an additional function. We believe that the behavior function is more noticeable and the expression by means of the behavior modulation is implicit and less intense. Mood is a less intense affective state, compared to emotion. We thus believe that the affect expressed by our expression is more like mood.

The expression by means of behavior modulation is a believable way of expressing robot mood. Mood is implicit in nature, sometimes even obscured by humans. A robot aiming for natural interaction should not express mood consciously and intentionally. Our mood expression is implicit and thus is suitable for indicating internal states like mood of a robot. Expressions for indicating internal states should be distinguished from expressions used as emotional labor [61], such as receptionists showing smile to welcome guests or nurses showing smile to comfort patients. The latter is likely to be perceived as conscious and intended behavior, if not pretended or fake. We believe that people believe more in the robot mood showed by our expression.

One of the additional reasons of studying bodily mood expression is that mood typically is a more integral part of ongoing behavior [62, 63]. An individual is at any given time in a more or less positive or negative mood. Integrating mood into the robot body language may provide a robot with a more stable channel for communicating affective information than by means of explicit emotion expression. Another reason is that effort has been mostly put into developing and studying bodily emotion expression of robots, while bodily mood expression of robots still needs to be explored. The ability of expressing mood provides an alternative of expressing robot affect and thus adds to the expressiveness of a robot. Moreover, because the mood expression based on behavior modulation lasts for a relatively longer time, the expression can prolong the exposure of a human to the robot affect and thus may enhance the effects of the robot affect on humans.

1.4. Related Work

The affective states of a robot or a virtual agent can be expressed nonverbally by poses and movements of facial and body components. In several studies, expressive body movements are built by simulating human body movements (e.g., [54–57, 59, 60]). These studies exhibited the potential of using behavior parameters to control behavior expressivity. For example, fast speed was used for the joy expression in [56]; large arm expansiveness was used for the surprise expression in [60]. However, parameters were not explicitly and systematically defined in their behavior models. The behaviors cannot be modulated after creation.

Several studies have investigated parameters that control the expressivity of human body movements. Atkinson et al. [64] studied how exaggeration of body movement influences the recognition of emotions from body. Parameters such as speed, jerkiness, spatial extent were used by actors to render different exaggeration levels. Wallbott [65] investigated whether body movements, body posture, gestures, or the quantity and quality of movement in general allow us to differentiate between emotions. This study found that qualities of movement (movement activity, spatial extension, and movement dynamics) and other features of body motion can indicate both the quality of an emotion as well as its quantity. Laban movement analysis (LMA) [66] models body movements of dancers using four major components: body, space, effort, and shape, characterized by a broad range of parameters. These studies shed light on using parameters to control body movement of virtual agent and robots.

Parameters of body movement have been used for synthesizing the behavior of virtual agents. Rose et al. created expressive body movement for animated characters by means of motion interpolation and extrapolation [67]. The parameters used in their approach are the coefficients of the interpolation and the timing of the animation. In our model and some other studies, higher-level parameters that describe the characteristics of movement are used. The relations between the high-level parameters and emotions are clearer. Rose et al. conceptualized the movement and the control of the variations in the movement as "verbs" and "adverbs". This is consistent with our idea of separating behavior functions and behavior styles. Some studies apply parameters to existing movement in a post-processing fashion. Amaya et al. [68] extracted emotional transforms using signal processing technique and applied two resulting parameters, speed and spatial amplitude to existing motions to generate emotional animation. Based on LMA, Chi et al. [69] developed the EMOTE framework that uses post-processing of pre-generated behaviors to generate expressive gestures for virtual agents. In contrast, the model developed by Pelachaud et al. [70] modifies gestures before generating actual movements. This model distinguishes spatial, temporal, fluidity, power, overall activation, and repetition aspects of behavior. It has been applied to the Greta virtual agent [71] for communicating intentions and emotions. They applied the model to the NAO humanoid robot [72]. Physical constraints of the robot were reported to limit the expressivity of the original model. In contrast, we do not impose an existing model on a robot. In our model, behavior parameters are defined when the robot behavior profile is synthesized, and physical constraints of the robot body are modelled at the same time. The ranges of behavior parameters are determined when the parameters are defined to make sure that modulation will not cause collision with other parts of the robot body.

Yamaguchi *et al.* proposed a model for expressing categorical emotions through setting different values for three motion parameters (amplitude, speed, and position). They applied the model into single-arm behaviors of a humanoid virtual agent [73] and the AIBO robot [74]. The robot behavior only involved three degrees of freedom (DOFs) and a pose parameter only controls one or two joints. Whether the emotion expression by means of behavior modulation is effective for a high-DOF robot platform (e.g., a humanoid robot) remains a question, as a single parameter has to control more joints. Lin *et al.* [75] built a hierarchical model to link categorical emotions to motion parameters including fluidity, stiffness, speed, power, and spatial extent. With this model, motions of different styles can be generated for virtual agents to express emotions. Our model adopts the layered architecture, and we studied high-DOF behaviors with this model. Different from previous research, in our model affect is represented as a dimensional variable. The behavior parameters can change continuously based on a numerical function of the affect variable. Another approach is to use the body resources that are not required by functional behaviors to express affect (e.g., [76]). In our model, when head movement is not part of the functional behaviors, head movement is used for expressing mood if needed. A step forward of our work is that we not only develop a parameterized behavior model for generating expressive body language of (high-DoFs) humanoid robots, but also investigate the body language in interaction scenarios.

1.5. RESEARCH QUESTIONS

THE goal of the thesis is to develop a parameterized behavior model for a humanoid robot to express mood through existing functional behavior, so that the robot can express mood during task execution. This thesis focuses on the following general research questions.

- *Model* - Which parameters of robot behaviors are effective in expressing mood? How should these parameters be modulated for different moods?
- *Evaluation* - Can humans recognize the mood expression generated by the behavior parameter modulation?
- *Effects* - What are the effects of the mood expression in a human-robot interaction?

Behavior parameters, controlling spatial and temporal extent, are inherent properties of a robot behavior. Our first task is to figure out: which parameters can be used to express different moods by means of modulating these parameters; what the correlations between these parameters and the expressed moods are. We attempt to find generic parameters that can be used for mood expression across behaviors. A unified model can be applied to a broad range of behaviors. Second, we evaluate whether mood can be recognized from modulated behaviors. We evaluate the expression not only in a pure recognition experiment in which the only task for participants is to recognize mood or distinguish different mood levels from the behavior, but also in real interaction scenarios in which the interaction task and many other factors may influence the recognition. Third, we investigate the effects of the mood expression in human robot interaction. As the robot becomes "moody", mood may be induced to people who interact with the robot. The perception of the robot expressing different moods also varies. The changes in people's mood and perception of the robot could further influence the behavior and performance of the people.

The specific research questions that we address in this thesis are the following.

Q1) Which parameters of robot behaviors and what modulation principles of these parameters can be used for mood expression? (Chapter 2)

Q2) What is the relative importance of the parameters? (Chapter 3)

Q3) What are the interrelations between the parameters? (Chapter 3)

Q4) Is the mood expression based on behavior modulation recognizable? (Chapter 4, 5, and 6)

Q5) Does our mood expression produce mood induction effects on the humans in an interaction context? (Chapter 5, 6, and 7)

Q6) Does our mood expression influence task performance of humans in an interaction context? (Chapter 5 and 6)

Q7) Does our mood expression influence humans' perception of the robot and the interaction experience in an interaction context? (Chapter 6 and 7)

1

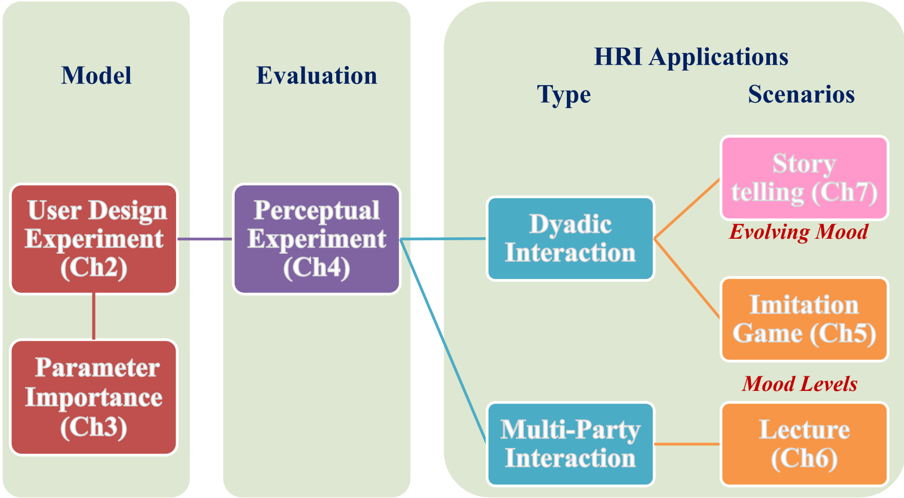


Figure 1.3: The outline of the thesis

Q8) Can our mood expression express a mood that is changing over time? (Chapter 7)

Q9) Does our mood expression enhance the perceived mood in a spoken story told by the robot? (Chapter 7)

1.6. THESIS OVERVIEW

THE chapters in this thesis are based on peer-reviewed papers. Most of the papers have been published. The general background in the introduction part of each paper may overlap. As we want to keep each chapter self-contained, we did not change the original papers. Instead, a short paragraph on the first page of each following chapter elucidates the cohesion between the chapters. The outline of the thesis is illustrated in Figure 1.3. Here we give a brief overview of each chapter.

- *Chapter 2* In this chapter, we answer the question about which parameters can be used for mood expression. We further propose how these parameters should be modulated for different moods. We create a prototype of the parameterized behavior model and evaluate it in a user study. This chapter is based on the publication [77].

- *Chapter 3* In this chapter, we analyze the parameter settings created by the participants in the user study presented in Chapter 2. We show which parameters the participants think are important. Designers may focus more on these important parameters. We also show how the parameters are correlated, aiming to simplify the modulation principles. These findings also provide more insights in behavior modulation based expressions. This chapter is based on the publication [78].

- *Chapter 4* Mood expressions generated by means of parameter modulation from Chapter 2 are evaluated in a recognition task without an interaction context. We answer the question: can people distinguish different mood levels expressed by differently modulated robot behaviors? This chapter is based on the publication [79].

- *Chapter 5* The parameterized behavior model is applied to the gestures used in an imitation game. We show that the mood expression integrated with functional behaviors (i.e., the game gestures) can be recognized in a dyadic interaction. We report on what effects these expressions have on the users in the interaction. Moreover, we show how the difficulty of the interaction task influences the recognition and the effects. This chapter is based on the publication [80], which is an extended version of the publication [81].

- *Chapter 6* In this chapter, we evaluate the recognition of the mood expression and report on the effects of the mood expression in a robotic lecture scenario. We apply our model to the coverbal gestures of the robotic lecturer. This interaction scenario is more close to a public setting in terms of that more people are involved in the interaction and the awareness of other person's presence may influence one's mind and behavior. This chapter is based on the publication [82], which is an extended version of the publication [83].

- *Chapter 7* This chapter presents our investigation into whether behavior modulation is able to express a continuously changing mood. The parameterized behavior model is applied to the coverbal gestures of a robotic storyteller. The gestures are modulated according to the current story mood. We also study the interaction between the bodily mood expression and other modalities of mood expression. The other modality of the mood expression is the semantic content of the story. We report on whether listeners perceive the mood expressed by behavior modulation is as congruent with the story mood. We also show that the bodily expression has effects on the listeners' perception of the story mood, the mood induction process caused by the story per se, and the listeners' experiences. This chapter is based on the paper [84].

Chapter 8 concludes the thesis and summarizes the findings. We discuss the results and limitations of our work, envision possibly interesting research directions based on our findings, and propose potential applications.

1.7. List of Publications

The chapters in this thesis are based on publications in scientific journals and peer-reviewed conference proceedings. The full list is given below. The publication 1 is an extended version of the publication 5. The publication 2 is extended from the publication 4.

1. **J. Xu**, J. Broekens, K.V. Hindriks, M.A. Neerincx, *Mood Contagion of Robot Body Language in Human Robot Interaction*, Journal of Autonomous Agents and Multi-Agent Systems, 29(6), pp. 1216–1248, Springer US, 2015.

2. **J. Xu**, J. Broekens, K.V. Hindriks, M.A. Neerincx, *Robotic Lecturer with Affective Body Language*, Journal of Computer & Education, submitted, 2015.

3. **J. Xu**, J. Broekens, K.V. Hindriks, M.A. Neerincx, *Effects of a Robotic Storyteller's Moody Gestures on Storytelling Perception*, International Conference on Affective Computing and Intelligent Interaction, pp 449–455, IEEE, 2015.

4. **J. Xu**, J. Broekens, K.V. Hindriks, M.A. Neerincx, *Effects of Bodily Mood Expression of a Robotic Teacher on Students*, IEEE International Conference Intelligent Robots and Systems (IROS). Chicago, United States. pp 2614–2620, 2014.

5. **J. Xu**, J. Broekens, K.V. Hindriks, M.A. Neerincx, *Robot Mood is Contagious: Effects of Robot Body Language in the Imitation Game*, Proceedings of the international conference on Autonomous agents and multi-agent systems (AAMAS). Paris, France. pp 973–980, 2014. **Best 10% Papers**.

6. **J. Xu**, J. Broekens, K.V. Hindriks, M.A. Neerincx, *Bodily mood expression: Recognize moods from functional behaviors of humanoid robots*, International Conference on Social Robotics (ICSR). Bristol, United Kingdom. pp 511–520, 2013.

7. **J. Xu**, J. Broekens, K.V. Hindriks, M.A. Neerincx, *The relative importance and interrelations between behavior parameters for robots' mood expression*, Proceedings of IEEE International Conference on Affective Computing and Intelligent Interaction (ACII). pp 558–563, 2013.

8. **J. Xu**, J. Broekens, K.V. Hindriks, M.A. Neerincx, *Mood expression through parameterized functional behavior of robots*, Proceedings of IEEE International Symposium on Robot Human Interactive Communication (RO-MAN), Gyeongju, Korea, pp 533–540, 2013. **Best Paper Award**

2

Mood Expression through Parameterized Functional Behavior of Robots

This chapter describes the architecture of our parameterized behavior model, and elaborates a user study for validating the parameters we employed from literatures and for obtaining modulation principles of the parameters.

This chapter is based on J. Xu, J. Broekens, K.V. Hindriks, M.A. Neerincx, *Mood expression through parameterized functional behavior of robots*, Proceedings of IEEE International Symposium on Robot Human Interactive Communication (RO-MAN), pp 533–540, 2013. Best Paper Award.

ABSTRACT

Bodily expression of affect is crucial to human robot interaction. We distinguish between emotion and mood expression, and focus on mood expression. Bodily expression of an emotion is explicit behavior that typically interrupts ongoing functional behavior. Instead, bodily mood expression is integrated with functional behaviors without interrupting them. We propose a parameterized behavior model with specific behavior parameters for bodily mood expression. Robot mood controls pose and motion parameters, while those parameters modulate behavior appearance. We applied the model to two concrete behaviors — waving and pointing — of the NAO robot, and conducted a user study in which participants (N=24) were asked to design the expression of positive, neutral, and negative moods by modulating the parameters of the two behaviors. Results show that participants created different parameter settings corresponding with different moods, and the settings were generally consistent across participants. Various parameter settings were also found to be behavior-invariant. These findings suggest that our model and parameter set are promising for expressing moods in a variety of behaviors.

2.1. INTRODUCTION

THE expression of affect (e.g., emotion and mood) is one of the key social abilities of social robots [26]. Affect can be conveyed outwards through nonverbal expressions like facial expressions, gestures, or postures. Robots' bodily expression of affect is crucial to human robot interaction (HRI), since it enables humans to predict robots' actions by understanding their internal states (e.g., beliefs, intentions, and emotions), and improves the naturalness of HRI and the life-like quality of robots [24]. Bodily expression is also important for robots that lack sophisticated facial features such as NAO, QRIO and ASIMO. Recently, bodily expression of emotions for social robots has been extensively discussed (e.g., [54–56]). For example, raising both hands shows happiness; arms akimbo shows anger; and covering eyes shows fear. However, these body actions used for expressing emotion rise and dissipate quickly and do not extend over time. For example, robots raise hands for seconds for showing happiness, and then the hands will return to neutral positions. It is unnatural for robots to raise hands for long. Moreover, body actions dedicated to expressing affect may interfere with task-related functional actions. As a result, robots' affects are not visible in between expressions or during a task execution. Our work aims at mood expression, which can indicate robots' affect while performing a task.

Parkinson proposed that moods may be expressed via bodily postures [63]. Breazeal *et al.* [58] defined *implicit communication*, which convey robots' internal states via behavioral cues. Amaya *et al.* [68] extracted emotional transforms through signal processing and applied them to existing motions to generate emotional animation. Inspired by them, we believe that mood can be expressed through affective cues in robots' behaviors.

We propose a layered behavior model (Figure 2.1) that generates behavior variations through behavior parameter modulation, and the variations provide affective cues. In our model, moods do not trigger behaviors but influence the behavior appearance. Hence, our mood expression does not disorder task scheduling. We applied this model to two concrete behaviors of the NAO robot, and selected behavior parameters related

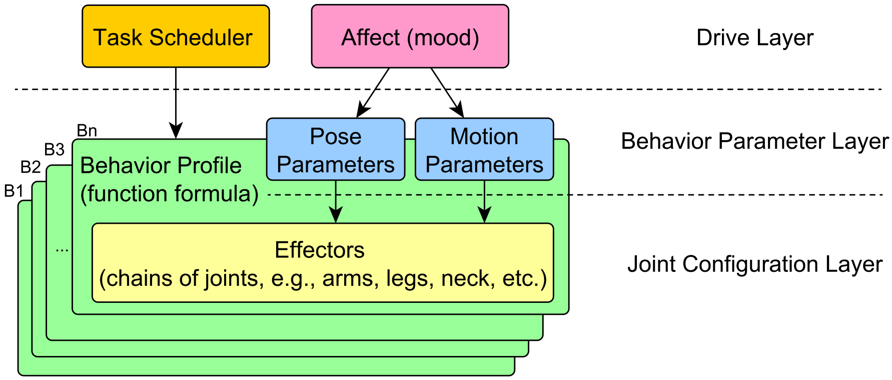


Figure 2.1: The multi-layered behavior model

to behavior expressivity (i.e., *how* a behavior is executed) [70]. To clarify whether our model and parameter set are suitable for mood expression and what the parameter values should be for different moods is unclear, we conducted a user study in which participants were asked to create mood expression through our model.

The remainder of the chapter is organized as follows. Section 2.2 illustrates the challenges of expressing affect during task execution, and reviews the research that motivates our work. Section 2.3 describes our behavior model and the implementation into concrete behaviors; Section 2.4 describes the experiment method and procedure. Section 2.5 analyzes the experiment data and draws the results; Section 2.6 discusses the remaining challenges and the potential for improving our model; Section 2.7 concludes the main findings of this study.

2.2. RELATED WORK

RECENT research sheds light on the importance of bodily expression of affect for humanoid robots. Although facial expression is one of the main channel of nonverbal expression [24, 54, 55], both [54] and [55] showed that bodily expression improved the recognition rate of robots' emotion. Bodily expression of emotion is typically designed as explicit behavior including static postures and dynamic movements, which are constructed as a whole by “mimicking" those of human beings. For example, body postures were constructed by professional artists [54]; body movements were created according to psychological findings [56]; bodily expressions were collected using motion capture system [85]. Nevertheless, these body postures and movements are difficult to perform while executing a task.

Affect can also be expressed by performing a behavior in different ways, for example, by means of motion interpolation and extrapolation [67], and by behavior parameters. Laban movement analysis (LMA) [66] is a multidisciplinary approach to modeling body movements in general by a broad range of parameters. It has been used in the synthesis of expressive movements for virtual agents [69] and robots [86, 87]. Wallbott [65] studied humans' emotional bodily movements, and annotated behavior patterns as movement "quality" defined by three dimensions. Pelachaud *et al.* [70] characterizes the expressivity of nonverbal behavior using six parameters: spatial, temporal, fluidity, power, over-

2

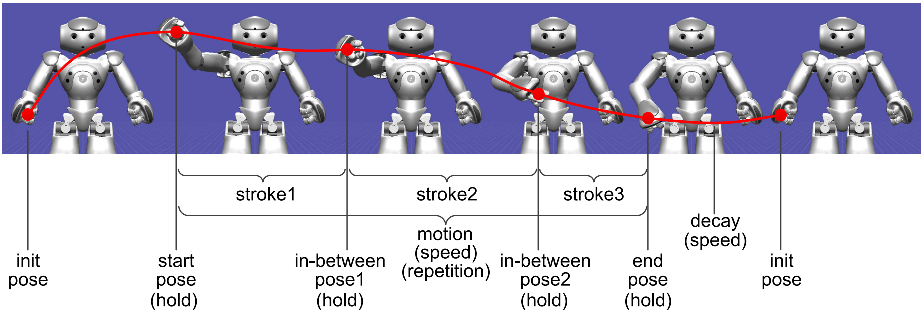


Figure 2.2: The pose and motion parameters. The figure is adapted from [89]

all activation, and repetition. They were applied to an embodied conversational agent Greta, so that Greta can communicate her cognitive and affective states through modulated gestures. All the above research suggests that affect can be reflected by different styles of executing the same type of behavior. With these methods, affect is reflected by the behavior "styles" rather than the behavior "contents" per se. However, effort is still needed to transform these abstract parameters into concrete ones while applying them to particular behaviors. Our goal is to define a set of more specific parameters that can be directly applied to a range of behaviors.

Layered models that link the affect of robots or virtual agents to the behavior parameters have been developed. Yamaguchi *et al.* [74] proposed a model in which (four categorial) emotions can be expressed through modifying three motion parameters (amplitude, speed, and position). They applied the model into single-arm behaviors of the AIBO robot. However, the robot behavior only involved three degrees of freedom (DOFs). Whether this method is effective for a high-DOF platform (e.g., a humanoid robot) remains a question. Lin *et al.* [75] built a hierarchical model to link affects to motion parameters including fluidity, stiffness, speed, power, and spatial extent. With this model, motions of different styles can be generated for virtual agents to express emotions. Our model adopts the layered architecture, and we studied high-DOF behaviors with this model.

Unused body parts can also vary behavior patterns without disturbing task execution. Brooks and Arkin proposed a behavioral overlay model that alters the overall appearance of robots' instrumental behaviors by overlaying them with behaviors of unused body resources [76]. The internal states like attitudes and relationship can be communicated non-verbally through the overlayed behaviors while the instrumental behaviors still function properly. Beck *et al.* [88] investigated the effects of head position on emotion interpretation with an ultimate purpose of establishing an "Affect Space" for bodily expression. Through experiments with static postures, head position was found to have a strong impact on the identification of displayed emotions. We adopt the head movement as a behavior with which task-related behaviors are overlaid.

2.3. THE DESIGN OF MOOD EXPRESSION

2.3.1. GENERAL PARAMETERIZED BEHAVIOR MODEL

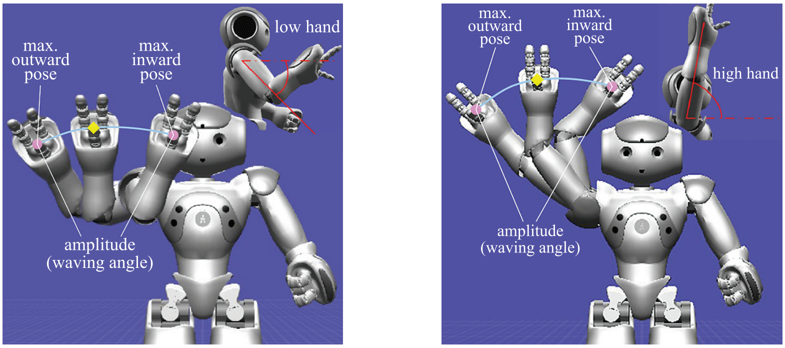
THIS study aims at expressing moods simultaneously with executing functional behaviors. We developed a multi-layer parameterized behavior model. The parameterized behavior model (Figure 2.1) consists of three layers: 1) a drive layer; 2) a behavior parameter layer; and 3) a joint configuration layer. The drive layer contains the task scheduler and the affect generator. Moods, for instance, can be modeled as dimensional variables in the affect generator, while the task scheduler decides which behavior should be performed. The behavior profile describes behavior functions, while affect determines behavior parameters without breaking the functions, resulting in different behavior patterns. Thus, from the top layer, task scheduler and affect generator can work simultaneously and separately (without interfering with each other).

The behavior parameter layer contains *Pose* Parameters and *Motion* Parameters. These parameters serve as interfaces via which affect can stylize behaviors. To describe the parameters, we employed and modified the synchronization model from [89]. This model describes stroke phases and the time points for synchronization (see Figure 2.2). Pose parameters focus on effector positions (related to the spatial parameters in [70]). They not only influence positions when an effector is static, but also influence stroke curves when an effector is moving. Start pose, end pose, in-between poses, and stroke curves compose motion trajectories (Figure 2.2). Motion trajectories specify behavior styles, and it is possible to change motion trajectories without disturbing behavior functions. Pose parameters are closely related to specific behaviors, although their abstract form may be the same. Detailed parameters are introduced in Section 2.3.2. Motion parameters depict the dynamics of a motion. In this study, we investigate four motion parameters: *motion-speed*, *decay-speed*, *hold-time* and *repetition* (see Figure 2.2). The velocity and hold-time relate to the temporal extent and fluidity in [70].

Joint configuration layer generates a list of joint values for one motion frame (one pose). Joint values need to meet certain constraints placed by behavior functions. However, their values can be modified by behavior parameters within functional bounds. One behavior parameter may influence multiple joints. In our work, the mapping from behavior parameters to joint values is based on numerical functions (for key-points) and interpolations (for in-between points).

2.3.2. IMPLEMENTATION OF THE MODEL

The behavior model was applied to two behaviors, waving and pointing. In HRI, waving is a frequently used gesture for greeting, saying goodbye and drawing attention, while pointing is a common deictic gesture. These behaviors have only one primary functional effector (the right arm), so the number of the parameters for these behaviors is appropriate for experiments. We selected three pose parameters and four motion parameters for each behavior. Beck *et al.* reports that head movements have a strong effect on expressing affect [88]. Therefore, we added the head to the two behaviors as an effector with two pose parameters, head-up-down (vertical) and head-left-right (horizontal). Thus, each behavior has nine parameters in total. The motion-speed, decay-speed and hold-time for the head movement used the same values as the arm movement, and the



(a) waving mode I (b) waving mode II

Figure 2.3: The pose parameters of waving behavior

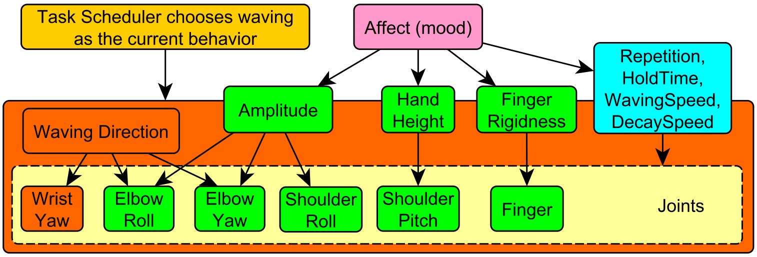


Figure 2.4: The parameterizations of waving behavior

head movement is never repeated.

A humanoid robot NAO of academic version 3.3 was used in this study. There are six DOFs in each arm including *Shoulder (Pitch, Roll)*, *Elbow (Yaw, Roll)*, *WristYaw*, and *Fingers*, and two DOFs including *Head (Pitch, Yaw)* in the neck. Although NAO emulates the human body, differences remain in the arm. The wrist-pitch is missing, and the angle range of shoulder-roll and elbow-roll is limited.

WAVING

We define waving as one hand swinging between two horizontally aligned positions repeatedly, and the palm should always face forward. The concrete parameterized behavior model of waving (Figure 2.4) embodies the general model (Figure 2.1). The behavior profile constrains the joints according to the definition of waving, while affective variations can be generated by modifying pose and motion parameters. The two end poses of arm-swings — the maximum inward and outward poses (Figure 2.3) — are determined by the pose parameters including *a*) *hand-height*, *b*) *finger-rigidness*, and *c*) *amplitude*. Since the palm needs to face forward and NAO's arm does not have wrist-roll joint, the pose of the forearm is fixed. Hence, the *hand-height* can be controlled only by the shoulder-pitch joint, which controls the inclination of the upper-arm (see top-right figures in Figure 2.3). The waving of a human mainly relies on the movement of elbow joint (the corresponding joint of NAO is elbow-roll). However, it is impossible for NAO to generate a natural waving with enough amplitude merely by the elbow-roll joint, due to its angle range (-2° to 88.5°). In our model, therefore, waving has two general modes that are switched according to the hand-height: arm-swings are realized by controlling elbow-yaw and shoulder-roll joints when hand-height is low (Figure 2.3a), and by controlling elbow-roll and shoulder-roll joints when hand-height is high (Figure 2.3b). The *amplitude* specifies the waving angle, and in practice the angle is allocated to the elbow and shoulder. The finger-rigidness controls the straightness of the fingers. Other joints are computed to keep the palm facing forward.

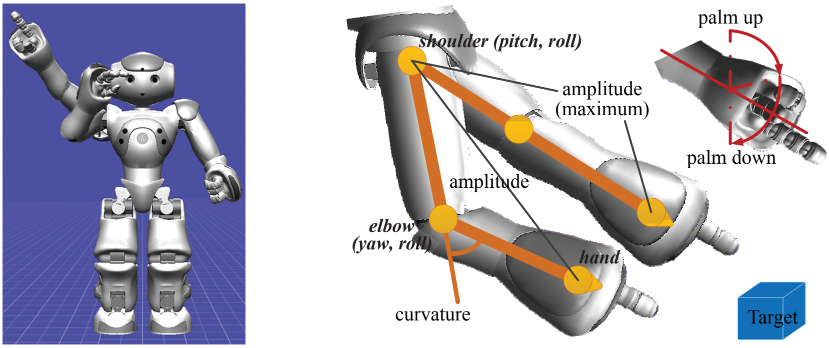
Motion parameters concern the dynamics of the joints. *Waving-speed (motion-speed)* controls the velocity of the arm-swings. *Decay-speed* controls the velocity of the arm returning to the initial pose. The value of the speed is a fraction of the maximum motor speed. *Hold-time* [0.0, 5.0] (seconds) specifies the halting duration when the arm is in the outward or inward poses. It influences the rhythm and fluency of the motion. *Repetition* [1, 10] controls the number of the arm-swing cycles. One cycle is the arm swinging from the outward pose to the inward pose and return to the outward pose. The swing always starts from the outward pose.

POINTING

We define pointing as the arm stretching out from the *preparation pose* to the *pointing pose* (Figure 2.5a). Since NAO's three fingers cannot be controlled separately, we stuck two of them to the hand allowing only one finger to move as index finger. The concrete parameterized behavior model of pointing (Figure 2.6) embodies the general model (Figure 2.1). The behavior profile constrains the joints according to the definition of pointing, while affective variations can be generated by modifying pose and motion parameters. The pointing pose is determined by pose parameters including *a*) palm-up-down, *b*) amplitude, and *c*) finger-rigidness. *Palm-up-down* controls the palm direction of the pointing pose (see the top-right of Figure 2.5b). The palm direction is controlled by the wrist-yaw and elbow-yaw joints, whose values are computed according to the normal vector to the palm. *Amplitude* is defined as the outstretching extent of the arm. It is controlled by the curvature of the elbow. Figure 2.5b illustrates the amplitude and its maximum state. *Finger-rigidness* is the straightness of the index finger. The finger cannot be fully bent to avoid the deviation of the pointing direction. The values of other joints are computed according to the pointing direction. NAO has only one DOF (WristYaw) in the wrist, and NAO's fingers can only be straight or bent, so the pointing direction is almost in line with the direction of the forearm (see Figure 2.5b). In the experiment, the pointing direction is fixed to the right-up of the robot (Figure 2.5a).

Regarding motion parameters, *pointing-speed (motion-speed)* refers to the velocity of the arm moving from the preparation pose to the pointing pose. *Decay-speed* refers to the velocity of the arm returning to the initial pose from the pointing pose. *Hold-time* [0.0, 5.0] (seconds) refers to the time that the pointing pose persists before decaying. *Repetition* [0, 5] refers to the frequency of the arm returning to an *intermediate pose* and moving to the pointing pose again after the first pointing pose. Each joint of the intermediate pose (J_{int}) is interpolated between the preparation pose (J_{pre}) and the pointing pose (J_{pnt}):

$$J_{int} = J_{pre} + \alpha \times (J_{pnt} - J_{pre}) \tag{2.1}$$



(a) preparation & pointing (b) pose parameters

Figure 2.5: The pose parameters of pointing behavior

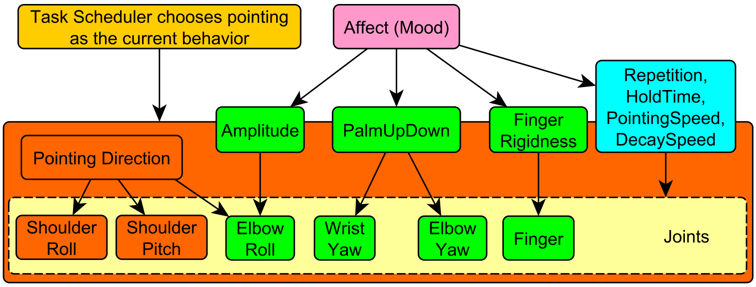


Figure 2.6: The parameterizations of pointing behavior

α is a percentage set to 0.5.

2.4. EXPERIMENTS

2.4.1. RESEARCH QUESTIONS AND THE INITIAL DESIGN

THIS study aims at designing mood expression superimposed on behaviors of a humanoid robot. A parameterized behavior model has been developed so that moods can be expressed through behavior variations. We applied the model to two functional behavior prototypes (waving and pointing), for which the pose and motion parameters can be set and assessed. The research questions are

Q1) Can our model and behavior parameter set be used for expressing mood?

Q2) What values should those parameters have?

To answer the questions, we created initial settings for both behaviors for the positive and negative moods. Then we conducted an experiment to test whether people are able to use the parameters in our model to generate different affective robot behaviors corresponding with different moods, and whether their deign principles are consistent with ours for the initial design. Based on literature (e.g., [64, 65, 88]) and our

Table 2.1: The principles of the initial design

Parameters		Waving		Pointing	
		Positive	**Negative**	**Positive**	**Negative**
Motion	MotionSpeed	fast*	slow*	fast*	slow*
	DecaySpeed	fast*	slow*	fast*	slow*
	HoldTime	short	long	long	short
	Repetition	high*	low*	high*	low*
Pose	HandHeight	high	low	/	/
	PalmUpDown	/	/	up	down
	FingerRig.	straight*	bent*	straight*	bent*
	Amplitude	large*	small*	large*	small*
	HeadVer.	up*	down*	up*	down*
	HeadHor.	look at you	look away	look at you/target	look away

* general principles

experience, we formulated our design principles summarized as follows and outlined in Table 2.1.

- *Hand-height* A higher hand pose presents a more positive mood. When waving is in mode II (Figure 2.3b), the whole-arm activation shows more positive moods.
- *Palm-up-down* Palm facing up shows openness for positive moods while facing down shows defensiveness for negative moods.
- *Finger-rigidness* Bent fingers generally show reluctance or unconcern reflecting a negative mood; straight fingers show seriousness reflecting a positive mood.
- *Amplitude* A large waving angle represents expansiveness indicating a positive mood; a small waving angle represents narrowness indicating a negative mood. For pointing, an outstretched arm increases the hand traveling distance and the arm rigidness, indicating a positive mood; an unextended arm shows unconcern or reluctance indicating a negative mood.
- *Motion-speed* Fast motion speed expresses positive moods (e.g., happiness and excitement); slow motion speed expresses negative moods (e.g., sadness).
- *Decay-speed* Fast decay speed expresses elation or excitement; slow decay speed expresses fatigue or sadness.
- *Hold-time* Short hold time makes body movements fluent and smooth, indicating elation or delight; long hold-time makes body movements jerky or sluggish, indicating sadness or depression. We used this principle for waving, whereas for pointing we used long hold-time to show emphasis or willingness (to show directions) for positive moods, and short hold-time for negative moods. Particularly, zero hold time will cause the pointing pose to decay immediately. The resulting non-persistence shows unconcern, fatigue, and reluctance.
- *Repetition* Repeated movement shows excitement or elation. Non-repeated movement stands for neutral or even negative moods like boredom, fatigue, or depression. For pointing, repetition also shows emphasis.

- *Head-up-down* Raised head indicates a positive mood while lowered head indicates a negative mood.

- *Head-left-right* Generally, head turning away from users (to avoid eye-contact) indicates a negative mood, while facing users indicates a positive mood. In addition, to indicate a negative mood through pointing the head should turn away from both users and the pointing direction, while to indicate a positive mood the head can face either users or the pointing direction.

According to the above principles, we created parameter settings across mood levels (the initial settings) using a user interface which was used in the experiment.

2.4.2. Design

User Design Experiment

The objective is to embed affective cues of different moods in waving and pointing by modulating behavior parameters. The parameters can be adjusted using sliders or numeric boxes on a user interface. Participants can click a "play" button to display the adjusted behavior on the real NAO robot, so that they were able to observe the behaviors from different positions and view-angles. Thus, they can test the effect on the behaviors caused by the changes they made intuitively. The goal is to design behaviors that display the mood that the robot is supposed to have. In this study, the mood is represented only by *valence* with five levels ranging from negative to positive: *very unhappy*, *unhappy*, *neutral*, *happy*, and *very happy*. The experiment is a within-subject design. Each participant needed to set values for the nine behavior parameters for each behavior and mood condition. The behavior parameters were reset to neutral values each time a participant started designing for another valence level. The order of the behavior and mood conditions was counter-balanced: *a*) Pointing → Waving, Negative → Positive; *b*) Pointing → Waving, Positive → Negative; *c*) Waving → Pointing, Negative → Positive; *d*) Waving → Pointing, Positive → Negative.

Comparison Experiment

In the design experiment, participants may fail to find the parameter settings they would have preferred most due to the complexity of the parameter space and the limited time. It is easier to identify a preferred design by comparison. Hence, after the design experiment, participants were asked to compare their own design and the initial design. They were not informed about who created either of these two designs. They were asked to choose the one they preferred and provide reasons.

2.4.3. Participants

Participants were recruited by advertisements. 24 university students (14 males, 10 females) with an average age of 23 (*SD*=4) participated in this experiment. They were all studying industrial design, and all had some experience of design. A pre-experiment questionnaire confirmed that none of the participants had any expertise related to this study per se. Each participant received a ten-euro coupon as a compensation for their time.

Table 2.2: Results of repeated-measures ANOVA

Waving				Pointing			
Parameters	**F(4,20)**	**Sig.**	η^2	**Parameters**	**F(4,20)**	**Sig.**	η^2
HandHeight	105.79	***	0.955	PalmUpDown	3.36	*	0.402
FingerRig.	17.82	***	0.781	FingerRig.	1.80	0.168	0.265
Amplitude	5.31	**	0.515	Amplitude	22.47	***	0.818
Repetition	22.01	***	0.815	Repetition	13.67	***	0.732
HoldTime	2.66	0.063	0.348	HoldTime	3.53	*	0.414
DecaySpd	16.75	***	0.770	DecaySpd	6.84	**	0.578
WavingSpd	42.39	***	0.894	PointingSpd	37.31	***	0.882
HeadVer.	75.58	***	0.938	HeadVer.	42.55	***	0.895
HeadHor.	1.39	0.274	0.217	HeadHor.	0.70	0.602	0.123

$*$ $p<0.05$, $**$ $p<0.01$, $***$ $p<0.001$

2.4.4. PROCEDURE

During the experiment, participants sat at a desk to manipulate the robot through a user interface. The chair position was fixed by aligning the chair arms with two markers on the desk. The robot stood on the desk and its location was fixed by markers underneath. Thus, the relative position between the participant and the robot was fixed to minimize the bias on participants' perception of the robot head direction. A NAO robot of grey-white color was used to minimize the impact of color on participants' perception of moods.

After signing a consent form and filling in a pre-experiment questionnaire, each participant received an explanation of the tasks for both experiments. Before the actual experiment, participants were asked to familiarize themselves with the behavior parameters during a trial session and they can ask the experimenter to clarify anything unclear. Then the actual user design experiment began. Participants were asked to adjust the parameters and test the behavior on the robot. For each behavior participants can proceed to the next mood by clicking a "next" button if they are satisfied with their design for the current mood. They were allowed to modify saved parameters of previous moods by clicking a "previous" button. However, after they proceeded to the second behavior, they were not able to modify the first one.

The comparison experiment started after participants completed the user design experiment. For each behavior and mood, participants were asked to display two parameter settings on the robot by clicking buttons on the user interface. They were asked to select the one they preferred most and provide reasons. The mood levels for each behavior were presented in a random order, and the order of behaviors were counter-balanced. After finishing the experiment, participants filled in a post-experiment questionnaire and were informed about the purpose of the study. On average, the experiment took 90 minutes per participant.

2.5. ANALYSIS AND RESULTS

2.5.1. CORRELATION BETWEEN VALENCE AND BEHAVIOR PARAMETERS

THIS section investigates in detail the correlation between valence and the nine behavior parameters of our model. Valence is the independent variable (within-subjects

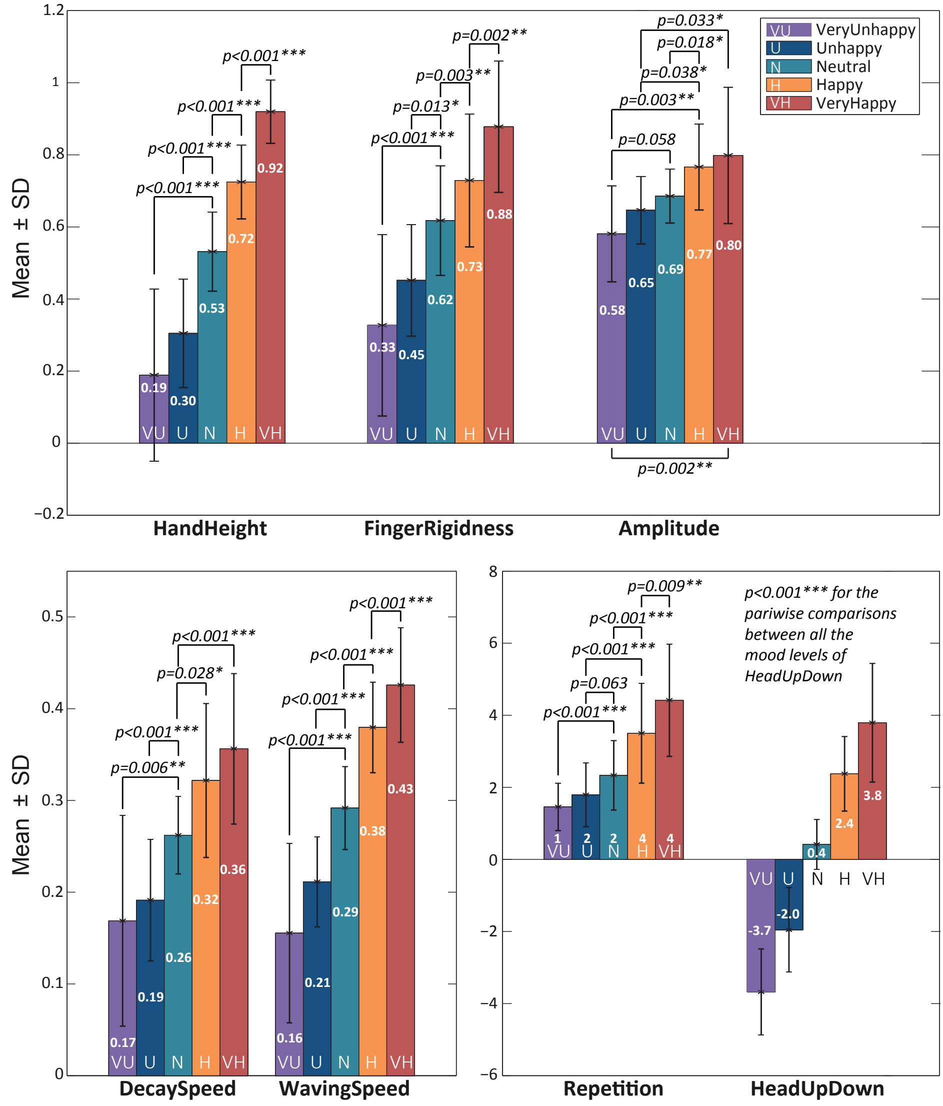


Figure 2.7: pairwise comparison between valence levels of waving behavior parameters

factor), and the nine parameters are the dependent variables. We used one-way repeated-measures *Analysis of Variance (ANOVA)* to analyze the user settings to test whether significant difference of each parameter exists between valence levels. Table 2.2 shows the results and effect size η^2. Results show that for both behaviors almost all parameters vary significantly with mood. For the hold-time of waving, the difference is approaching significance level. Therefore, it indicates that for both behaviors participants can create parameter settings corresponding with different moods.

The results of pairwise t-tests with Bonferroni correction are provided in Figure 2.7

and Figure 2.8 for the parameters that have significant difference between valence levels. The parameter means are annotated on the bars. For waving, the values of hand-height, finger-rigidness, amplitude, repetition, decay-speed, waving-speed, and head-up-down increase with increasingly positive valence. Participants selected the hand-height value of waving mode I for happy and mode II for very-happy (see Figure 2.3). As a result, we conclude that waving mode II displays more happiness than mode I. For pointing, the values of palm-up-down, amplitude, decay-speed, pointing-speed, and head-up-down increase with increasingly positive valence. Overall, for these parameters the user design is consistent with the initial design (see Table 2.1), except for the repetition of the pointing, which does not increase with increasingly positive valence (see Figure 2.8).

2.5.2. PATTERNS OF PARAMETERS

By connecting the points in the scatter plots of the parameter means, we obtain global patterns (Figure 2.9) for the initial (blue) and the user (red) settings. The mean of each parameter is scaled using the formula:

$$P_{scaled} = \frac{P_{orig} - P_{grandmin(n,m)}}{P_{grandmax(n,m)} - P_{grandmin(n,m)}} \tag{2.2}$$

n is the number of participants. m is the number of moods. The grandmin/grandmax is the minimum/maximum value of the parameter among the total n×m samples of the user settings. The patterns reveal the interrelations between parameters for each behavior and mood condition. Although exact parameter values may differ between behaviors, similar patterns are found in both behaviors for the same mood level (see Figure 2.9). The patterns of negative moods are similar for the two behaviors: the values of finger-rigidness, amplitude, decay-speed and motion-speed are moderate; the repetition is low; the head is lowered. The patterns of positive moods are similar: the values of finger-rigidness, amplitude, decay-speed and motion-speed are large; the repetition is high; the head is raised.

2.5.3. DIFFERENCES FROM THE INITIAL DESIGN

Although the user design is overall consistent with the initial design, differences of exact parameter values exist between them. Participants provided reasons in the comparison experiment. Participants' choices are shown at the top of each figure in Figure 2.9. Binomial tests suggest participants' choice is not random for neutral ($p<0.005$) and happy ($p=0.064$) pointing. One reason provided by participants is that they judged that the initial design was more positive than it should be. Another reason is that participants thought palm facing up looked unnatural. This also occurs for very-happy pointing (see Figure 2.9). Participants selected a different value for palm direction than the initial design for neutral ($t=-7.88$, $p<0.001$) and positive moods (happy: $t=-6.78$, $p<0.001$; very-happy: $t=-7.68$, $p<0.001$). Although more participants turned the palm up for positive moods, still over 60% participants did not turn the palm up. Five participants explicitly mentioned in the comparison experiment that the palm should be down, and some of them thought palm facing up looked weird. It seems that the usual function of palm up to display openness does not apply in the case of pointing.

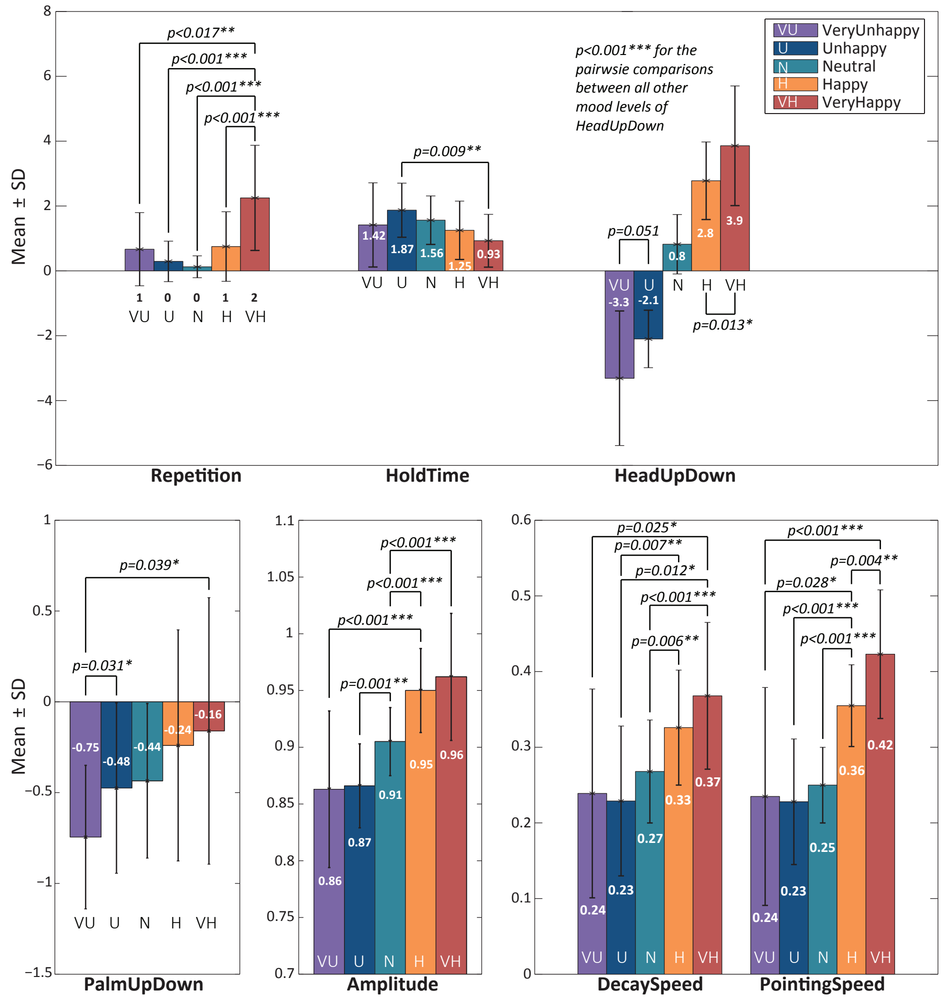


Figure 2.8: pairwise comparison between valence levels of pointing behavior parameters

We also discuss some of the salient differences between the initial and user designs that are apparent from Figure 2.9. One-sample t tests were used to identify the differences. For the very-unhappy waving, although participants set decay and waving speed slow, they are not as slow as the initial design (decay-speed, t=4.21, p<0.001; waving-speed, t=1.78, p=0.089). These participants considered the robot to be "sad" or "dejected". Interestingly, some participants set the speeds very fast because they considered the robot to be "angry" or "mad". Similarly, participants set faster speeds for the negative pointing than the initial design (very-unhappy: decay-speed, t=5.65, p<0.001; pointing-speed, t=3.59, p<0.005; unhappy: decay-speed, t=4.40, p<0.001; pointing-speed, t=2.20, p<0.05;). About 25% participants set the speeds very fast for the negative pointing because they considered the robot to be "mad", "annoyed", "aggressive", or "impatient".

These settings often have short hold-time and multiple repetition as well. Interestingly, one participant seems to have intended to create a pointing with staring by making the head face down, pointing-speed very fast (max), decay-speed very slow (min), and hold-time very long (max). Although participants set larger amplitude for neutral and positive waving, they did not set as large as the initial design (neutral: t=-6.20, $p<0.001$; happy: t=-4.26, $p<0.001$; very-happy: t=-4.71, $p<0.001$). They mentioned that the initial design made the motion more rigid and unnatural. Five participants set the amplitude small for the positive waving, because the small amplitude with fast speed caused whole-body shaking of the robot, which was perceived as happy or excited. For the negative pointing, participants considered the finger may influence the pointing direction, so they did not set the finger as bent as the initial design (very-unhappy: t=3.79, $p<0.001$; unhappy: t=2.07, $p<0.05$).

2.5.4. BEHAVIOR-INVARIANT PARAMETERS

Participants created different settings between the two behaviors for some parameters of the same type, because these parameters have different functions for the behaviors. Whereas most participants set the hold time for waving within one second, they set it much longer for pointing. Possible reasons can be that hold time influences the fluency of waving, but in the case of pointing it indicates the emphasis on the target. The head-left-right parameter is related to eye-contact for both behaviors, but for pointing it also emphasizes the pointing direction. Most participants turned the robot head sideways for both behaviors of a very-unhappy mood. For neutral and positive moods, almost all participants made the robot head face themselves for waving, but for pointing almost all participants made the robot head face either themselves or the pointing direction. Finally, numerous repetition seems more natural for waving than for pointing, and bent finger may influence the function of pointing. Whereas these parameters are found to vary with behaviors, we also found parameters that are in essence behavior invariant. As mentioned in Section 2.5.1, the same trends can be found in amplitude, decay-speed, motion-speed, and head-up-down for both behaviors. Moreover, the patterns of finger-rigidness, amplitude, decay-speed, motion-speed, repetition and head-up-down are similar between behaviors for positive and negative moods. Therefore, we believe it will be possible to generalize our findings to mood-modulation of other behaviors.

2.6. DISCUSSION

BEHAVIORS are parameterized in this study, and we intended to address the effect of individual parameters on users' perception of mood in the behaviors. However, participants' perception is usually an overall assessment of the behavior as a whole instead of assessments of individual parameters. Moreover, parameters are probably interdependent. One parameter may cause different effect on users' perception when other parameters changed. Thus, more careful experiment control is needed to address the individual effect and interdependency of the parameters.

Although we only investigated the valence dimension in this study, some parameters may relate more to the arousal dimension (active vs. passive moods). For example, the participants that set the speeds fast considered the robot was angry (high arousal), while

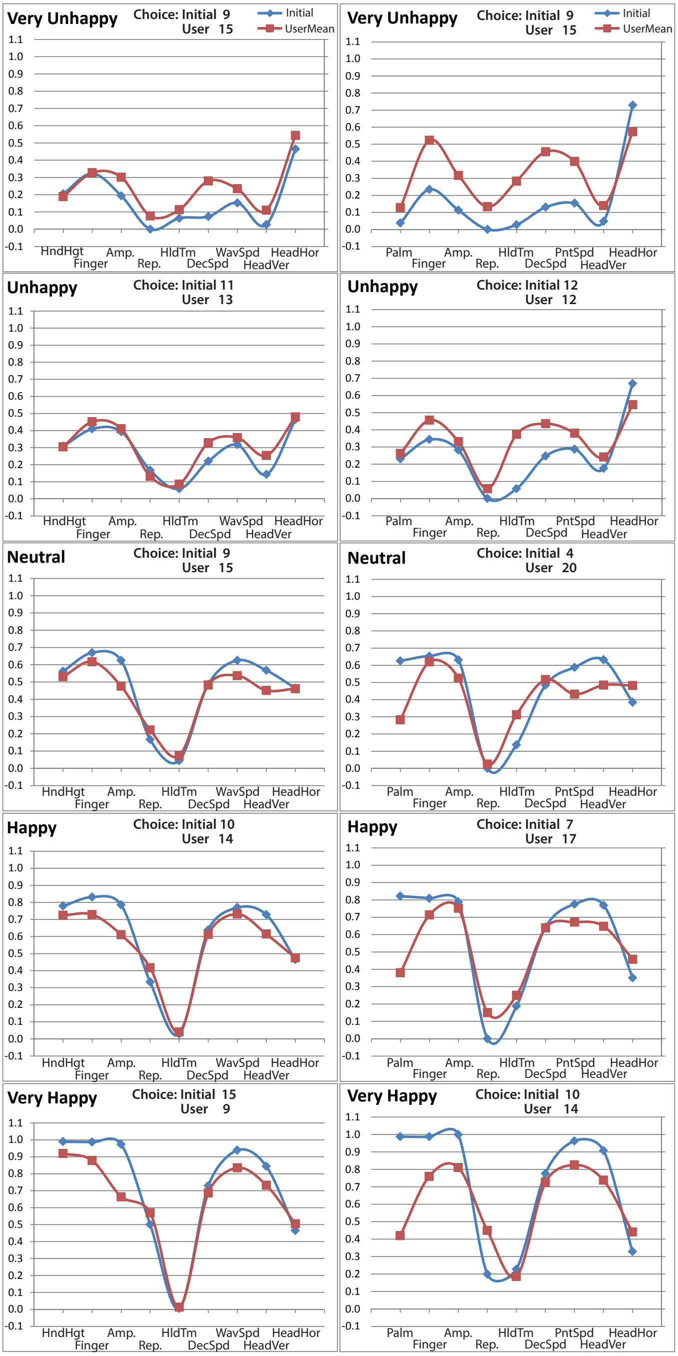


Figure 2.9: The patterns of the means for the initial and user designs. left column: waving; right column: pointing.

the ones that set the speeds slow considered the robot was sad (low arousal). We will add the arousal dimension to our model and study the correlation between behavior parameters and this dimension.

Experiment shows that creating settings for pointing seems more difficult than waving. It implies that the expressivity of behaviors per se may differ from each other, i.e., modulating parameters of the same type may produce different quantity of affective cues for different behaviors. The effect sizes of ANOVAs indicate that the strength of the association between valence and each behavior parameter may be different (see Table 2.2). With quantitative assessment of affective cues provided by each parameter, a robot system can select parameters for expressing mood quantitatively. Combined the quantitative assessment with a further study of generic (behavior-invariant) parameters, a minimum parameter set can be found for each behavior.

For each behavior and mood condition, we created weighted settings that integrate the findings from the user study and our design principles (see Section 2.4.1). The video clips of the initial and weighted design can be found on our website[1]. An evaluation of the generated mood expression in which participants recognize mood from behaviors will be done in the future. Numerical functions that correlate valence with each parameter can be established using the weighted settings and interpolation. These functions can be evaluated through experiments and improved by tuning the interpolated points.

2.7. CONCLUSION

THIS study indicates that with our model affect can be expressed through ongoing behavior of robots during a task. In our model, affect (mood in our particular case) is expressed through affective cues provided by behavior variations, and the variations are generated by behavior parameter modulation. Experimental results show that our model and parameter set are able to generate such behavior variations. Our model contains specific parameters that can be directly used for modifying robot behaviors. Moreover, various parameters were found to have identical function of expressing moods for the two behaviors. This suggests that some of our parameters can be used as generic ones in a variety of behaviors, and the design principles of these parameters can also be applicable to other behaviors. The contribution of this study is to enrich the affective expression of social robots by enabling them to express affect through body language during task execution.

[1] http://ii.tudelft.nl/~junchao/moodexpression.html

3

The Relative Importance and Interrelations between Behavior Parameters for Robots' Mood Expression

This chapter describes the statistic analyses of the user-designed parameter settings from Chapter 2 that we performed in order to figure out the relative importance of the parameters and the correlations between the parameters.

This chapter is based on J. Xu, J. Broekens, K.V. Hindriks, M.A. Neerincx, *The relative importance and interrelations between behavior parameters for robots' mood expression*, Proceedings of IEEE International Conference on Affective Computing and Intelligent Interaction (ACII). pp 558–563, 2013.

ABSTRACT

Bodily expression of affect is crucial to human robot interaction. Our work aims at designing bodily expression of mood that does not interrupt ongoing functional behaviors. We propose a behavior model containing specific (pose and motion) parameters that characterize the behavior. Parameter modulation provides behavior variations through which affective behavioral cues can be integrated into behaviors. To investigate our model and parameter set, we applied our model to two concrete behaviors (waving and pointing) on a NAO robot, and conducted a user study in which participants (N=24) were asked to design such variations corresponding with positive, neutral, and negative moods. Preliminary results indicated that most parameters varied significantly with the mood variable. The results also suggest that the relative importance may be different between parameters, and parameters are probably interrelated. This chapter presents the analysis of these aspects. The results show that the spatial extent parameters (hand-height and amplitude), the head vertical position, and the temporal parameter (motion-speed) are the most important parameters. Moreover, multiple parameters were found to be interrelated. These parameters should be modulated in combination to provide particular affective cues. These results suggest that a designer should focus on the design of the important behavior parameters and utilize the parameter combinations when designing mood expression.
Keywords: *nonverbal cues; bodily expression; affect; mood; behavior model; parameterization; social robots; HRI;*

3

3.1. INTRODUCTION

BODILY expression of affect is a key ability of social robots [26]. It is crucial to human robot interaction (HRI) because it helps humans to perceive the internal states (e.g., beliefs, intentions, and emotions) of robots, and it improves the naturalness of HRI and the life-like quality of robots [24]. Bodily expression is also important for robots that lack sophisticated facial features such as NAO, QRIO and ASIMO. Current bodily expression of affect usually consists of body actions that express emotions deliberately. For example, raising both hands shows happiness [54]; arms akimbo shows anger [55]; covering eyes by hands shows fear [56]. However, these body actions rise and dissipate quickly and do not extend over time. Moreover, these body actions may interrupt functional behaviors during a task; functional behaviors also hinder such actions from expressing a long-term affect like mood. For example, a robot cannot express an excitement mood by raising both hands repeatedly while the robot is pointing to the object that makes it excited for long. Parkinson proposed that moods may be expressed via bodily postures [63]. Breazeal *et al.* [58] defined implicit communication (i.e., robots do not communicate deliberately), which conveys robots' internal states via behavioral cues. Inspired by them, we believe that mood can be expressed implicitly through affective behavioral cues. Our work aims at integrating bodily expression of mood with task-related behaviors, by embedding affective behavioral cues into these functional behaviors. As a result, robots can convey affects continuously over time, even during a task execution. Therefore, our proposed bodily mood expression may enhance the effect of the affective expression on HRI.

We propose a layered behavior model that generates behavior variations through behavior parameter modulation, and the variations provide affective cues. The model contains parameters (e.g., speed, amplitude, and repetition) that are applicable to a broad range of behaviors. In our model, moods do not trigger behaviors but influence the behavior appearance. As a result, mood expression does not interrupt task scheduling. In previous work [77], we applied this model to two concrete behaviors of the NAO robot, and studied the relation between mood variables and behavior parameter modulation and obtained general design principles for each parameter. This chapter addresses the relative importance and the interrelations between parameters. The results provide insights into behavior parameter modulation for expressing moods, and provide criteria for simplifying the behavior generation system of a robot. Designers may focus more on the highly important parameters when designing bodily expression of mood. The parameter space of bodily expressions can be less complex by removing the less important parameters. Moreover, we also found that multiple parameters have to be modulated in concert to express a particular mood, and some of them vary correlatively. In this case, less parameter modulation principles are needed when one function is built to map mood variables to interrelated parameters as a whole.

The remainder of the chapter is organized as follows. Section 3.2 introduces the research on parameterized behavior models. Section 3.3 describes our behavior model and the implementation into concrete behaviors; Section 3.4 describes the experiment and the initial findings. Section 3.5 reports our findings about the relative importance and interrelations between behavior parameters; Section 3.6 concludes the main findings of this study and proposes the future work.

3.2. RELATED WORK

ONE way of generating affective behavioral cues is to modulate behavior parameters. In this way, affect can be reflected by the same behavior executed in different "styles", rather than the behavior "contents" per se. Laban movement analysis (LMA) [66] is composed of a broad range of parameters that models body movements from different aspects, e.g., effort and shape. It has been used in expressive gesture synthesis for virtual agents (e.g., EMOTE [69]) and emotion expression for robots (e.g., [86]). Unlike EMOTE, which performs as a post-process of generated behaviors, we define interfaces (i.e., behavior parameters) simultaneously we create the functional profile of the behavior, so that mood expression (by modulating these parameters) can exist in concord with behavior functions. Wallbott [65] studied humans' bodily movements that express emotions. The behavior pattern is annotated as movement "quality" defined by three dimensions. Pelachaud [70] characterized the expressivity of nonverbal behavior (i.e., how a behavior is executed) using six parameters: spatial, temporal, fluidity, power, overall activation, and repetition. They were applied to an embodied conversational agent Greta, so that Greta can communicate her cognitive and affective states through modulated gestures. The parameters in the above studies are abstract and have to be transformed into concrete ones while applying them to a particular behavior. Several concrete parameters can represent the same abstract one. For example, the spatial extent [70] can present horizontal extent (amplitude or wideness), vertical extent (height), or radial extent (e.g., the outstretching extent of an arm). The speed parameter can present the speeds of different phases of a behavior (e.g., motion speed and decay speed). These different transformed parameters may produce different affective cues. Moreover, when applying these parameters to a functional behavior of a particular robot, some of them may be restricted by the behavior function and the physical constraints of the robot. We study behavior parameter modulation for mood expression with the parameters that exist inherently in the behavior and can be modulated without interfering with behavior functions.

The robotic behaviors which parameter modulation has been applied to usually involved merely a few degrees of freedom (DOFs) [74, 86]. Whether parameter modulation of a high-DOF behavior is effective for mood expression remains a question, especially in the presence of the behavior function. In addition, the underlying control mechanism of high-DOF behaviors can be more complex. It may be difficult to apply a complex parameter modulation model to those behaviors. Parameter modulation can be simplified by selecting a sufficient set of parameters that can express moods efficiently. Criteria are needed for selecting a minimum set. Yet, the priorities of parameters are not clear. Moreover, modulating a single parameter may be insufficient for expressing a particular mood. Crane *et al.* showed that some parameters need to be modulated in combination for expressing a particular affect [90]. Yamaguchi *et al.* [74] proposed a model in which four emotions can be expressed through modifying amplitude, speed, and position. They applied the model into single-arm behaviors of an AIBO robot. They also found certain emotions could not be expressed only by a single parameter. For example, fast motion can be applied to both joy and anger. Thus, other parameters have to be applied together. For high-DOF behaviors, interrelations between parameters also become more complex. It is necessary to clarify the interrelations between parameters to find such combinations for expressing affect more efficiently. We studied high-DOF functional behaviors and investigated these issues by an experiment in which participants were involved in designing mood expression through parameter modulation.

Layered models (e.g., [74, 75]) were developed to link the affect of robots or virtual agents to behavior parameters. Our model adopts the layered architecture. Unused body parts can also vary behavior styles without interrupting task execution. Brooks and Arkin [76] proposed a behavioral overlays model that alters the overall appearance of robots' functional behaviors by overlaying behaviors of unused body resources. Beck *et al.* [88] report that head movements have a strong effect on expressing affect. Therefore, we added head into functional behaviors with two pose parameters, head-up-down, and head-left-right.

3.3. Behavior Model and Implementations

3.3.1. General Behavior Model

The parameterized behavior model (Figure 3.2 and 3.4) consists of three layers: 1) a drive layer; 2) a behavior parameterization layer; and 3) a joint configuration layer. The drive layer contains the task scheduler and the affect generator. We modeled mood using dimensional variables in the affect generator. The task scheduler decides the current behavior to be performed according to behaviors' functional profiles. Each behavior has its own functional profile that constrains the joints, while affect determines the behavior parameters which change the joints within functional bounds, generating be-

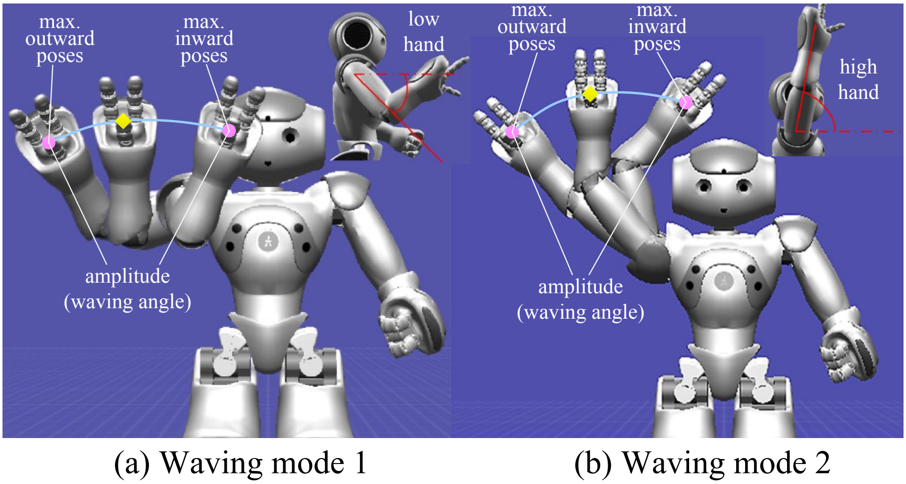


Figure 3.1: The pose parameters of the waving behavior

havior variations. Thus, from the top layer, the task scheduler and affect generator can work simultaneously and separately without interfering with each other. In the behavior parameter layer, pose and motion parameters serve as interfaces for the drive layer to stylize the behavior. Pose parameters control the key postures (position, shape, and direction) of effectors (a chain of joints, e.g., arm, leg, and neck), while movements are generated by these key postures and interpolation. Motion parameters depict the dynamics of a motion including velocity, continuity, and repetition. We constructed the behavior profiles by mimicking humans' behaviors and according to social conventions (i.e., people understand the behaviors with common sense). The parameters were defined during the construction of behaviors' functional profiles so that balance of behavior variations and the maintenance of the behavior function can be better achieved.

3.3.2. IMPLEMENTATION

The behavior model was applied to a greeting gesture, waving (Figure 3.1) and a deictic gesture, pointing (Figure 3.3) of a NAO robot (academic version 3.3). For each behavior we used three pose parameters for the right arm and four motion parameters. Six DOFs (degrees of freedom) exist in the arm including Shoulder (Pitch, Roll), Elbow (Yaw, Roll), WristYaw, and Fingers, and two DOFs including Head (Pitch, Yaw) in the neck. Although NAO emulates the human body, differences remain in the arm. The wrist-pitch is missing, and the angle range of shoulder-roll and elbow-roll is limited.

We define waving as one hand swinging between two horizontally aligned positions repeatedly, and the palm should always face forward. Pose parameters determine the maximum inward and outward poses (Figure 3.1). The pose parameters of waving are hand-height, finger-rigidness, and amplitude. Hand-height determines the vertical position of the poses, while amplitude determines the horizontal. Figure 3.1 shows low and high hand positions. In our design, waving has two modes, which are switched according to the hand-height. Waving can be generated by controlling ElbowYaw and Shoulder-

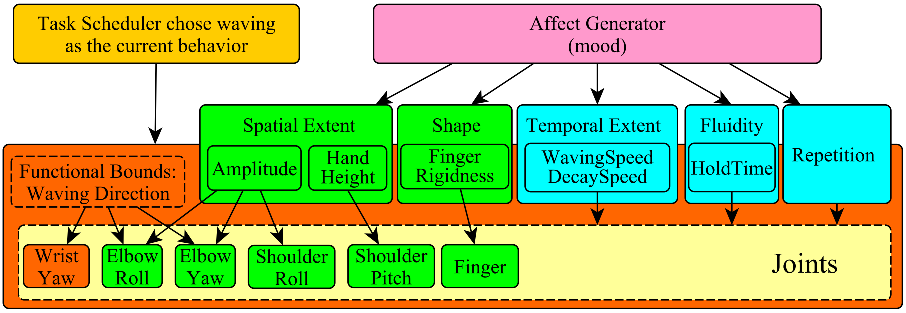


Figure 3.2: The parameterization of the waving behavior

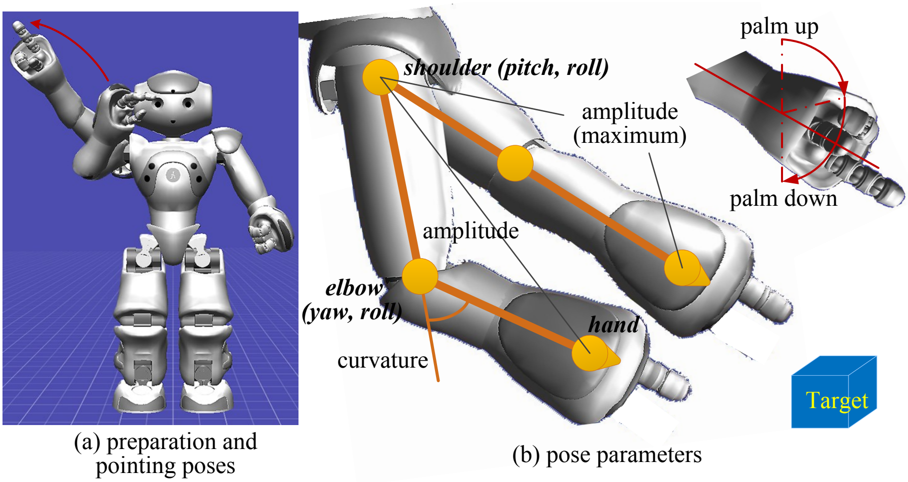


Figure 3.3: The pose parameters of the pointing behavior

Roll joints when the hand-height is low (Figure 3.1a), and by controlling ElbowRoll and ShoulderRoll joints when the hand-height is high (Figure 3.1b). The amplitude is the waving angle. Finger-rigidness controls the straightness of NAO's fingers. Other joints (WristYaw and ElbowRoll when the hand-height is low; WristYaw and ElbowYaw when the hand-height is high) are constrained to keep the palm facing forward.

We define pointing behavior as the arm stretching out from the preparation pose to the pointing pose (Figure 3.3a), with which the index finger aims at a specified target (Figure 3.3b). Since NAO's three fingers cannot be controlled separately, two of them were stuck to the hand allowing only one finger to move as index finger. The pose parameters of pointing are palm-direction, finger-rigidness, and amplitude (Figure 3.3b). Palm-direction controls the facing direction of the palm for the pointing pose (shown in the top-right figure of Figure3b). Amplitude determines the outstretching extent of the arm for the pointing pose. Finger-rigidness controls the straightness of the index finger, which is constrained as the pointing finger cannot be fully bent in the pointing pose.

Four motion parameters were adapted from [70] and [89]: 1) Motion-speed (tempo-

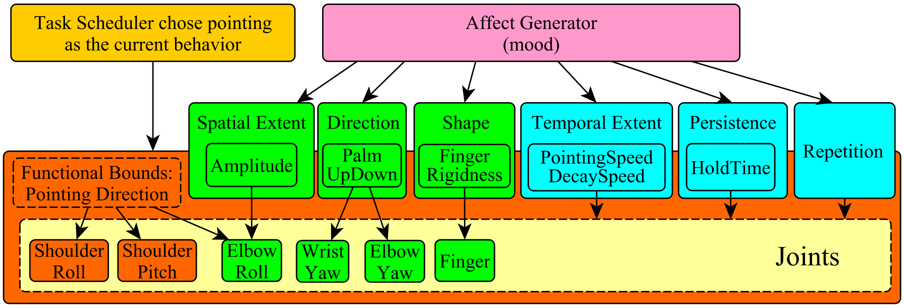


Figure 3.4: The parameterization of the pointing behavior

ral extent) refers to the velocity of the arm swings for waving (waving-speed), or the arm outstretching from preparation pose to the pointing pose for pointing (pointing-speed). 2) Decay-speed (temporal extent) refers to the velocity of the arm returning to initial pose. 3) Repetition is the number of swings for waving, and the number of outstretching actions for pointing. 4) Hold-time (fluidity) determines duration of the arm waiting at the endpoints of a swing for waving, or at the pointing pose for pointing. For the head, we used the same values for motion parameters as used for the arm movement except for the repetition (the head never repeats). Thus, each behavior has nine parameters in total.

3.4. EXPERIMENT AND INITIAL FINDINGS

To study the parameterized behavior model, we conducted an experiment in which participants were asked to design mood expression by adjusting the nine parameters for each of the two behaviors corresponding to different moods characterized by valence. Although valence is a dimensional scale, five different levels were used for the experiment. We used very-unhappy, unhappy, neutral, happy, and very-happy to describe to ensure that participants can understand them. We did not constrain the context of arousal. Participants can display adjusted behaviors on a real NAO robot, so that they can test resulting behaviors. They were also asked to provide their design rationale. In this way, participants provided various self-evaluated parameter settings to us, and we extracted design principles from their settings and comments. 24 university students (14 males, 10 females) with an average age of 23 (*SD*=4) participated in this experiment. More details can be found in [77].

We have analyzed the participants-created settings using repeated-measures ANOVA, and obtained the relation between valence and behavior parameters [77], which we summarize as follows. Results showed that almost all parameters of both behaviors varied significantly with valence. This indicates that our model and behavior parameter set are promising for generating behavioral cures for mood expression. Moreover, the results of pairwise t tests suggest that most parameters are positively correlated with valence (Table 3.1). Since these parameters follow the same trend, we speculate that some parameters are probably interrelated, and they should probably be modulated in combination when expressing a particular mood. The interrelations can also simplify the mapping

Table 3.1: Parameters that vary significantly with mood

Waving				Pointing			
Parameters	*Trend*†	*Sig.*‡	η^2	*Parameters*	*Trend*†	*Sig.*‡	η^2
HandHeight	+	***	0.955	**HeadVer.**	+	***	0.895
HeadVer.	+	***	0.938	**PntSpd**	+	***	0.882
WavSpd	+	***	0.894	**Amplitude**	+	***	0.818
Repetition	+	***	0.815	**Repetition**		***	0.732
FingerRig.	+	***	0.781	**DecaySpd**	+	**	0.578
DecaySpd	+	***	0.770	**HoldTime**		*	0.414
Amplitude	+	**	0.515	**PalmDir**	+	*	0.402
HoldTime			0.348	**FingerRig.**			0.265
HeadHor.			0.217	**HeadHor.**			0.123

† *These parameters increase with increasingly positive valence.*

‡ ** $p<0.05$, ** $p<0.01$, *** $p<0.001$*

from mood variables to behavior parameters. Moreover, the effect sizes η^2 of ANOVAs indicated that the strength of the association between valence and each behavior parameter may be different. Therefore, we speculate that the importance of each parameter is different. Parameters in Table 3.1 are sorted by the effect size η^2. In this chapter, we looked at the parameters with large (above 0.5) effect size, and the relative importance is further assessed by analyzing the parameter settings and the empirical data provided by participants. The importance provides a benchmark for simplifying the behavior model by removing the less important parameters.

3.5. Relative Importance and Interrelations

3.5.1. Data Reliability

Questions (using 5-point Likert scale) about participants' confidence of their designs (*Mean*=3.85, *SD*=0.58), whether the moods can be recognized (*Mean*=4.08, *SD*=0.58), and task complexity (*Mean*=3.33, *SD*=0.87) suggested that participants were successful at the task. Before the main analysis, Cronbach's α was used to test whether the values for each parameter of five mood levels are consistent across 24 participants. The data reliability indicates the validity of the results of the main analysis. Based on the reliability, we can select parameters for the main analysis. Results show that the data of the head-left-right of both behaviors are unreliable (below 0.60). The data of all other parameters are reliable: for waving the α values from 0.833 to 0.994; for pointing the α values range from 0.729 to 0.990. Therefore, all parameters except the head-left-right were selected for the main analysis.

3.5.2. The Relative Importance of Parameters

The relative importance of parameters was assessed through the user settings (objective data) and the user ranks (empirical data) of parameters. Multivariate linear regression was used to analyze the relationship between the mood variable (outcome variable) and each behavior parameter (predictor variables). The standardized coefficient β and ΔR^2

3

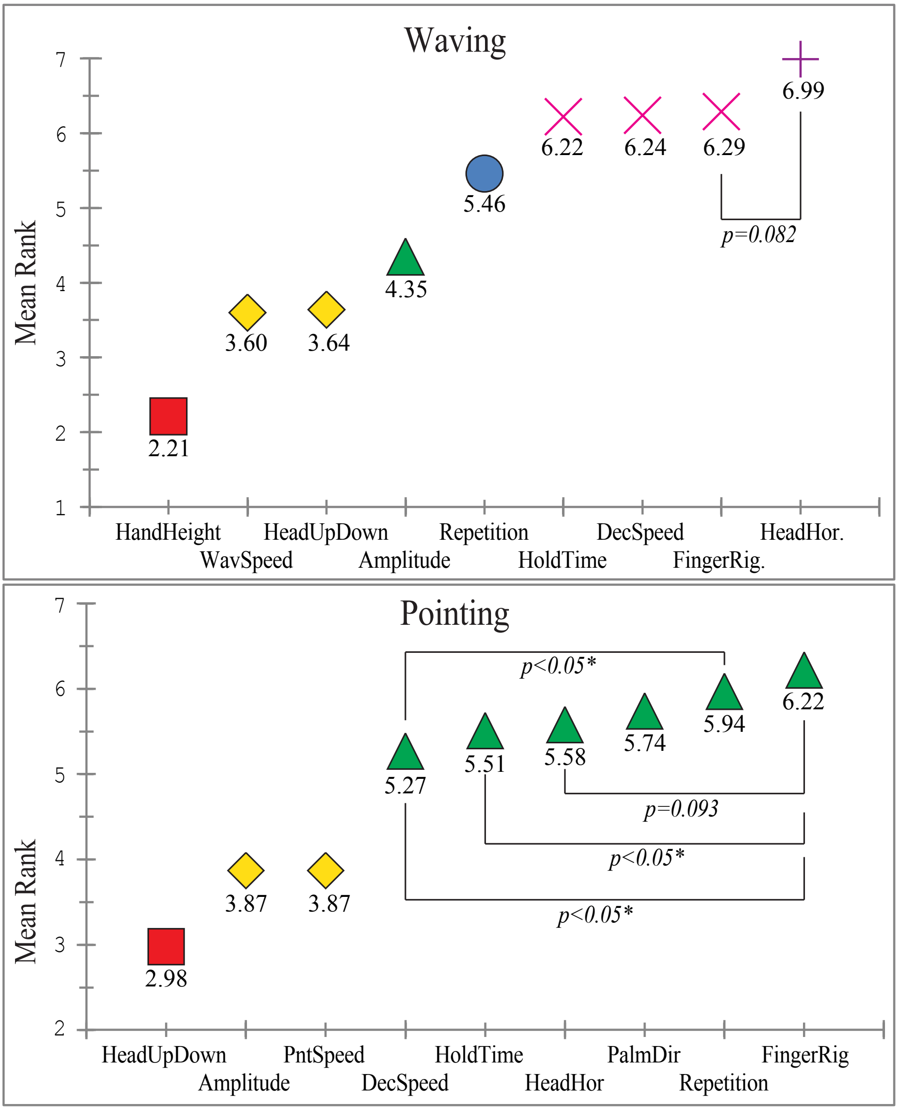


Figure 3.5: The results of Friedman test and Wilcoxon tests for the two behaviors across all mood levels; the mean ranks are denoted under each symbol; the significances are uncorrected

of each predictor indicates its contribution to the outcome variable, i.e., its importance in the model. Among the parameters that have high reliability, the behavior parameters that vary significantly with mood (see Section 3.4) were selected as predictors. The important parameters were selected using backward-stepwise method (to reduce Type II error). Afterwards, we entered these parameters hierarchically (blockwise entry) to obtain a forward change statistics. Table 3.2 shows the minimum set of parameters for waving and pointing behaviors in order of importance suggested by the multivariate regression results.

Table 3.2: Importance suggested by multivariate regression

Waving	***Coefficients***		***Change Statistics***				
Parameters	β	***Sig.***	***step***	R^2	ΔR^2	ΔF	***Sig.***
HeadVer.	0.483	0.000	1	0.842	0.842	627.436	0.000
HandHeight	0.236	0.000	2	0.886	0.044	44.953	0.000
WavingSpd	0.212	0.000	3	0.907	0.021	25.436	0.000
Repetition	0.071	0.077	4	0.910	0.003	3.723	0.056
Amplitude	0.065	0.054	5	0.913	0.003	3.790	0.054
Pointing	***Coefficients***		***Change Statistics***				
Parameters	β	***Sig.***	***step***	R^2	ΔR^2	ΔF	***Sig.***
HeadVer.	0.727	0.000	1	0.767	0.767	389.083	0.000
Amplitude	0.149	0.007	2	0.783	0.016	8.879	0.004
PointingSpd	0.094	0.085	3	0.788	0.005	3.014	0.085

Each parameter was entered for each step, and the coefficients of the final step are shown.

Friedman test with Kendall's W was used to analyze the user ranks of parameters. The analysis was performed across all mood levels to assess the relative importance of each parameter, and performed for each mood level separately to test how the importance of each parameter varied with mood levels. Kendall's W was used to assess the consistency of participants' ranks. The results show that the importance of waving parameters is different ($\chi^2(8) = 334.211$, p<0.001, $W = 0.348$), and the importance of pointing parameters is also different ($\chi^2(8) = 164.327$, p<0.001, $W = 0.171$). Figure 3.5 shows the mean rank of each parameter. Parameters with high importance (low mean rank) are sorted to the left of the horizontal axis. Then we used Wilcoxon tests to compare the importance of parameters in pairs. Parameters are grouped according to their importance; different groups are marked with different symbols and colors (Figure 3.5). Significance was found between each pair of the parameters from different groups, except for the annotated one. Therefore, we obtained the relative importance of each group. The results of analyzing the parameter settings and the empirical ranks are overall consistent. Combining these results, we conclude that the minimum parameter set of waving is 1) hand-height, 2) waving-speed, 3) head-up-down, 4) amplitude, and 5) repetition, and the minimum set of pointing is 1) head-up-down, 2) amplitude, and 3) pointing-speed. Moreover, the head-up-down, motion-speed, and amplitude were ranked most important for both behaviors. Thus, these parameters are probably also important for other behaviors.

Friedman tests were also carried out for each mood level separately to test how the importance of each parameter varied with mood levels. Results show that the mean ranks of each parameter in different mood conditions are consistent with the overall result, although they vary slightly with moods. Among the five important parameters of waving, across all mood levels the hand-height is top ranked, followed by waving-speed, then amplitude, and then repetition; The head-up-down was top ranked for negative moods, while it dropped to the middle for positive and neutral moods. This suggests that a lowered head is important for showing negative moods, while a raised head is relatively less important for showing positive moods. However, among the three important parameters of pointing, the head-up-down was top ranked for all moods except neutral, followed by the pointing-speed and amplitude. It seems more difficult to express moods by arm movement for pointing than waving, since the head-up-down played a more important role in expressing positive moods for pointing.

3.5.3. Interrelations between Parameters

This section focuses on the interrelations between behavior parameters. From the design rationale provided by participants, we found that participants considered several parameters in combination when they were designing a particular expression. To clarify how general these patterns were among participants, we categorized participants' parameters settings using hierarchical clustering analysis with behavior parameters as predictors, and labelled the parameter modulation patterns of these combinations according to their design rationale. Table 3.3 show these combinations and their occurrence. The mood levels we chose for this test are 1) very-unhappy (negative condition), and 2) very-happy (positive condition), because the change of each parameter is larger in these extreme conditions and thus less susceptible to the individual differences. To minimize the random effect caused by individual differences on the neutral point, we subtracted the parameter value of each sample (N=24) of very-unhappy and very-happy from its corresponding neutral value.

We interpret these patterns in light of participants' rationale as follows. For the waving of a negative mood, the majority of participants combined slow waving-speed and decay-speed with small amplitude making the movement small and less energetic to show sadness. With this settings, some participants increased the hold-time to make the movement sluggish and even slower overall. This combination expresses a mood of depression. Some participants combined large amplitude and slow waving-speed to express boredom. When speed is slow, large amplitude made the speed of the overall movement even slower. Similarly, small amplitude made the speed of the overall movement rapid when the speed parameters were set fast. Two participants combined fast waving-speed and decay-speed with a small amplitude to express anger. For the waving of a positive mood, the majority combined fast waving-speed with large amplitude to show happiness, while five participants further increase the waving-speed and combined more repetition and short hold-time to express elation. Six participants combined fast waving-speed but small amplitude to create a feeling of rapidness for expressing excitement. Here, the hand-height was set high to present a positive feeling, otherwise the rapidness may be confused with a negative mood. Thus, the amplitude played different roles in mood expression when combined with different speed conditions. In addition,

Table 3.3: The Modulation of Parameters in Combination

			Waving			
Expressed Mood		***Parameter Modulation***				***Freq.***
Negative	**angry**	MS+	DS+	AMP-		2
	bored	MS-		AMP+		5
	sad	MS-	DS-	AMP-	HT-	7
	depressed	MS-	DS-	AMP-	HT+	8
Positive	**excited**	MS+	AMP-	HH+	HT-	6
	happy	MS+	AMP+		HT-	12
	elated	MS++	AMP+	REP+	HT-	5
			Pointing			
Expressed Mood		***Parameter Modulation***				***Freq.***
Negative	**mad/aggressive**	MS++	DS++		REP+	3
	angry	MS+	DS+			5
	sad	MS-	DS-			12
Positive	**elated**	MS+	AMP+	HT-	REP++	5
	happy	MS+	AMP+		REP+	14
	pleased	MS+	AMP+		REP=0	2

MS: motion-speed, DS: decay-speed, AMP: amplitude, HT: hold-time, REP: repetition, HH: hand-height. The +/- symbols mean increase/decrease from the neutral values. The ++ means great increase, and it is differentiated from + based on clustering.

waving-speed correlates with decay-speed for both negative and positive conditions (Table 3.4). Participants also mentioned that these two speeds are related and fast waving-speed combined with fast decay-speed gave an "aggressive" feeling to express a negative mood. Besides, almost all participants set waving-speed faster than decay-speed across all mood levels. The finger-rigidness was also found to correlate with both speeds (Table 3.4). Bent fingers usually express a fatigue (low energy) feeling, while straight fingers accord better with fast speed showing high energy.

For the pointing of a negative mood, half the participants combined slow pointing-speed and slow decay-speed to express sadness. Five participants combined fast pointing-speed and fast decay-speed to show anger. Some of them also decreased the hold-time, because short hold-time caused the pointing pose to decay immediately showing impatience, which enhanced the anger expression. Three participants further increased waving-speed and decay-speed and combined with more repetition to show "madness" or "aggressive". In addition, the decay-speed positively correlates with the pointing-speed (Table 3.4). The head-up-down positively correlates to the repetition and two speed parameters, since a lowered head accords with a "sad" mood but not an "angry" mood. The finger was also found to correlate positively with these parameters for matching the energy level. For the pointing of a positive mood, the most frequent combination used by participants is fast pointing-speed and large amplitude, which shows pleasure. When they are combined with a moderate repetition (1 to 3), the pointing looks happier. When they are combined with a high repetition (4 to 5), the pointing shows elation. Besides, the hold-time was found negatively correlated with the repetition (Table 3.4). Participants explained that both repeated pointing and long-hold pointing pose could show emphasis on the target. Using both cues is unnecessary. The pointing-speed positively

Table 3.4: Regressions between Parameter Increments

Waving	***X***	***Y***	***Model***	R^2
Negative	ΔWavingSpeed	ΔDecaySpeed	y=0.663x-0.003	0.409
	ΔDecaySpeed	ΔFingerRigidness	y=1.568x-0.144	0.385
Positive	ΔWavingSpeed	ΔDecaySpeed	y=0.779x-0.010	0.390
Pointing	***X***	***Y***	***Model***	R^2
Negative	ΔPointingSpeed	ΔRepetition	y=4.961x+0.614	0.497
		ΔDecaySpeed	y=0.624x-0.020	0.383
		ΔFingerRigidness	y=0.734x-0.028	0.424
		ΔHeadUpDown	y=8.272x-4.013	0.317
Positive	ΔPointingSpeed	ΔRepetition	y=14.229x-0.341	0.423
	ΔRepetition	ΔHoldTime	y=-0.522x+0.475	0.462

The symbol Δ means the increment from the neutral value.

correlates with the repetition because fast speed accords better with repeated motion.

In sum, the same parameter may function differently for expressing moods when other parameters have changed. These findings provide a general principle for designing bodily expression of mood using parameter modulation: it is more important to modulate a combination of parameters to produce particular affective cues rather than a single parameter. In addition, one function can be established to link the mood variable to these interrelated parameters as a group, while they link to each other internally by functions that describe their interrelations (Table 3.4). In our case, a link can be built between mood variables and the motion-speed, to which other parameters can be linked otherwise. Thus, research can be focused on the mapping from mood variables to multiple parameters as a whole instead of to each individual one.

3.6. CONCLUSION

THIS chapter presents our study on the relative importance of the behavior parameters and their interrelationships in a behavior model used for mood expression. Results indicate that the importance of each parameter is different, and thus it is possible to express moods by modulating only the important parameters. In our case, the parameters of spatial extent (amplitude and hand-height), the vertical position of the head, and the temporal extent (motion-speed) are the most important factors for expressing moods in both behaviors. These parameters are probably important for a variety of behaviors. However, this study covered only two behaviors. More behaviors need to be investigated to validate this point.

This study also shows that some parameters are interrelated and they should be modulated in combination to produce the behavioral cues that express a particular mood. From the perspective of designers, one function can be used to map mood variables to the interrelated parameters as a group. In this way, the robot system can also be simplified.

In the future we plan to conduct a recognition experiment, in which designed behaviors will be evaluated and whether the unimportant parameters can be removed without reducing the recognition rate of moods will be tested. Moreover, the importance suggests how easily moods can be recognized through the modulation of each parameter may be different. This will also be addressed in the recognition experiment. Furthermore, these design principles will be applied to more behaviors and evaluated in real HRI scenarios.

4

Bodily Mood Expression: Recognize Moods from Functional Behaviors of Humanoid Robots

This chapter describes a recognition task that evaluates how people recognize the modulated waving and pointing behaviors generated based on the user-designed parameter settings from Chapter 2. The behaviors are also modulated by adjusting only the "important" parameters or "unimportant" parameters according to the results from Chapter 3. We test the recognition of the behaviors to figure out whether the "important" parameters are sufficient in expressing moods and whether the "unimportant" parameters can still express "weak" moods.

This chapter is based on J. Xu, J. Broekens, K.V. Hindriks, M.A. Neerincx, *Bodily mood expression: Recognize moods from functional behaviors of humanoid robots*, Proceedings of International Conference on Social Robotics (ICSR). pp 511–520, 2013

Abstract

Our goal is to develop bodily mood expression that can be used during the execution of functional behaviors for humanoid social robots. Our model generates such expression by stylizing behaviors through modulating behavior parameters within functional bounds. We have applied this approach to two behaviors, waving and pointing, and obtained parameter settings corresponding to different moods and interrelations between parameters from a design experiment. This chapter reports an evaluation of the parameter settings in a recognition experiment under three conditions: modulating all parameters, only important parameters, and only unimportant parameters. The results show that valence and arousal can be well recognized when the important parameters were modulated. Modulating only the unimportant parameters is promising to express weak moods. Speed parameters, repetition, and head-up-down were found to correlate with arousal, while speed parameters may correlate more with valence than arousal when they are slow.

4

4.1. Introduction

Nonverbal expression of affect, as a key ability of social robots, helps humans to understand robots' internal states (e.g., emotions, moods, beliefs, and intentions) and improves the life-like quality of robots [31]. Besides facial expression, bodily expression is a major communication channel of affect. Experimental studies showed that people can recognize these expressions (e.g., [54], [55], [56], and [57]). Furthermore, bodily expression improved humans' recognition of robots' emotion ([54], [55]). In addition, bodily expression is important for robots that lack facial features (e.g., NAO and ASIMO). One way of constructing bodily expression is to build from scratch by "mimicking" humans' behaviors (static postures and dynamic movements). These bodily expressions are typically designed as explicit behaviors. They usually consist of body actions that express emotions deliberately. For example, raising both hands shows happiness [54]; arms akimbo shows anger [55]; covering eyes by hands shows fear [56]. However, these body actions rise and dissipate quickly and do not extend over time. Thus, we believe that this type of expression is suitable for expressing emotions, but not moods. Moreover, these body actions may interrupt functional behaviors. For example, a robot cannot express excitement while it is pointing to the object or person that makes it excited by raising both hands. Our work aims at integrating bodily expression of mood with functional behaviors, e.g., task execution, communicative gestures, walking, etc. To this end, we parameterized functional behaviors so that modulating parameters can generate affective cues. Hence, moods can be reflected from the same behavior executed in different "styles", rather than the behavior "contents" per se. As a result, mood can be expressed continuously over time, even when robots are executing tasks. Therefore, we believe that this method is suitable for mood expression. Moreover, bodily mood expression may enhance the affective interaction by prolonging it and providing more modalities.

We investigated our behavior model with a humanoid robot NAO, with interests in whether parameter modulation can be effectively applied to a robotic platform for showing mood. In particular, mood is expressed less explicitly through our approach. In addition, we studied high-DOF functional behaviors, allowing us to define more parameters that may enrich the mood expression. We are also interested how behavior parameters

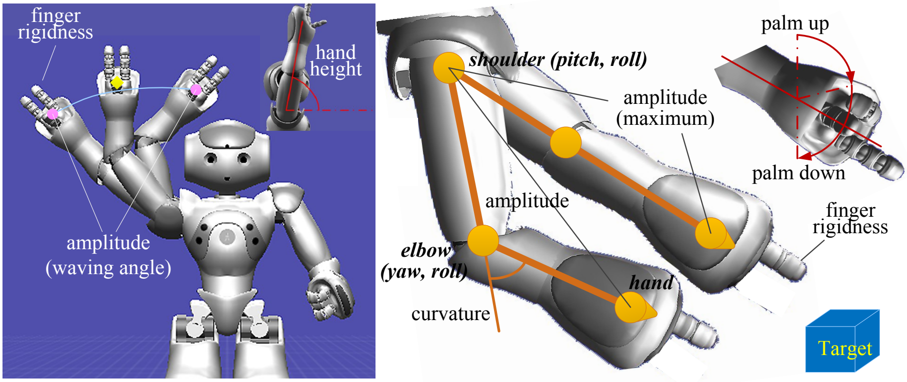


Figure 4.1: The parameterized waving (left) and pointing (right) behaviors: our model contains three pose parameters of the arm shown in the figure, two pose parameters of head (head-vertical and head-horizontal), and four motion parameters containing motion-speed, decay-speed, repetition, and hold-time. More details can be found in [77].

can be combined to show different moods. In previous work [77], our model has been applied to two functional behaviors, waving and pointing (Figure 4.1), and we obtained general design principles about the relations between mood variables and behavior parameter modulation from a design experiment, in which participants were asked to design mood expression according to five levels of valence labeled by very-unhappy, unhappy, neutral, happy, and very-happy. In addition, the relative importance and the interrelations between parameters were investigated [78]. Table 4.1 summarizes the main findings. It is not clear whether people can recognize moods in the presence of behavior functions, since people may devote their attention to behavior functions. This chapter reports the findings of a study on people's recognition of the mood expressions resulted from the design experiment, and whether the conclusions of the design experiment correspond to people's perceptions.

Table 4.1: The design principles and parameter importance

Waving	HandHeight	Finger	Amp	Rep	HoldTime	DecaySpd	MotSpd	HeadVer.	HeadHor.
Relation[1]	+	+	+	+		+	+	+	
Import.[2]	2		5	4			3	1	
Pointing	PalmDir.	Finger	Amp	Rep	HoldTime	DecaySpd	MotSpd	HeadVer.	HeadHor.
Relation[1]	+		+	*	*	+	+	+	
Import.[2]			2				3	1	

[1] */+ *denotes significant correlations with valence; + denotes increase with valence;*
[2] *The number denotes the importance: small - important; unnumbered - unimportant.*

Several studies addressed behavior parameter modulation. Wallbott [65] studied the emotional bodily movements and postures of actors/actresses. His study indicated that the body movement "qualities" can reflect emotions. Laban movement analysis [66] models body movements from different aspects, e.g., effort and shape. Chi *et al.* [69] developed EMOTE framework for synthesizing expressive gestures of virtual agents. An evaluation of effort elements showed that trained observers can recognize the displayed effort at a moderate rate, whereas this study also indicated that prominent effort elements may mask other elements when they are showed in combination. In contrast to EMOTE, which performs as a post process of pre-generated behaviors, Pelachaud [70] modifies gestures before the computing the animation. They characterized behavior expressivity using six parameters: spatial, temporal, fluidity, power, overall activation, and repetition. Their model was applied to an embodied conversational agent for communicating cognitive and affective states through modulated gestures. Evaluation showed that spatial and temporal extents received high recognition rate, but power and fluidity quite low; abrupt and vigorous received high recognition rate but not for sluggish. To achieve a better concord between mood expression and behavior functions, our approach defines behavior parameters while defining the behavior functional profile, so behaviors are also modified first and then the robot joints are computed.

4.2. Experiment Design and Hypotheses

The recognition experiment first evaluated whether participants can differentiate the five valence levels from modulated behaviors of the design experiment [77]. Second, we tested whether people's recognition is different when modulating different parameter (sub)sets according to the relative importance [78]: 1) all parameters (APS); 2) only important parameters (IPS), which are numbered in Table 4.1; and 3) only unimportant parameters (UPS), which are unnumbered. We expect that modulating only the IPS parameters can still express moods without reducing the recognition rate considerably. Although statistical results and participants' ranks showed that the importance of the UPS parameters was low, but participants did modify them during the design. Thus, we suspect that the UPS parameters can express "weak" moods, which are more implicit and less intense, so we tested whether modulating only the UPS parameters can still express moods. Moreover, the behavior naturalness is one of participants' design criteria in the design experiment. Thus, we suspect that modulating all the parameters may result in more natural behaviors than modulating only IPS parameters. Hence, the behavior naturalness was assessed in the recognition experiment. Therefore, our hypotheses are formulated as follows:

- H1. People can distinguish different valence levels from modulated behaviors when all behavior parameters (APS) are modulated. The relationship between parameter settings and perceived valence levels is consistent with the relationship found in the design experiment;
- H2. People can perceive different levels of valence when only important parameters (IPS) are modulated; People can still recognize the valence when only modulating unimportant parameters (UPS), but the recognition rate is worse than the APS and IPS conditions;
- H3. The behaviors generated by modulating all the parameters (APS) are perceived more natural than the ones generated by modulating only the important parameters (IPS).

The test settings (videos can be found at our website[1]) for the recognition experiment is based on the average setting obtained from the design experiment [77]. An

[1] http://ii.tudelft.nl/~junchao/mood_expr_recog.html

average setting may be not the best design due to the inconsistency and unnaturalness caused by mixture of different individual designs [91]. In our case, the diversity on the arousal dimension is averaged out: for the negative valence, most participants designed sadness (low arousal), but a part of participants designed anger (high arousal). Therefore, we corrected the weighted settings in terms of consistency and naturalness within the boundary of the design principles found in the design experiment, and added anger to recover the diversity on the arousal dimension.

Besides, we tested whether people can perceive arousal from the test settings, since the participants of the design experiment did consider the arousal dimension as just mentioned. We also studied whether parameter sets influence the recognition of arousal. Note that the important parameters (IPS) were obtained from the task where participants were asked to design mood expression only according to the valence. The importance may be only or more in regard with the valence. Thus, whether the parameter sets influence the perception of arousal was unclear.

Paired comparison was used to test how well people perceived valence and arousal from behaviors under APS, IPS and UPS conditions (H1, H2). This method provides more precise results in interval scales than a direct scaling, because it transforms the scaling task, which is difficult for humans, to a comparison task [92], [93]. Participants were asked to compare (not paired comparison) the naturalness of generated behaviors corresponding to each mood under the IPS and APS conditions respectively (H3). The notions of valence and arousal were explained to participants before the experiment using categorical emotion labels and SAM manikins. Naturalness was explained mainly in terms of natural interaction. Participants were provided a user interface for inputting answers and proceeding with the experiment. Two grey NAO robots were used to perform behaviors modified by two moods simultaneously to reduce participants' cognitive workload. Waving and pointing were arranged in a counter-balanced order. For each behavior, the six moods were presented in pairs in a random order, and they were presented under APS, IPS, and UPS conditions successively. 26 participants (13 females and 13 males) were recruited from Delft University of Technology. The participants' ages ranged from 21 to 35 years ($M = 28.6$, $SD = 3.3$). 13 participants are Chinese, and the other 13 are not. All the participants signed the informed consent form. A pre-experiment questionnaire confirmed that the participants had little experience of designing robots or animated characters. Each participant received a gift as compensation for their time.

4.3. Analysis and Result

The method based on Thurstone model from [93] was used to analyze the paired comparison data. To see how well participants recognized the moods under the APS, IPS, and UPS conditions, only the mood factor was input into the analysis. For convenience, all results are combined and illustrated in Figure 4.2. Assuming that valence and arousal are orthogonal [94], the tested moods are denoted in the valence-arousal space (Figure 4.2). First, we interpret the recognition of valence from the five settings derived from the design experiment; second, we interpret the recognition of arousal; finally, we interpret the additional mood anger.

To analyze the recognition of valence (H1), we first looked at the results under APS condition (Figure 4.2a, b). Regardless of anger (interpreted later), for both behaviors the

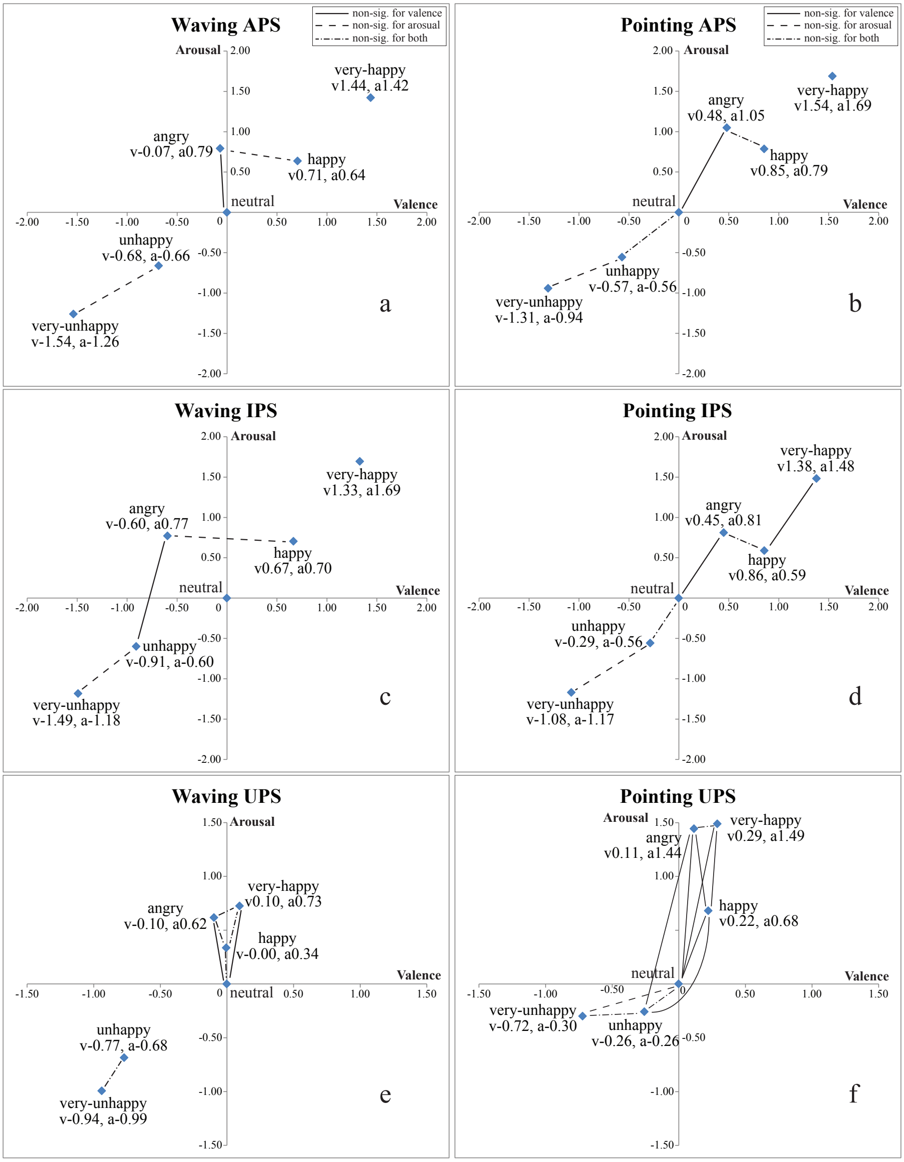


Figure 4.2: The figure shows the position of each perceived mood in the valence-arousal space under the APS, IPS and UPS conditions for the waving and pointing behaviors. The valence or arousal of unconnected moods was significantly differentiated, while for the connected ones either valence or arousal or both was not significantly differentiated.

valence of each pair of moods was significantly differentiated by participants except for unhappy and neutral pointing. This result shows that people can recognize the valence from the behavioral cues in general (H1). Pearson correlations between parameter values and the perceived valence scales (Figure 4.2a, b) were computed. The results (Table 4.2) show that the relationship between parameters and perceived valence is generally consistent (H1) with the findings of the design experiment (Table 4.1).

Table 4.2: The correlation (Pearson r) between parameters and valence or arousal

Waving	HandHeight	Finger	Amp	Rep	HoldTime	Decay	MotSpd	HeadVer.	HeadHor.
Valence	0.889	0.936	0.966	0.858		0.848	0.848	0.95	
Arousal				0.653	-0.976	0.977	0.977	0.797	
Pointing	PalmDir.	Finger	Amp	Rep	HoldTime	Decay	MotSpd	HeadVer.	HeadHor.
Valence	0.507		0.914	0.81	0.315	0.927	0.927	0.984	
Arousal				0.923		0.978	0.978	0.924	

Secondly, we interpret how participants' recognition under the IPS and UPS conditions differs from the APS condition (H2). To this end, we added the parameter set condition as a factor [93] to the paired comparison analysis. The overall result (Table 4.3) affirms that the parameter set condition influenced participants' perception significantly for both behaviors with regard to valence. In addition, we compared the parameter set conditions in pairs using the same method above. For both behaviors, there are no significant differences between the parameter set APS and IPS (Table 4.3), which suggests that modulating only the important parameters is capable of expressing valence almost equally well as modulating all the parameters. The generated scale of valence under IPS condition is similar with the APS condition (Figure 4.2c, d). The only difference is that the happy and very-happy pointing were differentiated under the APS condition but not for the IPS condition. Possible reason is that repetition increased for very-happy under the APS condition, but not for the IPS condition, since repetition was rated unimportant in previous study. Further study is needed to address whether repetition is important to valence in different situations.

Table 4.3: Significant differences of recognition between parameter set conditions

		Overall	APS vs. IPS	APS vs. UPS	IPS vs. UPS
Waving	Valence	$p < 0.001$***	$p = 0.205$	$p < 0.001$***	$p < 0.001$***
	Arousal	$p < 0.010$*	$p = 0.931$	$p = 0.026$*	$p = 0.001$**
Pointing	Valence	$p < 0.001$***	$p = 0.671$	$p < 0.001$***	$p < 0.001$***
	Arousal	$p = 0.006$**	$p = 0.879$	$p = 0.011$*	$p = 0.001$**

**p<0.05, **p<0.01, ***p<0.001*

The recognition of valence under APS and IPS conditions is significantly better than UPS condition (Table 4.3). The high-arousal moods (anger, happy, and very-happy) and neutral were less successfully differentiated by participants for waving (Figure 4.2e). Similar results were obtained for pointing (Figure 4.2f). Besides, the unhappy and neutral pointing were not significantly differentiated. This suggests that none of the UPS parameters is sufficient to present the valence of high-arousal moods. However, as we

4

hypothesized, some moods can still be recognized even without modulating important parameters. The valence of unhappy and very-unhappy waving was significantly differentiated from waving of neutral and high-arousal moods (Figure 4.2e). The long hold-time, slow decay-speed, head turning away from both hand and the front distinguished the unhappy and very-unhappy. We exclude finger since few participants mentioned it in the post-questionnaire. For pointing, the valence of very-unhappy was significantly differentiated from other moods except unhappy. Thus, we conclude that the UPS parameters are promising for "weak" mood expressions for at least two valence levels: positive and negative.

Results also show that participants recognized arousal levels from behaviors. Under APS (Figure 4.2a, b) and IPS conditions (Figure 4.2c, d), the arousal of high-arousal moods and neutral was significantly differentiated for both behaviors, regardless of anger (integrated later). The arousal of low-arousal moods (unhappy and very-unhappy) was significantly differentiated from high-arousal moods and neutral for waving, whereas only very-unhappy was significantly differentiated form high-arousal moods and neutral for pointing. Statistically, there are no significant differences of perceived arousal between the APS and IPS conditions for both behaviors (Table 4.3), which suggests that the IPS parameters are capable to express arousal equally well as the APS parameters. However, the perceived arousal under UPS condition differs significantly from either the APS or IPS condition (Table 4.3). For waving (Figure 4.2e), the arousal of very-happy and anger significantly differentiated from neutral, whereas other high-arousal moods were not. Possible reasons are that the zero hold-time and fast decay-speed of angry and very-happy waving made the overall movement fast and fluent, resulting in the perception of a high arousal. The arousal of high-arousal moods was better recognized for the pointing behavior than waving behavior. For pointing (Figure 4.2f), the arousal of all high-arousal moods was significantly differentiated from neutral, and very-happy was differentiated from happy. Fast decay-speed and high repetition may account for this. This suggests that the decay-speed and repetition correlate more with arousal than valence. They were actually considered unimportant to valence.

The arousal of unhappy and very-unhappy waving was significantly differentiated from other moods (Figure 4.2e), but unhappy and very-unhappy were not differentiated from each other. For pointing, the arousal of neither unhappy nor very-unhappy was significantly differentiated from neutral (Figure 4.2f). In fact, the arousal between unhappy and very-unhappy was not significantly differentiated for both behaviors under all conditions, but their valence was significantly differentiated under APS and IPS conditions. The arousal-correlated parameters (e.g., speed, repetition) seem not able to render arousal for low-arousal moods. Back to the UPS condition (Figure 4.2e, f), we found that the very slow decay-speed distinguished the valence of very-unhappy from neutral. It seems that the speed parameter like decay-speed may correlate more with valence when it is slow, whereas correlates more with arousal when it is fast.

The recognition of angry waving showed the promise of expressing anger through parameter modulation. The valence of anger was perceived as negative for all conditions (Figure 4.2a, c, e), although it was not significantly differentiated from neutral under APS and UPS conditions. Surprisingly, the valence was better differentiated from neutral under the IPS condition (Figure 4.2c). We considered that the longer hold-time under IPS condition caused the movement jerkier resulting in a more negative perception, whereas the zero hold-time and the faster decay-speed under APS condition made the movement smoother resulting in a relative more positive perception. Furthermore, the head turned away from the moving hand in the APS condition, which made the robot seem to avoid the eye-contact resulting in a feeling of fear, while fear has a more positive valence than anger [94]. The valence of anger was recognized better for waving than pointing, since it was recognized as positive for pointing under all conditions. Perhaps, the presence of arousal (by large amplitude, repeated movements, and fast speed) in angry pointing was dominant and masked the expression of negative valence, which led people to consider the mood as excitement.

As discussed before, the arousal of anger was recognized significantly higher than neutral and low-arousal moods for both behaviors under all conditions. Interestingly, the perceived arousal of angry pointing and waving under UPS condition was as high as very-happy (Figure 4.2e, f), whereas in other conditions it is significantly lower than very-happy. Possible reason is that most parameters were set to the same value between these two moods under the UPS condition. However, the only element that made the arousal of the very-happy pointing under APS and IPS conditions higher than angry pointing is the high-raised head. This suggests that head-up-down correlates with arousal. According to the above discussion, we summarize the parameters that correlate with arousal in Table 4.2, where Pearson correlation was computed between parameter values and the perceived arousal scale.

Binomial tests were used to analyze whether behaviors under the APS condition was perceived more natural than the IPS condition (H3). Participants' choices between the APS and IPS conditions are not significantly above chance level for each mood and behavior. Thus, our study did not show that modulating UPS parameters improves the behavior naturalness. We also tested the effect of gender and culture (Chinese and Non-Chinese) by adding them as a factor into paired comparison analysis separately. The results do not show any significant differences between gender and culture conditions.

4.4. DISCUSSION

THE modulation of the important parameters expresses moods better than unimportant parameters. Most important parameters like hand-height, amplitude, motion-speed, and repetition are "global" parameters, which influence the overall movement. Changing these parameters will alter the movement appearance noticeably. Head position also has strong effect on affect expression [57], probably because the head is a special body part that people usually pay attention to during interaction. The unimportant parameters are "local" parameters that influence only a small region of the body parts (e.g., finger-rigidness, palm-up-down) or a short period (e.g., hold-time and decay-speed are temporally local) of the whole movement. Thus, they may not produce sufficient affective cues or people may not even notice them. Hence, behaviors with more "global" parameters may be more affectively versatile, For example, waving has higher expressivity than pointing. In fact, moods were recognized better through waving than pointing in general.

Interactions may exist between valence and arousal. According to Table 4.1 and Table 4.2, parameters like motion-speed, head-up-down and repetition of waving were found to correlate with both valence and arousal. In addition, a 5-point Likert scale (from 1: "extremely disagree" to 5: "extremely agree") post-experiment questionnaire suggests that the participants generally agreed on that valence and arousal are related. The mean rating is 3.85 (*SD*=0.88). Several studies also reported that valence and arousal are not orthogonal [95]. The interaction between valence and arousal should be taken into account when we design mood expressions.

Our model is possible to be generalized to other behaviors in terms of the relations between behavior parameters and mood variables. As in our model parameters are defined at the stage of constructing behavior functional profiles, parameters are dependent on behavior functions. Thus, the same parameters may have different meanings for different behaviors. Despite the differences, design principles may still hold. For example, although the amplitude is the swing angle for waving but the arm extension for pointing, larger amplitude corresponds with a positive mood for both behaviors. However, design principles may also be different for the same parameters. For example, the hold-time means smoothness for waving but persistence for pointing. Hence, shorter hold-time (smoother movement) corresponds with a positive mood for waving, whereas longer hold-time (more persistent) of pointing generally expresses a positive mood. We suggest designers pay attention to the meaning of a parameter for specific behaviors when modulating the parameter to express mood.

4.5. Conclusion and Future Work

This chapter presents a study on people's recognition of humanoid robots' bodily mood expression through behavior parameter modulation. The results indicated that five valence levels can be expressed through parameter modulation for the two behaviors studied. Arousal can also be expressed with at least four levels. The important parameters that influence the behavior overall have a major effect on both valence and arousal. The unimportant parameters can express "weak" moods for at least two levels of valence and three levels of arousal for both behaviors, but no effect on naturalness of these parameters was observed. The speed parameters, repetition, and head-up-down were found to correlate with arousal. Speed parameters are capable to render arousal when they are fast, but not when they are slow. In the future, we will improve the angry pointing and study the relation between the pointing direction and mood expression. While mood expressions via parameter modulation can be recognized in an experimental setting, whether people can recognize them correctly, even notice, in real HRI scenarios still remains a question. We will apply the design principles into more behaviors used in HRI and address the question in the future.

5

Mood Contagion of Robot Body Language in Human Robot Interaction

This chapter demonstrates our first attempt of applying the parameterized behavior model to HRI scenarios. The interaction scenario is dyadic – a game between a user and a humanoid robot. The game gestures of the humanoid robot were modulated to show mood during the game. This study showed that users can recognize the expressed mood in an interaction task without priming. This study also showed the effects of the robot mood expression on users' affective states and game performance.

This chapter is based on J. Xu, J. Broekens, K.V. Hindriks, M.A. Neerincx, *Mood Contagion of Robot Body Language in Human Robot Interaction*, Journal of Autonomous Agents and Multi-Agent Systems, 29(6), pp 1216–1248, 2015.

ABSTRACT

The aim of our work is to design bodily mood expressions of humanoid robots for interactive settings that can be recognized by users and have (positive) effects on people who interact with the robots. To this end, we develop a parameterized behavior model for humanoid robots to express mood through body language. Different settings of the parameters, which control the spatial extent and motion dynamics of a behavior, result in different behavior appearances expressing different moods.

In this study, we applied the behavior model to the gestures of the imitation game performed by the NAO robot to display either a positive or a negative mood. We address the question whether robot mood displayed simultaneously with the execution of functional behaviors in a task can (a) be recognized by participants and (b) produce contagion effects. Mood contagion is an automatic mechanism that induces a congruent mood state by means of the observation of another person's emotional expression. In addition, we varied task difficulty to investigate how the task load mediates the effects.

Our results show that participants are able to differentiate between positive and negative robot mood and they are able to recognize the behavioral cues (the parameters) we manipulated. Moreover, self-reported mood matches the mood expressed by the robot in the easy task condition. Additional evidence for mood contagion is provided by the fact that we were able to replicate an expected effect of negative mood on task performance: in the negative mood condition participants performed better on difficult tasks than in the positive mood condition, even though participants' self-reported mood did not match that of the robot.

Keywords Human Robot Interaction (HRI), Mood Expression, Nonverbal Cues, Behavioral Cues, Body Language, Social Robots.

5.1. INTRODUCTION

IN human-robot interaction (HRI), expressions of a robot facilitate human understanding of the robot's behavior, affects (e.g., emotions and moods), rationale, and motives, and is known to increase the perception of a robot as trustworthy, reliable, and life-like [32]. To participate in affective interaction, robots must be able to communicate their affective state to others [31]. Among the many ways of showing affect, such as speech, voice, facial expressions, bodily expressions, color, and lights, we are interested in bodily expressions of humanoid robots. Studies showed that a considerable portion of communication in human-human interaction is through body language [50]. People have sophisticated skills at interpreting meanings from body cues. Expressing robot affect through the body enables people to use those skills to better understand robots. Moreover, a study showed that bodily expressions in addition to facial expressions improved the recognition of affect [53]. Making the robot body expressive thus may improve people's understanding of robot affect. Physically, the body is also a large part of many humanoid robots, and many robot behaviors involve the body. The body is a particularly important way for humanoid robots that lack facial features to express affect nonverbally, such as the NAO, ASIMO, and QRIO.

This study aims to investigate how a social robot expresses affect through body language during task executing in the context of a dyadic human robot interaction. More specifically, we would like to figure out how robot affect can be shown through body language while the robot is performing body actions required by the interaction at the same time. Our motivation stemmed from a game between a humanoid robot and a child. In this game, the robot performs gesture sequences and the child imitates the sequences. This imitation game has been developed to foster the relationship between a personal robot assistant and children with diabetes [96]. For the better part of the interaction, the robot is performing gestures (details see Section 5.4.2), and children pay attention mainly to the gestures.

Before introducing our work, we first briefly discuss the concepts of affect, emotion, and mood. Affect is an umbrella term in psychology that refers to the experience of feelings, emotions, or moods. Our work focuses on mood. Distinctions between affect, emotion, and mood are explained in [34], [35], [36], [37], [38]. Here, we highlight the distinctions between mood and emotion that are related to expression: emotion is a short-term, intense affective state, associated with specific expressive behaviors; mood is a long-term, diffuse affective state, without such specific behaviors. Mood emphasizes a stable affective context, while emotion emphasizes affective responses to events.

Expressing affect through ongoing functional behavior as opposed to expressing affect with explicit categorical expressions is relevant for the following reasons. First, expressions based on explicit body actions show affect for a brief period of time and interrupt functional behavior. For example, raising arms akimbo to display anger [55]; covering eyes by the robot's hands to display fear [56]; and raising both hands can be used to display the emotion of happiness [54]. Although clearly recognizable, such explicit gestures cannot be used when a robot is, e.g., carrying a box that requires the use of both arms and hands. To express affect through ongoing functional behavior the expression needs to be integrated into the robot behavior in a more or less continuous fashion, which is quite different. In this chapter, we used the imitation game as an interaction scenario and studied the use of body language for expressing mood. We extend previous work reported in [77], [78], [79] on a parameterized behavior model for expressing mood. The model is adapted here to enable the continuous display of mood through game gestures (see Section 5.4 for more details).

Second, affect expression that is integrated with the functional behaviors of robots provides a way of expressing mood. Bodily expression of emotion has been extensively studied, while bodily mood expression yet needs to be explored. Compared to emotion, which is a short-term and intense affective state, mood is a more long-lasting and less intense affective state. An individual is at any given time in a more or less positive or negative mood. Integrating mood into the body language of a robot therefore may provide a robot with an alternative, more stable but less specific, affective communication channel. This may also contribute to the believability, reliability, and lifelike quality of a robot, since robots are enabled to show another form of affect, mood, and with mood expression robots can show affect more often and continuously over time.

Our research questions in this study are whether (1) people, while interacting with a robot, can recognize mood from positively versus negatively modulated robot behaviors and, (2) how this influences a person's own affective state and interaction behavior. For example, it is well known that mood can transfer between persons and has specific effects on behavior [97] and it is useful to gain insights into the effects and possible transfer of mood from a robot to an individual.

The remainder of this chapter is organized as follows. Section 5.2 discusses related work. In Section 5.3 we elaborate the parameterized behavior model for mood expression and the modulation principles, and we explain the rationale behind our claim that the expression by means of behavior modulation is suitable for expressing mood. We also briefly describe the evaluation of the model in a recognition task. We describe the interactive game we used in our study and the integration of the behavior model into the game gestures are introduced in Section 5.4. Importantly, we demonstrate the motivation of our investigation of using the bodily mood expression in an interaction scenario. In Section 5.5, we formulate our main research questions and hypotheses. Section 5.6 discusses the experimental setup and Section 5.7 presents the results. We discuss these results in Section 5.8. Finally, the chapter is concluded and the future work is discussed in Section 5.9. In addition, we provide examples of how to construct parameterized behaviors computationally in Appendix A.

5.2. Related work

The affective states of a robot or a virtual agent can be expressed nonverbally by poses and movements of facial and body components. Facial expressions have been used in embodiments such as Kismet [24], iCat [98], Greta [70], and Max [99], while bodily expression has been used for ROMAN [55], NAO [56], [57], KOBIAN [54], Greta [70], and Max [99]. In these studies, it has been experimentally demonstrated that people generally are capable of recognizing the affective states that are expressed. Furthermore, [55], [54] showed that bodily expression combined with facial expression may significantly enhance the recognition of a robot's emotion expression.

Bodily expression can be generated by directly simulating human static postures and movements as done in, e.g., [54], [57]. A more generic approach for generating expressive behaviors, however, is to modify the appearance of a behavior via the modulation of parameters associated with that behavior. Wallbott [65] investigated whether body movements, body posture, gestures, or the quantity and quality of movement in general allow us to differentiate between emotions. This study found that qualities of movement (movement activity, spatial extension, and movement dynamics) and other features of body motion can indicate both the quality of an emotion as well as its quantity. Laban movement analysis (LMA) [66] models body movements using four major components: body, space, effort, and shape, characterized by a broad range of parameters. Based on LMA, Chi et al. [69] developed the EMOTE framework that uses post-processing of pregenerated behaviors to generate expressive gestures for virtual agents. The model developed by Pelachaud et al. [70] modifies gestures before generating actual movements. This model distinguishes spatial, temporal, fluidity, power, overall activation, and repetition aspects of behavior. It has been applied to the Greta virtual agent [71] and the NAO robot [72] for communicating intentions and emotions. These methods can be applied to functional behaviors in order to express affect of a robot while it is performing a task. In our model, behavior parameters are defined when the behavior profile is synthesized. One advantage of doing so is that we can model the physical constraints of the robot body at the same time. The ranges of behavior parameters are determined when the parameters are defined to make sure that modulation will not cause collision with other parts of the robot body. Another approach is to use the body resources that are not required by functional behaviors to express affect (e.g., [76]). In our model, when head movement is not part of the functional behaviors, head movement can be used for expressing mood if needed.

Affect expression of robots has many positive impacts on human-robot interactions including the following aspects: the way of interacting with a robot, the attitude towards a robot, the effectiveness of assistive tasks. A long-term field study showed that facial expression of robot mood influenced the way and the time that people interact with a robot [42]. Emotional behaviors made elderly participants perceive a robot as more empathic during their conversation [4]. Emotional gestures improved participants' perception of expressivity of a NAO robot during a story-telling scenario [43]. In an application of a robot companion that is capable to play chess with children [48], robot emotion expression that varied with the state of the game was used to help children better understand the game state. A preliminary evaluation also suggested that the emotional behavior of the robot improved children's perception of the game. In another study [44], this robot responded empathically to children's affective states. Results suggest that the robot's empathic behaviors enhance children's attitude towards the robot. Adaptive multimodal expression was studied with children using a quiz game [45]. Expressive behaviors were selected based on events in the environment and internal parameters. The study showed positive effects of the adaptive expression on children and the children's preference for bodily expression. In a personal assistant application for children [46], robot emotion expression was shown to improve the effectiveness of the robot when used as companion, educator, and motivator. Robots equipped with minimally expressive abilities were developed to help children with autism with their social abilities [47]. Facial and bodily expressions of the robot were used to help children learn to recognize these expressions and use their own expressions by imitating the expressions of the robot. These robot expressions were found to attract children, improve and maintain engagement of the interaction, and evoke emotional responses [7].

Affect expression also influences users that interact with virtual agents (see [100] for a review). The review focused on the effects of affective expression of virtual agents on users' perception/attitude towards the agent (e.g., likeability, trustworthiness, and warmth), users' behavior (e.g., attention, concentration, motivation), and users' task performance in the interaction. Most studies suggested that people perceived agents as more positive when they display emotions. More importantly, we would like to highlight the studies that suggested effects on users' (affective) states and performance, since they are closely related to our study. Several studies showed that affective agents were able to reduce negative affective states of users. Prendinger et al. [101] investigated the effect of a virtual agent with affective behavior on a user in a mathematical game scenario. Participants who interacted with the agent displaying empathy were significantly less stressed according to physiological measurement. A similar effect was also found in a virtual job interview scenario. Klein et al. [102] and Hone [103] reported that an interactive affect support agent was able to alleviate frustration in games that were designed to frustrate players on purpose. Hone found that an embodied agent was more effective in reducing frustration and a female embodied agent was more effective than a male. Similar results were obtained in Burleson and Picard's study [104]: agents with affective support was reported to reduce participants' feeling of frustration in a learning context, and this affective intervention was found to be more effective in girls.

Several studies also reported effects of affective virtual agents on performance. In Klein's study [102], participants who interacted with the affective support agent played the game significantly longer. Maldonado et al. [105] found that participants who interacted with the emotional agent performed better in a test in a language learning context. Berry et al. [106] studied the effects of the consistency between emotion expressions and persuasive messages about healthy diet using the GRETA agent. Results showed that GRETA with consistent emotion expression resulted in better performance of memory recall. Emotion expression was reported to have effects on users' affective states and behaviors. Tsai et al. [107] found that happy expressions of both still images and virtual agents can induce an increase of users' happiness. Interestingly, when cognitive load is increased by decision-making, this emotion induction is dampened. Okonkwo and Vassileva [108] found that the agents with facial expressions improved concentration and motivation in subjects. In Gong's study [109], a talking head agent presented happy and sad novels with either a happy or a sad facial and vocal expression. Results showed that the happy agent elicited greater intent to buy the books and more positive evaluation of the novel books and the book reviews. All these studies suggested that affective expressions of virtual agents have effects on the users during interaction. Our study investigated whether affective expressions of robots have similar effects on users. In particular, [107] also looked at the mediating effects of task load. We also studied the effect of task load by varying game difficulty.

In previous work, a parameterized behavior model for expressing mood using body language while performing (functional) behaviors was proposed [77]. We have adapted this parameterized behavior model for this work. The model is based on a set of generic parameters that are associated with specific body parts and that are inherently part of related body movements. These parameters subsequently are modulated in order to express various moods. This model allows us to integrate mood into functional behaviors in a manner that does not interfere with the functions of these behaviors. The model was validated by evaluating whether users could recognize robot mood in a recognition experiment. The results obtained showed that participants who were asked to rate valence and arousal were able to differentiate between five valence levels and at least four levels of arousal [79].

In this chapter, we ask the question whether a robot's mood can be transferred from robot to human. Some evidence that supports this has been found by Tsai et al. [107] who showed that even still images of virtual characters can induce mood. Their study also revealed an interaction effect between cognitive load and contagion in a strategic game: the contagion effect was reduced by the mobilization of more cognitive resources required for the decision-making task. The application of robot bodily expression in an HRI scenario and its effects on the interaction, however, are still largely unexplored. To investigate these effects, in the study reported in this chapter bodily mood expression has been used that can be displayed simultaneously with functional behaviors. In particular, we address the question whether these body expressions can produce a well-known psychological effect – emotional contagion (in our case robot mood transferred

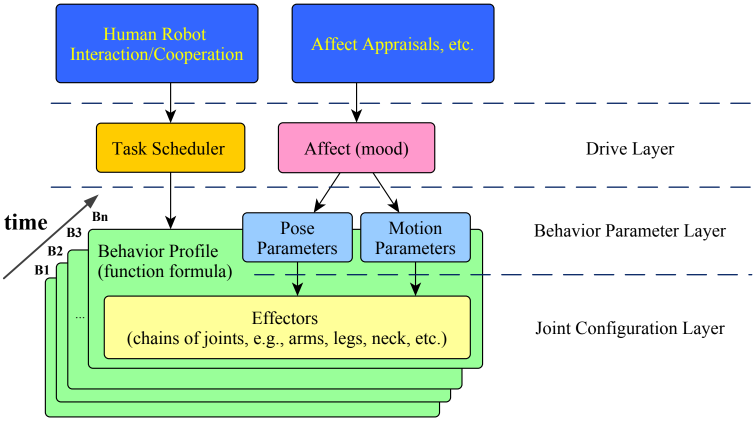


Figure 5.1: General Parameterized Behavior Model

to humans) – during human robot interaction.

5.3. PARAMETERIZED BEHAVIOR MODEL FOR MOOD EXPRESSION

5.3.1. MODEL CONCEPT

To enable a robot to express a long-lasting affective state during task execution, a mood, we applied a previously developed model for integrating affect expression with functional behaviors (e.g., task behaviors, communicative gestures, and walking). In this model, behaviors are parameterized (see Figure 5.1), and by varying behavior parameters different moods can be expressed. The set of parameters is generic and can be used to modulate behavior parameters of arbitrary behaviors. Example parameters include the speed of movement and the amplitude of a movement. A parameter may also be associated with a particular body part of the robot (e.g., head, hand palm, and finger). For a specific behavior, one only needs to specify which parameters should be varied to express mood while performing that behavior. Moreover, by varying these parameters the "style" of executing a particular functional behavior can be modified without changing the particular function of that behavior. Different styles thus can be used to express a range of affective states. This way, affect can be displayed throughout a series of behaviors.

The parameterized behavior model (Figure 5.1) consists of three layers: 1) a drive layer; 2) a behavior parameter layer; and 3) a joint configuration layer. The drive layer contains the task scheduler (the task part) and the affect generator (the affect part). Robot affect state can be determined by, for instance, appraisal models, while the affect state controls the parameters. The task scheduler decides which behavior should be performed at each moment according to the task requirements. From the top layer, task scheduler and affect generator work simultaneously and independently (without interfering with each other).

5.3.2. Mathematical representation of pose modulation

This section focuses on the modulation of behavior poses. The modulation of motion dynamics is straightforward, so is not included in this chapter but details can be found in [77]. A behavior in this study is defined as a sequence of movements of effectors transiting from one pose to another. A *behavior profile* describes the *behavior function* that conforms to social conventions or fulfils certain physical operations of objects. For example, we define the profile of the waving behavior as one hand swinging between two horizontally aligned positions repeatedly, where the palm should always face forward. Taking pointing behavior as another example, we define pointing as the arm stretching out from the preparation pose to the pointing pose. Put differently, a behavior profile defines the set of poses in a behavior and the order of transitions between poses. Note that a pose of a behavior is not fixed but can vary within a certain range. The following equation depicts the set of poses in one behavior, while the transitions between poses form the movement.

$$Behavior = (\Sigma, \{Pose_1, Pose_2, \ldots, Pose_k\}) \tag{5.1}$$

5

Σ defines the order of the poses in the movement. A *pose* is a set of joint variables of an effector.

$$Pose_i = \{j_i^1, j_i^2, \ldots, j_i^n\} \tag{5.2}$$

i=1,2,...,k; j denotes a joint; the *i-th* pose contains n joints. The poses that correspond to a particular behavior must meet certain conditions that represent the behavior function. Put differently, some of the joints should meet the requirements specified by a certain formula for each pose. We use B to denote, for example, a linear function that represents the behavior function. Hence, $\exists\{j_i^m\} \subset Pose_i, m \le n$, *s.t.*

$$B(j_i^m) = 0 \qquad OR \qquad B(j_i^m) > 0 \qquad OR \qquad B(j_i^m) < 0 \tag{5.3}$$

The solution (the value of the joint variable j_i^m) to the above equations or inequations is usually not unique. This allows for the use of pose parameters to vary the control a part of the joints $j_i^r \in \{j_i^m\}$, while at the same time making sure that these joint variables still meet the required equations. Note that we also use pose parameters to control the joints ($j_i^{ur} \in Pose_i, j_i^{ur} \not\in \{j_i^m\}$) that are not related to behavior functions. We use M to denote modulation formulas that represent the relations between pose parameters p_t to joints.

$$j_i^r = M_i^r(p_t) \qquad OR \qquad j_i^{ur} = M_i^{ur}(p_t) \tag{5.4}$$

As a result, different behavior patterns can be achieved without violating the behavior function. An example can be found in Appendix A.

5.3.3. Modulation principles

To evaluate the feasibility of the mood expression model, we initially applied the model to two typical behaviors in HRI, waving and pointing, and we defined parameters for the two behaviors based on the findings about human behaviors from literatures. Our aim was to figure out what parameters can be modulated to express mood and how to modulate them to express different moods. Instead of applying the modulation principles from the literature directly to the robot behaviors, we decided to conduct a user study [77] to collect data from users. Participants were asked to set a value for each parameter of the robot behaviors to match a given mood (i.e., a given valence level). A graphic user interface was designed for participants to set the parameter value and play the behavior on a real robot.

One advantage of doing so is that we can obtain opinions from more general end-users of the robot in the daily life about how the behaviors should be like for expressing a specific mood. Put differently, how users think the parameters should be modulated to express a mood. We also expected the user-designed expressions to result in higher recognition rate. Although expert designers (actors/actresses or researchers on human behavior modeling) used in some studies (e.g., [54]) can produce more versatile expressions, sometimes the expressions are not interpreted as intended by normal people. The reason might be that normal people do not have the same expertise of recognizing behavioral affective cues as the experts do. Moreover, in this way we can test whether robot mood can be expressed by parameter modulation. More details about the user study setting can be found in [77].

Results showed that participants created different parameter settings corresponding to different valence levels. This supported that it is feasible to use behavior parameter modulation to express mood. We also found that the spatial extent parameters (hand-height and amplitude), the head vertical position, and the temporal parameter (motion-speed) are the most important parameters. These parameters are "global" features that shape the overall quality of behaviors. Moreover, multiple parameters were found to be interrelated. Modulating these parameters in combination provides particular affective cues. More details of the analysis and discussion about the relations between parameters can be found in [78].

5.3.4. BODILY MOOD EXPRESSION

We consider that the expression by means of behavior parameter modulation is particularly suitable for expressing mood. First, the expression extends over time, since it can be used even when a robot is performing tasks. It is suitable to express a long-term affect. Second, an expression does not show a particular action tendency. Behaviors are triggered by the task scheduler, but not the affect. The affect only influences the "styles" of the behaviors. Third, the expression relies on the behavior cues that result from behavior modulation. Compared to the meaning or functions of the behavior, we believe that the affect in the behavior is more implicit and less intense. Mood is also a less intense affective state, compared to emotion. Therefore, we believe that our way of expressing affect is suitable for expressing mood.

5.3.5. EXPRESSING MOOD WITHOUT A CONTEXT

To validate the modulation principles obtained from the user study [77], we first conducted a recognition experiment in a laboratory setting using mood expression resulting from the user study. This is a pure perceptual task without an interaction context. We adopted a paired comparison approach: five mood levels were presented to participants in pairs. Participants were asked to compare which of the two robot behaviors has higher valence and arousal. Paired comparison gave us more accurate results of

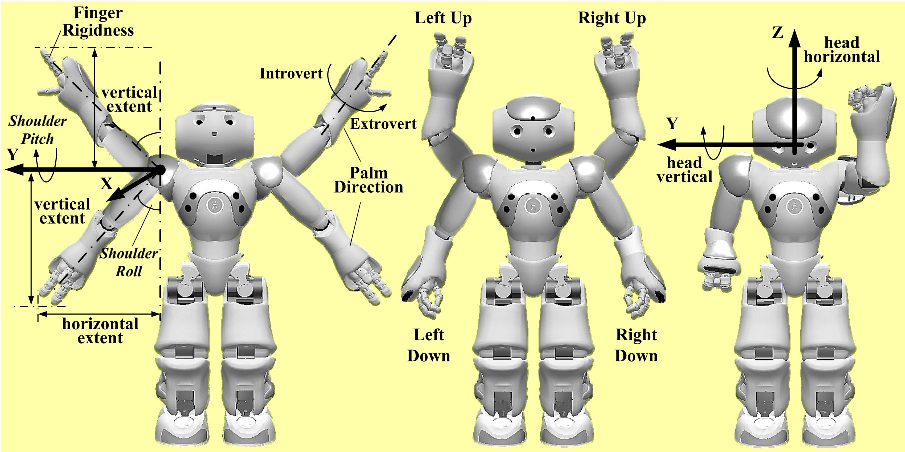


Figure 5.2: Modulated gestures for the imitation game: figure (a) shows the four elementary gestures modulated for a positive mood; figure (b) shows the four mirrored elementary gestures for a neutral mood; figure (c) shows the slope-right gesture modulated for a negative mood. Pose parameters (amplitude-vertical, amplitude-horizontal, palm-direction, and finger-rigidness) are annotated on the figure.

5

whether participants can distinguish these mood levels, especially the adjacent levels. We tested the recognition under three conditions: modulating all parameters, only important parameters, and only unimportant parameters, as the user study suggested that the contribution of each parameter to the mood expression is different [78]. Although in our model mood is characterized using valence, we also tested whether the perceived arousal also changed with the valence. The results showed that valence and arousal can be well recognized as long as the important parameters are modulated. Modulating only the unimportant parameters might be useful to express weak moods. We also found that speed parameters, repetition, and head-up-down correlate with arousal. Thus, the modulated behaviors do not only display the valence of the robot mood but also the arousal. More details about the recognition experiment can be found in [79].

5.4. EXPRESSING MOOD IN AN INTERACTION CONTEXT

THE main contribution of this work is that we investigated mood expression in the context of an actual HRI interaction task. We now describe the task, the gestures used, and the rational for our hypotheses.

5.4.1. IMITATION GAME

The interaction scenario we used in this study is an imitation game, in which the humanoid robot NAO performs a sequence of gestures that are shown to a human player who is asked to imitate the gestures in the same order. Eight gestures were used to form the sequences in the game; single left arm pointing to left of robot in upward direction, left arm pointing left and downward, right arm pointing right and upward, and right arm pointing right and downward (see Figure 5.2b). The left and right arm movements were also performed at the same time, resulting in four more gestures: both up, both down,

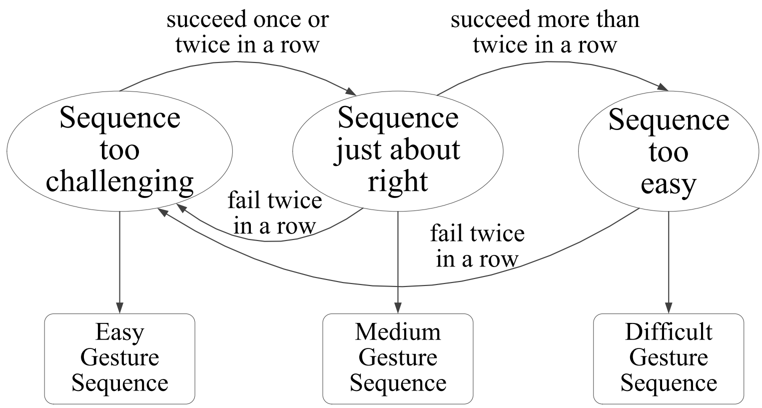


Figure 5.3: Item selection strategy of the imitation game

slope left (left up right down), and slope right (right up left down). The left and right were mirrored between participants and the robot. For example, when the robot performs a left-arm gesture, the participant should perform a right-arm gesture with the same up or down direction.

The classification of participants' gestures into one of the eight types of gestures was done by one of the experimenters. Using this input, the robot system evaluated whether the participant's gestures correctly replicated its own gestures in the right order and provided feedback by means of speech. The feedback text was selected randomly from a predefined list of sentences, e.g., "Yes, those were the right gestures" for a correct imitation, or "No, those were not the right moves" for an incorrect imitation.

To make the game more entertaining and keep the human player engaged, the system adaptively changes the difficulty of the gestures to be imitated according to the estimated level of the participant. Each gesture has an associated difficulty rating that has been defined based on studies with the Glicko system [110]. Each participant starts with an average difficulty level. When a participant correctly imitates a gesture, the participant's level goes up, and the system selects a next gesture with a slightly higher difficulty rating. When a participant incorrectly imitates a gesture, the participant's level goes down, and the system selects a next gesture with a slightly lower rating. For stability of the participant's level, in practice the participant has to succeed or fail twice in a row before the level changes (see Figure 5.3).

5.4.2. MOOD EXPRESSION IN THE GESTURES OF THE IMITATION GAME

One of our goals of the study we performed is to apply and evaluate this model in a more interactive scenario as a step towards the application of this mood expression model in real-life application context. To this end, we used the imitation game introduced above. The robot gestures used in this game were adapted using the design principles (Table 5.1) gained from previous studies [77], [78], [79] in order to express robot mood while the robot is playing the game, i.e., performing various gesture sequences that are to be imitated.

The robot arm movements are the primary relevant movements for the imitation

Table 5.1: Design principles for mood expression

Parameters	Quality	Valence	Arousal
Amplitude	large	positive	/
	small	negative	/
Palm Direction	extrovert	positive	/
	introvert	negative	/
Finger Rigidness	straight	positive	/
	bent	negative	/
Motion Speed	fast	positive	active
	slow	negative	passive
Hold Time	short	positive	active
	long	negative	passive
Head Vertical	raised	positive	active
	lowered	negative	passive
Head Horizontal	follow arm[1]	positive	/
	look forward	negative	/

[1]look forward when two arms act.

game. Three pose parameters, amplitude, palm-direction, and finger-rigidness, were used for the arm. The amplitude relates to three aspects: vertical extent, horizontal extent, and arm extension; these are controlled individually by the joints shoulder-pitch, shoulder-roll, and elbow-roll (see Figure 5.2a). We also used two pose parameters for head movement (see Figure 5.2c). Two motion parameters, motion-speed and hold-time, were used to modulate the motion dynamics. Decay-speed was used in [77] to control the speed of movements when robot actuators return to its initial poses. In this study, we used motion-speed as decay-speed because decay-speed was found to correlate with motion-speed in [78]. The resulting gestures for positive and negative moods are illustrated in Figure 5.2a, c. A video clip of the gestures used in this study and gestures modulated by mood on a continuous scale is available in the supplementary materials or online. The concrete modeling of the game gestures can be found in Appendix A.

5.4.3. Rationale for studying mood expression during an interaction

Our ultimate goal is to apply robot mood expression to daily human robot interaction. Different from the recognition experiment, in which participants were asked explicitly to recognize the mood from the robot behaviors, during daily interaction people will not be asked to do so. Expression based on behavior modulation is implicit (see Section 5.3.4). Chances are that people may even not pay attention to the affective cues in the robot behaviors. However, it is not uncommon that people spontaneously recognize the mood from the behavior of other people. We are thus interested in whether (a) people can recognize the robot mood from behavioral cues spontaneously, and, (b) the expression has any (positive) effects on the interaction and users, more specifically, effects on the users' affective states (affective effects) and task performance (cognitive effects)?

To answer these questions, we have used a gesture-based game in this study and we have applied the mood expression model to these gestures. Instead of explicitly asking a user to recognize mood, we asked users to play a simple imitation game with a robot and try to get a high score. Hence, we considered that there is a chance that people will ignore the affective behavioral cues, since people need to focus on the game to win a high score.

We briefly discuss here the effects that might be expected by varying task difficulty (i.e., the game difficulty) on the recognition and effects of an expression. For the same task, increasing difficulty mobilizes more attention and effort on the task. For instance, the difficulty of the imitation game was controlled by manipulating the sequence length and gesture combination. As the difficulty of the gesture sequence goes up, human players focus more attention and effort on remembering the sequence, and thus may pay less attention to the details of the robot behaviors. As a result, they may be less capable at recognizing the robot mood and thus less influenced by it. However, it is known from psychology that cognitive load should not influence the recognition accuracy of emotion [111], and as we in the long term aim at a model that is able to generate robot moods that are recognized by observers in a similar fashion as mood expressed by humans, it would be good if mood recognition results do not depend on the difficulty of the interaction task. A second reason to study the task difficulty is that we want to be able to replicate mood effects on task performance [112], [113], [114], [115], [116], as a behavioral measure for mood contagion (in addition to self-reported mood). Thus, we also studied how the task difficulty influences people's perception of the robot mood and how the task difficulty influences the aforementioned affective and cognitive effects of the mood expression on the interaction.

5

5.5. RESEARCH QUESTIONS AND HYPOTHESES

As discussed in Section 5.4.3, the main questions addressed in this study are

1. Can participants differentiate between positive and negative robot mood expressed in gestures during an interaction scenario, rather than in a pure recognition task?

2. Can mood expressed by a robot induce mood contagion effects in human observers?

3. Can the mood expression of a robot influence the performance of a human in an interaction task?

As a result, in this study we looked at the effect of robot mood (positive versus negative) and task difficulty (difficult sequences to imitate versus easy sequences) on three constructs: observed robot mood (participant-reported robot valence and arousal), observer own mood (self-reported valence and arousal), and task performance (percentage of correct imitation sequences). We formulated the following hypotheses:

1. Participants rate the robot mood more positive when the robot behavior is modulated to display positive mood than when the behavior is modulated to display negative mood. This effect should not be dependent on the easy and difficult task conditions.

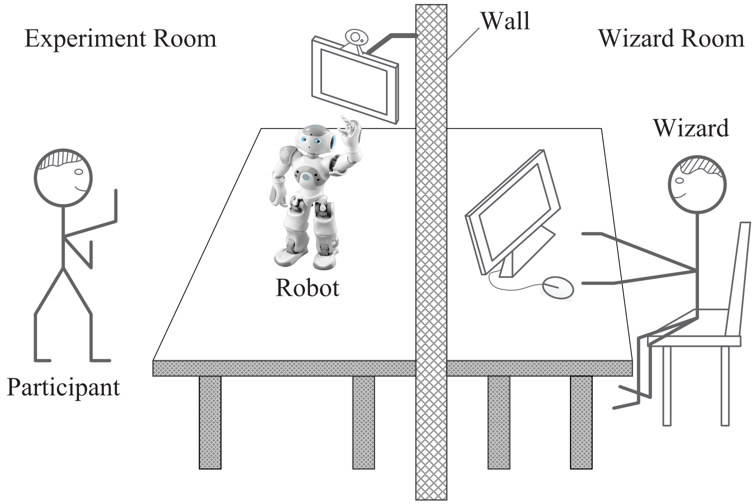


Figure 5.4: The Wiz-of-Oz setting: the wizard recognized the gestures of the participant and input into the system; the system selected next gesture sequence and the robot generated the mood-modified gestures automatically

2. Participants' affective self-reports are more positive in the positive robot mood condition than the negative robot mood condition.

3. Participants' task performance is better in the negative robot mood condition than in the positive robot mood condition.

The latter hypothesis needs some explanation. If robot mood influences participant mood, then we should be able to observe mood effects on task performance. The imitation game is a detail-oriented game in need of bottom-up attention because the goal is to watch and repeat robot movements exactly. It is well known that orientation towards details and bottom-up attention is favored in neutral-to-negative mood states, as opposed to creative and out of the box thinking in positive mood states [114], [115], [116]. Therefore, if mood contagion happens, we would expect to see higher task performance in the negative mood condition than in the positive mood condition.

5.6. EXPERIMENTAL SETUP

5.6.1. EXPERIMENTAL DESIGN

WE used a mixed model 2×2 design with game difficulty (easy/difficult) as a between-subject factor and robot mood (positive/negative) as a within-subject factor. Each participant plays with the robot in only one game difficulty condition (easy or difficult) and in both robot mood conditions (positive/active and negative/passive) in two sessions. Each session took between 6 and 10 minutes and involved 10 imitations. The game difficulty was manipulated by restricting the gesture sequences that the Glicko rating system could select (see Section 5.4.1): for an easy game condition, the item ratings ranged from 300 to 1500; for a difficult game condition, the item ratings ranged from 1501 to 2800. Mood was manipulated by controlling behavioral parameters as explained in Section 5.4.2. Task difficulty was manipulated by the length of the sequence and the variation of the gestures in the sequence. Participants were randomly assigned to the two groups (Table 5.2). The order of the mood conditions was counter-balanced. After the two sessions, participants were asked to fill out questionnaires.

Table 5.2: Experiment conditions and participant groups

Game Difficulty	Robot Mood	
	Negative/Passive	Positive/Active
Easy	Group A	Group A
Difficult	Group B	Group B

5.6.2. MEASURES

Both the recognition of the robot mood (H1) and the participants' affective states (H2) were measured in terms of valence and arousal after the two game sessions using the Self-Assessment Manikins (SAM) questionnaire [117] on a 9-point Likert scale (see Appendix 8.3.3). To gain more insights into how participants perceive the robot mood (related to H1), the participants were asked to describe how they thought the robot mood related to the behavior parameters listed in Table 5.1. This question was placed at the end of the questionnaire. Participants' game performance (H3) was assessed by the percentage of correct imitations during each session (the score of the participant for that session), where correct vs. incorrect was a binary choice rated by the Wizard observer as explained above.

5

5.6.3. MATERIALS

A Wizard-of-Oz method (Figure 5.4) was used in this experiment for the recognition of the participants' gestures. An operator was sitting in the room next door to the experiment room. He could see and hear the participants via a webcam and microphone. His task was to recognize the correctness of the participants' response. The operator classified all gestures made by the participants. Procedural instructions on how to classify were given to the operator: each gesture had to be classified as one of the eight gestures the robot displayed, and in the event that the operator could not classify a gesture (usually caused by the participant's hesitation) he was told to ignore that particular gesture and continue to see whether the participant's next gesture is correct. The operator had been trained before the experiment to minimize the chance that he made mistakes during the operation.

A screen (Figure 5.4) was placed on the wall just behind the robot so that participants knew that the "robot" could see their gestures. Participants were told that the screen was used for facilitating the recognition of gestures by the robot, while in fact this was the operator's view. A grey NAO robot (NaoQi version 1.14; head version 4.0; body version 3.3) was used with LED lights switched off. The robot provided oral feedback on the participant's imitation performance by indicating whether a sequence of gestures performed by the participant correctly reproduced the gestures performed by the robot. The robot accompanied its gestures with speech (e.g., "Left up." "Both down."). The robot voice and texts were affect neutral. That is, phrases such as "Excellent!" or "Very good!" were avoided. The robot (58cm tall) was placed on a desk (Figure 5.4) to ensure that participants could see the robot by facing the robot and looking straight ahead.

5.6.4. PARTICIPANTS

36 students (25 males and 11 females) aged 19 to 41 (*Mean* = 26.6, *SD* = 4.1) were recruited from the Delft University of Technology for this experiment. They were from nine different countries, but most of them are Dutch (N=13) or Chinese (N=13). A pre-experiment questionnaire confirmed that the participants had little expertise on the design of gestures or behaviors for robots or virtual agents. As compensation, each participant received a gift after the experiment.

5.6.5. TASK

Participants were asked to use a thumbs-up gesture to instruct the robot (actually the "Wizard") to start the game. When the robot was performing gestures, the only task for participants is to watch the robot and remember the sequence. They were asked to repeat the sequence after the robot finished the sequence. In addition, participants were asked to act slowly to ensure that the robot could recognize their gestures, and they were told that they did not need to mimic the exact movements of the robot, but to imitate the correct direction (of four possible directions). They were also asked to put their hands in front of their belly when they are not imitating gestures and not make any other gestures to avoid misrecognition. Participants were encouraged to achieve a high score: they were told beforehand that the winner would receive a prize.

5.6.6. PROCEDURE

Before the experiment, each participant was asked to fill in demographics, a general questionnaire about previous experiences with robots, and a consent form with regard to the general information of the experiment. Participants were told that the robot was autonomous (as is common in a Wizard-of-Oz setup). Participants were told to pay attention to the game in general, and we did not emphasize mood or behavior to try to eliminate a demand effect (participants rating what they think we want them to feel / see). They were informed that the experiment contains two sessions with different experimental conditions.

The robot started the interaction when the participant was ready. After the participant finished an imitation (sequence of movements), the robot told whether it was correct or not, and the score of the participant was updated in the system but not shown to the participant. Then the robot started the next turn and performed the next gesture sequence. Each session contained 10 turns. There was no break between the two sessions, but participants were clearly informed about the session switch.

After the two sessions, the participants filled in the SAM affect self-report (Appendix C) and the post-experiment questionnaires. The experiment took about 30 minutes on average. After the experiment, participants were fully debriefed, and each participant signed a consent form with regard to the video recording.

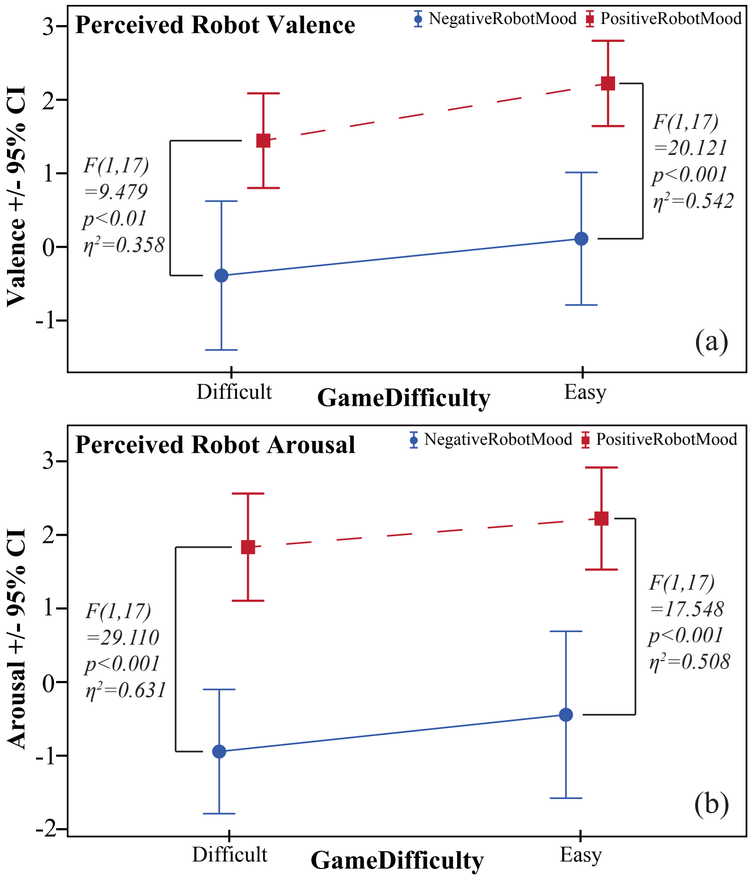


Figure 5.5: The participants' perceived valence and arousal of the robot mood during the interaction

5.7. RESULTS

5.7.1. MANIPULATION CHECK

TASK difficulty was effectively manipulated. The average difficulty ratings of the gesture sequences used in the easy condition is 1229 (*SD* = 100) and in the difficult condition is 1555 (*SD* = 51). An independent sample t test showed that the difference in correctness is significant between the easy (*Mean* = 72%, *SD* = 10%), and difficult (*Mean* = 33%, *SD* = 18%) conditions ($t(34) = 8.121$, $p<0.001$). In addition, we asked participants to rate to what extent they thought the game is challenging on a 5-point Likert scale (-2 to 2) after the experiment. Participants in the difficult-game group considered the game more challenging than those in the easy-game group ($t(34) = 2.428$, $p<0.05$).

5.7.2. Participants consistently differentiate between positive and negative robot mood

Participants were able to distinguish between positive and negative robot mood and this distinction was consistent across the two task difficulty conditions, as evidenced by a mixed (doubly) MANOVA with robot mood and difficulty as independent factors and perceived valence and arousal of the robot mood as dependent variable. This analysis (see Figure 5.5) shows that robot mood had a significant effect on participants' robot mood perception: $F(2,33) = 23.597$, $p<0.001$, $\eta^2 = 0.588$. The perceived valence and arousal were significantly different between positive and negative conditions: $F(2,33) = 27.008$, $p<0.001$, $\eta^2 = 0.443$ for the valence; $F(2,33) = 44.222$, $p<0.001$, $\eta^2 = 0.565$ for the arousal. In addition, task difficulty did not influence mood perception significantly ($F(2,33) = 1.589$, $p = 0.219$, $\eta^2 = 0.088$). These results directly support our first hypothesis (H1). Moreover, participants rated the positive robot mood as positive (one sample t-test on valence measure, $t(35) = 8.620$, $p<0.001$), and active during the interaction (one sample t-test on arousal $t(35) = 8.544$, $p<0.001$), and rated the negative robot mood as passive (one sample t-test testing on arousal $t(35) = -2.086$, $p<0.05$) but they did not rate it significantly more negative than neutral ($t(35) = -0.435$, $p = 0.666$). This further supports our first hypothesis (H1), as it shows that arousal manipulation was in the right direction for both positive and negative, and that valence of the positive mood was also perceived as being more positive than neutral.

5

5.7.3. Participants' mood depends on robot mood

Participants' affective states were influenced by the robot mood in the expected directions, supporting our second hypothesis (H2) that robot mood has a contagion effect on human observers. A mixed (doubly) MANOVA with robot mood and difficulty as independent factors and self-reported participant mood valence and arousal as dependent variables showed that both mood ($F(2,33) = 8.379$, $p = 0.011$, $\eta^2 = 0.337$) and task difficulty ($F(2,33) = 4.397$, $p<0.05$, $\eta^2 = 0.210$) influenced participants' self-reported mood. Post hoc analyses without adjustments showed that participant arousal ($F(1,17) = 20.302$, $p<0.001$, $\eta^2 = 0.544$) and participant valence ($F(1,17) = 10.000$, $p<0.01$, $\eta^2 = 0.370$) were significantly influenced in the easy task condition, but not in the difficult task condition (see Figure 5.6). This suggests that we were able to measure mood contagion effects with self-reported mood only for the easy task. In the difficult task, no contagion effect seems to be present.

Post hoc tests of the game difficulty factor without adjustments show that in the positive robot mood condition participants' valence is significantly higher in the easy game than the difficult game ($t = 4.049$, $p<0.0005$). Arousal is approaching significance ($t = 1.809$, $p = 0.079$). Moreover, correlations were observed between the perceived valence of the robot mood and the valence of the participants' moods: $r = 0.418$, $p = 0.011$ for the negative condition and $r = 0.520$, $p = 0.0012$ for the positive condition. The perceived arousal of the robot mood was also found to correlate with the arousal of the participants' moods: $r = 0.335$, $p<0.05$.

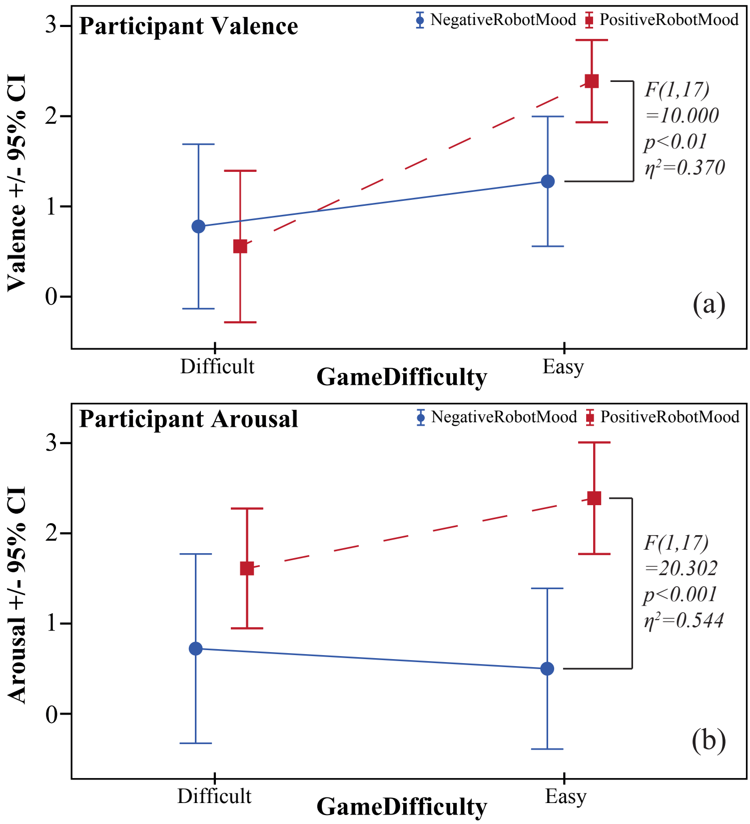


Figure 5.6: The participants' affective states

5.7.4. TASK PERFORMANCE DEPENDS ON ROBOT MOOD

Participants' game performances were influenced by the robot mood (H3). A mixed ANOVA showed that participants' scores (percentage of correct imitations) were significantly ($F(1,34) = 7.335$, $p = 0.011$, $\eta^2 = 0.177$) different when the robot showed a negative mood. Post hoc tests without adjustments showed that participants' scores were significantly different between the robot mood conditions for only the difficult game condition ($F(1,17) = 6.608$, $p < 0.05$, $\eta^2 = 0.280$), but not for the easy game condition (see Figure 5.7). The direction of the mood effect on task performance is exactly as one would expect based on psychological findings [114], [115], [116]: a neutral-to-negative mood state favors orientation towards details and bottom-up attention as opposed to a positive mood state. This type of processing is needed to perform well on the imitation task.

5.7.5. QUALITATIVE ANALYSIS OF PERCEIVED AFFECTIVE BEHAVIORAL CUES

To investigate what affective behavioral cues participants perceived exactly, we asked at the end of the post-experiment questionnaire how they recognized the robot's mood in general and what, according to the participant, the relations are between the robot mood and the following behavioral features (parameters): amplitude, palm direction,

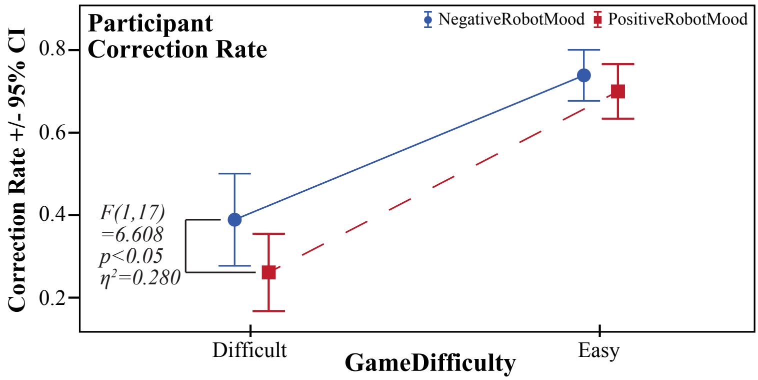


Figure 5.7: The participants' game performance

5

finger straightness, motion speed, hold time, head-up-down, and head-left-right. Participants were allowed to leave no comments on particular behavioral features if they did not notice a relation with robot mood, and were allowed to fill in "not related" if they considered particular features did not contribute to the robot mood. The number of participants that left a comment, the frequency of "not-related-to-mood" comments, and the extracted adjective keywords are summarized in Table 5.3.

The results show that the most noticeable behavior parameters related to robot mood are motion speed, amplitude, and head-up-down, while parameters like head-left-right, finger-straightness, and palm direction are less noticeable although they still have weaker contribution to the expression. We considered the number of participant leaving comments as an indicator of the parameter importance in terms of mood display. This is generally consistent with our previous findings with regard to the parameter importance [78], [79]: motion speed and amplitude are "global" parameters that change the overall quality of the behavior; finger-straightness and palm direction are "local" parameters that change the behavior quality of only a small area of the body parts. This result suggests that participants' perception of the affective behavioral cues were not influenced (at least not much) by an interaction task.

Moreover, the parameters hold-time and head-left-right become more important in this scenario, compared to our previous findings [78], [79]. Our explanation is that the hold-time changed the overall dynamics of the gesture sequence. Although a single gesture of the imitation game contains only one stroke, gestures are displayed in sequences. Thus, the effect of the hold-time on the fluency or smoothness of the gesture sequence is more noticeable. With regard to the head-left-right, participants commented that more movement made the head display more affective cues. In previous studies, the head only turned to a certain direction and then held until the end of a behavior. In contrast, in this scenario the head continuously turned to the direction where the arm was moving when the robot displayed a positive mood. As a result, the head performed more movement and thus displayed more affective cues. From the comments about the relations between parameters to valence and arousal, we gain insights into how participants interpreted the affective behavioral cues. We separate the adjective words that participants used to describe the relations into valence-oriented words (has a large ab-

Table 5.3: Perceived Affective Behavioral Cues from Behavior Parameters

Parameter	NoPC*	NR** Freq.	Valence Orientated Relation***	Arousal Oriented Relation***	Other****
motion speed	35	0	↑happy(5) ↑positive(3) ↑good(2) ↓bad(2) ↓depress(1)	↑excited(8) ↑enthusiastic(2) ↑energy(1) ↓calm(2) ↓bored(2) ↓relaxed(1)	↓serious(1)
amplitude	33	1	↑happy(9) ↑good(5) ↑positive(4) ↓negative(3) ↓bad(1) ↓sad(2)	↑excited(11) ↑enthusiastic(1)	↑playful(1) ↑aggressive(1)
head up down	27	2	↑happy(3) ↑positive(5) ↑good(2) ↓sad(5) ↓negative(1) ↓bad(4)	↑excited(2) ↓bored(2)	↑friendly(1)
hold time	23	2	↑sad(1) ↑depressed(1) ↑bad(1) ↓positive(2) ↓good(1)	↑calm(6) ↑bored(2) ↑patien*t*(1) ↓excited(3)	↑serious(1) ↓playful(1) ↓rushed(1)
head left right	17	4	follow arm: good(1) positive (1) look away: negative(1)	more movement: excited (4) less movement: bored(1)	playful(1) interested (1) irritated(1) serious(1)
finger straightness	16	2	↑happy(2) ↑positive(1)	↑excited(4) ↓calm(3) ↓relaxed(1)	↑thoughtful(1) ↓tense(1) ↓stressed(1)
palm direction	9	4	↑good(1) ↑happy(1)	/	/

* NoPC means the total number of participants that commented on the parameter.
** NR means participants commented that the parameter was not related to mood.
*** ↑adj.(#) means # participants commented that increasing the parameter value makes the robot mood appear adj. ↓ means decreasing value.
**** Compared to other adj., few participants used these words, and these words have different meanings.
NB. One participant could use more than one adj.

solute valence value but smaller absolute arousal value) and arousal-oriented words (a large absolute arousal value but smaller absolute valence value) according to the word distribution in Russell's circumplex affect space [94]. Based on the number of valence-oriented or arousal-oriented words (Figure 5.8) used to describe a parameter, we determine whether the parameter is more likely to be perceived to show valence or arousal.

The motion speed seems to have strong relations to both valence and arousal, and so does the amplitude. The motion-speed contributes slightly more to the arousal display and the amplitude contributes more to the display of valence. The results are consistent with the findings in [65], [118]: fast speed and large spatial amplitude usually show positive valence while slow speed and small spatial amplitude usually show negative valence. The result of motion speed also confirms the findings in [64], [119], [120]: varying movement speed influences the recognition of emotion intensity. The head-up-down seems to contribute mainly to the valence display, since most participants commented on it us-

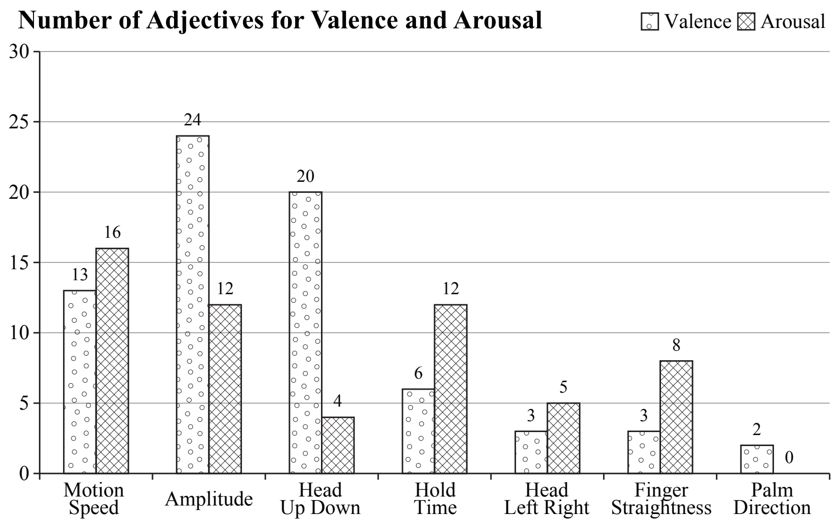


Figure 5.8: Number of adjectives that participants used to describe the relations between parameters and valence and arousal

ing valence-oriented words. This result confirms the findings in [88] that head position plays an important role in displaying valence and arousal. The hold-time influences the fluency of the movement, so it influences the perceived speed of the movement. Thus, the hold-time contributes mainly to the arousal display. There are two interpretation of the head-left-right: when it is interpreted as a posture, e.g., looking at the moving arm or not or looking at the participants or not, it is perceived to display valence; when it is interpreted as head movement, it increased the movement intensity or the overall activation of the behavior, and thus it is perceived to display arousal instead. The finger-straightness was perceived to show arousal, since this parameter controls the finger stiffness and shows the force of the finger. The palm-direction was only described using valence-oriented words.

In sum, parameters like the motion-speed and the hold-time that control the dynamics of a behavior, parameters like finger-straightness that present the force or stiffness of a body part, and parameters like head-left-right (movement interpretation) that change the overall intensity of movement are usually interpreted as showing arousal. Parameters like amplitude, head-up-down, finger-straightness, and head-left-right (posture interpretation) that control the posture and spatial extent of a behavior are usually interpreted as showing valence. These results are generally consistent with our previous findings [79], except that previously the head-up-down was also found to correlate with arousal to a large extent. In addition to our previous findings, the amplitude is perceived to correlate with arousal to a certain extent in this study.

5.8. DISCUSSION

FIRST and foremost, this study showed that our model for bodily mood expression of a humanoid robot successfully generalized to the behaviors needed in the imitation game: we applied the parameter modulation principles obtained in [77] to the imitation gestures directly (see Section 5.4.2); and results show that participants distinguish between positive and negative robot mood, even when they were faced with a high task load. Moreover, the recognition of the valence and arousal is consistent with the findings in [79]: modulating these behavior parameters varied both valence and arousal in the same direction. We would like to stress that this is an important contribution to the ability of appearance-constrained robots lacking facial expression capabilities to express affective signals. Further, this is an important step towards the expression of affect during task execution of a robot, something humans do automatically (e.g., walking in a sad, happy, or angry way looks very different).

Our aim in this study has been to use bodily mood expression that does not interfere with the behavioral functions of body movements and to study the effects of mood expression. This has been achieved by using a parameterized behavior model, but this does not necessarily mean that no additional effects besides the mood expression in an interaction scenario have been introduced. More specifically, effects on the game itself may have been introduced: mood expression potentially influenced game difficulty. For example, the use of head movements for expressing mood was reported by one participant as something that distracted attention and thus made it more difficult for that participant to remember the exact sequence. Another participant reported that the slow speed of the gestures in the negative mood condition increased the duration of the sequence, and consequently, increased the time that the participant needed to remember the sequence. On the other hand, slower movement may also make it easy to remember the gestures. Because mood and difficulty level are not entirely independent factors, we cannot fully rule out the possibility that the performance difference within a difficulty condition is not caused by the slight variation of the game difficulty that is caused by the gesture modulation. So formally, it is unclear if the performance difference between mood conditions on the difficult task is only influenced by the induced mood. To obtain a more reliable conclusion, further study is needed to investigate the effects of the participants' mood and the game difficulty on the game performance separately. To be able to claim that mood contagion happened and the effect on performance is due to the mood, a follow up priming study should be done in which participants are mood primed using prior robot gestures as primes (and a manipulation test afterwards), after which participants do a task at two difficulty levels.

We asked participants to report their own mood only after the two sessions, because we wanted to avoid introducing a demand effect in the second session. This may have influenced the self-reported mood because of mood decay effects or because of the different robot mood in the second session. In a mixed (doubly) MANOVA we found a significant interaction effect between mood condition and mood order on self-reported valence and arousal ($F(2,33) = 3.507$, $p<0.05$, $\eta^2 = 0.175$), primarily caused by a decay in self-reported arousal for the mood condition that was presented first. This shows that presentation of the second session indeed diminishes the self-reported contagion effect of the first session.

The results of the perceived behavior cues in Section 5.7.5 indicate that the participants consciously recognize the robot mood. Although some parameters are more noticeable, every parameter received attention, which means that modulation of these parameters did change the perception of the robot movement quality. The results also help us to identify the role of each parameter in the mood expression in terms of showing valence or arousal. This will help us to improve our behavior model. That is, it may be possible to use arousal as a second variable in our model to control the modulation of the parameters. Additional work is needed to address the modulation principles when arousal is introduced in the control mechanism of our model.

Participants' assessment of the robot mood is a comprehensive affective appraisal over all aspects on display including robot body movements, the robot's speech, game events, etc. In line with this, the attribution of a mood was explained differently by different participants even though only body language was varied in both sessions (see Section 5.6). Some participants thought the robot mood changed because of their performance within a session. For example, one participant said "the robot's mood was negative because I always made mistakes." Additional evidence that robot mood was consciously recognized by participants is provided by the fact that a participant indicated that the robot was happy because the robot did not display a negative mood even when she made many mistakes, whereas another participant indicated that the robot was not so happy because the robot did not praise and encourage him when he made a correct imitation. Some participants also said they recognized mood by means of the voice of the robot even though no changes were made to the robot's voice between the two sessions. This also indicates that participants were consciously aware that the robot mood changed. In addition, participants could have different interpretations for the same behavior parameters. For example, the head left right movement can be interpreted as either looking away (thus showing negative mood) or following the arm movement (thus showing more excitement). The variation of the interpretation may depend on people's personality, their own behavioral habit, or the scenes in their minds.

In this study, the bodily expression of robot mood produced contagion effect on the participants: 1) explicitly, participants' self-reported valence and arousal was significantly influenced by the robot mood under the easy game condition; and 2) implicitly, participants' game performance was significantly influenced by the robot mood under the difficult game condition, suggesting that participants' true mood might be influenced by the robot mood during task execution even though they did not report it after the task. We have no clear explanation for the absence of an influence on self-reported mood in the difficult condition, apart from the following two. Tsai et al. [107] proposed that the contagion effect of a virtual character still image was hindered by the occupation of cognitive resources by decision-making. It could be the case that in our study self-reported mood was somehow hindered by cognitive load. Another alternative explanation is that the participant's mood in the difficult task was more negative by default, because the task was difficult. The fact that the participant's negative mood was not rated even more negative could thus be due to a floor effect as one does typically not get into a very bad mood due to a game in an experiment. Hence, no effect of negative mood induction due to the robot mood was measured. The same sort of explanation would hold for why we did not find an effect of robot mood on participants' task performance in the easy task. Here we probably had a ceiling effect: the easy imitation game is so easy, that no matter what your own mood is, you can do it almost perfectly. Finally, we cannot completely rule out alternative explanations for our findings that would argue, e.g., that participants were entertained more in the positive condition and for this reason somehow performed worse. Even so, explanations like these would still suggest some kind of mood transfer would have happened.

We have used an imitation task in this study. The participants were asked to reproduce sequences of arm movements made by a robot. The robot's arm movements expressed different moods in two conditions. Although the participants were not asked to reproduce the exact "moody" movements, some participants still mimicked the movements to some extent, according to the recorded video. There is evidence that expression of nonverbal behavior associated with affective communication can cause experience of the relevant affect [121], [122], [123]. Moreover, the "motor mimicry" theory states that people catch others' feeling by unintentionally imitating others' expressions [97], [124], [125]. Thus, the imitation game task context of our study may have enhanced the mood contagion. We believe, however, that mood contagion would have also happened even if the participants would not have imitated the movements. That is, the imitation of the movements is only part of the causal chain of mood contagion but not the main factor, and imitation only enhanced the contagion. It remains, however, an important question for future work to verify whether the mood contagion effect observed in this study can be generalized in scenarios in which users do not perform actions that are directly related to the robot body language.

We recorded video of each participant during the game. The videos are meant to be analyzed for more objective evidence that supports mood contagion. We did a pilot for the video annotation. Two coders performed event based annotation on the videos. No significant results were found, because not enough cues from the participants' body actions or facial expressions were available to allow for interpretation of their emotions or moods. One explanation for the lack of cues may be that the participants were instructed not to make extra movements to avoid misrecognition of their gestures so the expressivity of their body movements is somehow constrained. Facial expressions also did not vary that much. The only evident facial expression in the videos is the smile. The participants mostly smiled when they made mistakes, but it remains difficult to interpret the relation between the smile and the robot expression.

5.9. CONCLUSION AND FUTURE WORK

THIS study shows that it is feasible to use parameterized behavior to express a robot's mood in an actual HRI interaction scenario. Results show that participants are clearly able to distinguish between positive and negative robot mood. They are able to recognize the parameters we manipulated during the interaction. The importance of each parameter seems to be consistent with previous results in [78]. Our results also suggest that mood contagion takes place between the robot and the human. We have evidence for this contagion effect in the following two forms: 1) participants self-reported mood matches that of the robot mood, and 2) participants' task performance is lower in the positive robot mood condition compared to the negative robot mood condition replicating a well-known mood-contagion effect.

To the best of our knowledge, this study is one of the very few in which the robot mood expressed by bodily expression is clearly distinguished by participants and the robot mood has an effect on participants, which we interpreted as mood contagion. Our study is unique in that a) robot mood expression was evaluated and investigated in a real HRI scenario, b) mood expression was realized by integrating robot body language into functional behaviors required by a task, and c) the participants were not primed to pay attention to any form of affective expression.

Our work provides an alternative way of expressing affect through robot body movement. The study presented in this chapter shows the effectiveness of modulation based expression in terms of recognition and influence on users. This indicates that our model has been successfully generalized to imitation game behaviors. We believe that our behavior model can be applied to a wide range of applications, since the modulation based expression has less interference with functional behaviors compared to the expressions based on additional body actions. One of our long term goals is to apply the model to more behaviors that are frequently used in HRI. One of our studies in this direction has focused on the design and evaluation of the behaviors of a robotic tutor [83]. Our model has been applied to the co-verbal gestures of the robotic tutor and the movements when the robot is idle. As we discussed above, the imitation of movements may contribute to mood contagion. In the robotic tutor scenario, students do not imitate the robot gestures. It is important to examine whether mood contagion still exists in that scenario.

Moreover, we believe that our work not only contributes to field of the robotics, but also contributes to the field of virtual agents. For virtual agents, extensive work regarding affective expression based on behavior modulation is usually on the communicative gestures of conversational agents (e.g., [70], [126]). Our method is similar to existing parameter based approaches in constructing communicative gestures. A difference is that our model is a step further in modelling the poses related to behavior functions for more complex behaviors such as waving (see Appendix A). There are also scenarios in which virtual agents perform body actions that are constrained by functional requirements and dimensions of the virtual environment. For example, the virtual agents in training system need to demonstrate standard operations (e.g., [127], [128], [129]). Our model can be used to parameterize these behaviors for modulation based expressions, while also modelling the functional and spatial constraints of these behaviors. Moreover, our work shows the mood contagion between a robot and a human via affective body language. This provides support that affective body language can produce mood contagion effect between agents in general and humans, and thus can be used as a support for mood contagion between virtual agents and humans via body language of the agents.

In this experiment, the robot mood condition was designed as a within-subject factor and presented in successive sessions. Thus, participants were able to compare the differences of the robot behaviors between the sessions. This differs from real recognition, which requires people to tell the robot mood without a reference. One way to test whether people can actually "recognize" robot mood is to put the independent variable (i.e., the robot mood) as a between-subject factor and ask people to rate the robot mood using scales (i.e., assigning values for valence and arousal). This is also a challenge since humans are not good at scaling and thus they may not be able to give accurate result. After all, this study is the first step toward the "recognition" of the robot mood from its behaviors.

An interesting topic would be to make the mood expression as a response to human players' task performance. Put it differently, the robot will change its mood according to whether human players imitate correctly or not. In this way, the functions of the bodily mood expression in HRI can be explored. For example, we can test the empathy effect by comparing the effects between the robot displaying a positive as a response to an incorrect imitation of the human player and displaying a negative mood. Moreover, we expect the effect of the bodily mood expression on the HRI to be strengthened, since mood can be expressed through behavioral cues more often or continuously. Another example is to use the mood expression as an indicator showing the stage of goal achievement in a learning-by-demonstration scenario in which humans teach a robot doing things. It is interesting to see whether the mood expression simultaneously expressed during the task will make the learning more efficient.

One additional interesting aspect that we found in our study is that participants attributed the robot mood to various factors that were not manipulated. In a complex interaction scenario such as the imitation game, participants may believe that the affective state of a robot is shaped by the events that happen during the game, the objects present in the interaction scenario, or, for example, by the (performance of) participants themselves. It is interesting to explore this conscious attribution of mood and its causes to a robot in more detail in future work. Moreover, when other modalities of expression are also used as well as modulation based expression. It is interesting to study the interaction between each modality. For example, a robot may change its tone to expression mood when it is talking, while the robot may also perform coverbal gestures. An interesting question is whether modulated coverbal gestures (for expressing mood) can enhance the overall mood expression, alongside with the vocal expression. It has been showed in [34], [36] that body action based emotion expression may significantly enhance the recognition of a robot's emotion when it was combined with facial expression. It is also interesting to test whether modulation based expressions can also enhance the recognition.

Finally, whether expression is universal or culturally-specific is another important question. Culture may influence the recognition of affect expression. Ekman has proved the existence of the universal facial expression [130]. For body language, Kleinsmith et al showed that cultural differences exist in recognition of affect from body postures [131], while many studies also found universal aspects of body expressions (see [132] for an overview). Culture differences in the recognition may also influence the contagion process. Besides, cultural difference may influence the contagion process indirectly. For example, there is evidence that cultural background has significant influence on the attitude towards the interaction with robots including the attitude to the emotions in the interaction with robots [133]. It was shown that attitudes influence emotional contagion process [134]. Perhaps, attitudes have an effect on the mood contagion process between humans and robots. Thus, it is important and interesting to validate our mood expression cross-culturally. Taking a step further, it would be useful to identify which parameters can be modulated to produce universal mood expression, or, just as important, to produce culturally-specific mood expression.

6

Robotic Lecturer with Affective Body Language

This Chapter describes our investigation of the robot mood expression by means of behavior modulation used in a one-robot-multiple-humans interaction scenario. Group processes occur when multiple humans are together and may influence the perception of the mood expression and the effects that the mood expression can have on the humans. As one-to-multiple interaction is common in real life applications, we aimed to test whether our mood expression is still effective in such a scenario.

Another objective is to test the utility of the mood expression in an educational scenario. Our results showed that the robot mood expression is able to raise students' arousal, while moderately high arousal was shown to improve learning. This means that our mood expression is promising to have positive effects in technology enhanced education.

This chapter is based on J. Xu, J. Broekens, K.V. Hindriks, M.A. Neerincx, *Robotic Lecturer with Affective Body Language*, Journal of Computer & Education, submitted, 2015.

Abstract

Robots can play an active role in education. In this chapter we investigate a humanoid robot NAO that is able to give a lecture to university students in a classroom setting. The goal is to investigate whether affective body language of the robot improves learning experience: 1) can affective body language of the robot induce an affective state in students that may benefit learning? 2) Can affective body language improve the students' perception of the robotic teacher?

We studied robot body language through its coverbal gestures. The coverbal gestures were constructed using a parameterized behavior model, and the gestures appear differently when the parameters, which control spatial extent and motion dynamics, were modulated. Different robot moods are expressed via the modulated gestures. Two groups of students listened to the same lecture presented by the robot, while the robot displayed a positive and a negative mood respectively.

Unique in this study on human-robot interaction is that (a) the robot gave an actual lecture to real students in a classroom setting that was kept as close to real life as possible, (b) the human-robot interaction is one-to-many and relatively long (30 min), and (c) the robot mood was expressed across a large set of modulated robot behaviors.

The results show that the arousal of the students' affective states was significantly higher in the positive mood condition compared to the negative mood condition, according to both self-reports and video annotation. Moreover, the video annotation shows that valence was also significantly higher. The students' ratings of lecturing quality and gesture quality of the robot are higher in the positive condition, demonstrating that the affective body language of the robot is able to improve the perception of a robotic teacher. As literature indicates that a positive valence and a moderate active arousal benefit learning performance and a positive attitude towards a teacher also increases learning motivation, our results show the potential of affective robot body language for improving learning outcomes of robot-enhanced education.

Keywords: intelligent tutoring system; improving classroom teaching; interactive learning environment; human-computer interface; evaluation of CAL systems

6

6.1. Introduction

Technology assisted education, also known as electronic learning (e-learning) or ICT (information and communication technologies) enhanced learning, has become popular in modern education [135]. Virtual reality (VR) based education stands out from other e-learning applications because VR provides an interactive and immersive synthetic environment and characters that allow multisensory interactions and authentic tasks [136]. Those embodied virtual characters are able to engage interlocutors [137], [138] and increase motivation of learners [139]; both engagement and motivation are important to learning performance.

Robots are also capable of providing interactive and engaging learning experience. First, robots can provide more engaging interaction experience because of its physical embodiment. Studies showed that people prefer to interact with physical robots over virtual characters, and have a more positive attitude towards robots compared to other modalities of computer-controlled interaction (e.g., virtual agents, robots in video) [140], [141], [142], [143]. Possible reasons are that robots share the same physical space with people, and thus have more social impact [142]. A study about a robots' physical presence and proximity to a person [143] showed that the physical embodiment of a robot is perceived as more trustworthy, altruistic, engaging, and as having a greater social presence compared to virtual characters and virtual representations of robots. Playing against a physical robot in a chess game was also reported to be more enjoyable than against a virtual agent [144]. The reasons provided by the authors are that physical embodiment provides more immersive user experience and more believable social interaction. Second, studies on robot-assisted education showed the value of using robots in learning. A physical robot is preferable in authentic learning environments. It was shown that a students' sense of authenticity, engagement, and motivation is stronger when learning with a physical robot [145]. The use of a real-robot was also shown to significantly improve learning effectiveness, collaboration, and motivation [146]. Moreover, physical embodiment of robots seems to produce a "social facilitation" effect. That is, the mere presence of a physical robot as an observer was shown to improve task performance [147]. In addition, a study of Ryu et al. [148] suggests that among physical robots, humanoid robots are the most preferable modality for teaching assistant robots. On the other hand, in the field of social robotics, social abilities of robots are developed and evaluated. We believe that these abilities can benefit education. Robot assisted education is also an interesting application for social robots [149]. In our work, we aim to apply social abilities of humanoid robots to education.

Informed by "active learning" and "constructive learning" theories, most studies on educational robotics focused on using robots as platforms to provide opportunities for a student to use a robot as a tool to complete an assignment or learning task by programming the robot [9]. In contrast, robots can also play an active role in learning activities instead of being used as "passive" tools, for example, in giving a lecture, telling a story, and playing educational games with students. Several studies (e.g., [150], [151], [152], [5] investigated the effects of social abilities (e.g., nonverbal feedback, gaze, affective expressions, empathy) of educational robots on learning outcomes. These studies only compared a robot that uses social abilities with a robot that does not use any social abilities. The effects of the quality of the social abilities on learning still need to be explored. For example, how different are the effects that positive and negative affective expressions of a robot have on learning. It is our aim here to study the affective quality of social abilities and differences in effects on students caused by varying quality levels. To this end, we integrated affective body language of a robot into a robotic teacher application, called RoboTutor, to test how the quality of the robot teaching behaviors influence students' learning experience. The robotic teacher is capable of giving a lecture in a typical classroom of a university, and able to use teaching facilities like slide shows and a microphone. This chapter presents the details of how we integrated both and a study on the quality of teaching behaviors of the RoboTutor, with the aim of improving learning experience.

Our work focuses on improving the learning experience provided by the RoboTutor in two perspectives. The first is whether the affective robot body language has positive effects on students' affective states during a lecture, so as to sustain their motivation and attention, and make them memorize the lecture materials better, i.e., to enhance their learning efficiency intrinsically. The second is whether the robot body language improves the perception of the robot as a teacher, i.e., to improve teacher quality of RoboTutor. With greater social acceptance, students may trust the robot more and engage more during the lecture. [153] shows that learning performance is better if students show more positive attitudes to their teacher. To this end, we focused on raising the robot behavior quality during the lecture. More specifically, we studied how affective body language of RoboTutor influences students' affective states and their perception of the robot as a teacher.

The reminder of the chapter is organized as follows: Section 6.2 presents a review of related work on educational robots. We also explain the interaction context of this study. We used a university lecture scenario, which is a one-to-multiple human robot interaction (HRI) scenario. How this context differs from dyadic interaction context is explained in this section. In Section 6.3, we explain the rationale of using affective body language to improve learning experience. In Section 6.4, we explain our rationale behind our claim that the robot affective body language by means of behavior modulation is suitable for expressing mood, is more believable, and has stronger effects on users during interaction compared to other forms of expressions. We elaborate our questions and hypotheses in Section 6.5. To give a clear picture of the experiment, we introduce our RoboTutor system in Section 6.6, while describe our body language model and how we integrated the model into the RoboTutor in Section 6.7. Details of the experiment are elaborated and the results are discussed in Section 6.8. In Section 6.9, we discuss the feedback obtained from an event for teachers, where we showed our RoboTutor application to real teachers. We reflect on this study and draw more general conclusions in Section 6.10, where we also discuss future work. Finally, Section 6.11 concludes the chapter.

6.2. RELATED WORK

ROBOTS have been used already in a range of educational scenarios. For the most part, studies in the field of educational robotics have focused on teaching how to construct robots, including aspects related to mechatronics, electronics and programming [9]. In these studies, robots, such as LEGO Mindstorms [154]and Arduino [155], were used as a platform on which students exercise skills such as hardware design, programming, and system design. In those studies, robots were used as a passive platform for students to work on. In our work, the robot plays the role of a lecturer that gives a presentation on learning materials and quizzes about the contents just taught. That is, the robot actively participates in the interaction with students during the learning activities.

Robots show great promise for playing an active role in learning activities. Several one-on-one teaching situations have been studied. Henkemans et al. [5] used a robot as a personal tutor for educating children with diabetes in health knowledge. To be personal, the robot asked children about their personal information, such as names, sports, and favorite colors, and referred to these personal data during the interaction. Results show that children gain knowledge about diabetes and children interact more with a personal robot. This study suggests that a robot can be used for educating children in an enjoyable way. Tanaka and Matsuzoe [156] inverted the common roles between robots and children: they let children teach robots. The results showed that this learning-by-teaching method promoted children's spontaneous learning and motivation in a study conducted at an English language school for Japanese children.

Some studies have used robots as teachers in public space. For example, Chang et al. [152] explored the possibility of using educational robots as an instructional tool for second language teaching in a primary school. They studied five typical scenarios in a classroom setting cooperatively with teachers. The feedback from teachers revealed several challenges associated with educational robots in classroom. First, they found a lack of movement while the robot was talking. Coverbal gestures and random leg movements in our study have been designed to improve the quality of the robot behavior in this regard. Second, they found their robot did not engage in sufficient emotional communication. Our study addresses this issue by exploring the use and effects of the robot mood expression through body language in the classroom. Third, robots were reported to elicit a high motivation of students to interact with the robot in the beginning, which may be due to the novelty effect, but this motivation did not persist. The body language we investigate in this chapter transfers, as we will argue, a robot's mood to students, and thus may positively influence students' motivation [157]. We also address the issue of the ease of use of an authoring tool to control the robot. We provide a script-based authoring tool, allowing non-technical people such as teachers on a primary school to create educational scenarios.

Affective expression has been shown to support learning in various ways. Bodily expression was used in a social assistive robot application for preschool education [8]. The robot expressed emotions by gestures, head movements, and eye blinking, corresponding to the emotion of the story sections. The results show that children's emotional involvement in the learning process is promoted. Affective expression was shown to improve motivation and reduce frustration. Okonkwo and Vassileva [108] incorporated emotional facial expression into an agent used in an interactive learning environment. They found that the emotional agent improved concentration and motivation in students, and was also perceived as more engaging and sympathetic than the agent without emotions. Burleson and Picard [104] found that agents with affective support reduce participants' feeling of frustration in a learning context, and this affective intervention was found to be more effective in girls. Affective expression may make user perception of educational robots more positive. The iCat robot was used in a chess lesson [44]. The results suggested that the emotional behavior of the robot improved children's perception of the chess game and the robot. Robot expression was used in a quiz game designed for children to gain knowledge of health care [45]. The study showed positive effects of the expression on children and the children's preference for bodily expression. Beale and Creed reviewed the influence of synthetic agent emotion on user attitudes and perceptions [100]. Many studies discussed in the review showed that people perceive agents with affective expressions more positively and have better attitudes to the agents. The review also pointed out that the role of agents in learning processes (e.g., learning companion or tutor) and the type of learning tasks (e.g., language learning or problem solving) may influence the effects of the agent expressions. It is thus important to study educational robots in different scenarios. We provide a study case of a robot teacher in a university course about artificial intelligence. It will be useful to compare our setting with the settings in other studies.

In our previous studies, we showed the effectiveness of robot body language in a dyadic interaction scenario in a laboratory. However, it is unclear yet whether the body language is effective in an environment that is closer to real life. Studies [158], [159], [160], [161] have shown that an experimental environment may strongly influence the results regarding human robot interaction. This is the case particularly when a robot application is used in a public space. It is thus important to bring robots out of laboratory environments and evaluate them in more realistic settings, in which conditions and contexts are closer to a situation where a robot will be eventually used.

Placing robots in real-life like scenarios might elicit responses from people that are more realistic and varied. For example, a study, in which a robotic receptionist that displays facial expressions interacted with people in a public setting for a long term [42], showed that the average interaction time positively correlated with the number of visitors, as long as the robot displayed facial expressions no matter positive or negative. Social acceptance was studied using an ACE robot by putting the robot in a street and having it ask for directions [162]. Results indicated that limitations of the robot were less tolerated by people in a public area right from the start of the interaction. This suggests that the first impression is important for extending human-robot interaction over time. Abildgaard and Scharfe [163] placed a Geminoid robot in a university course. The robot played the role of a lecturer and presented a lecture to a large audience. Interestingly, some students did not immediately realize that a robot was speaking. This study suggests that the perception of the robot varies with the distance to the robot and with gender. Moreover, people's expectations and requirements for social acceptance are higher in a real life scenario than in a laboratory setup [162]. Moreover, in a public space multiple people may interact with robots at the same time. In the study of the robotic receptionist [42], different interaction patterns have been observed for affective robot interaction with few and with many people. It is known that there exist many factors that influence emotional contagion between individuals within a group (see [164] for a review) such as group membership [165], affective context of the group [35], and social power relations. This means that we need to investigate to what extent our previous findings can be replicated in a group setting. Note that some group effects do not require physical interactions between individuals, such as the "social facilitation" effect [166], which influences people's performance and occurs as long as others are present nearby.

The RoboTutor application enables us to study the body language that we have proposed in earlier work in a more realistic environment. This is important for three reasons. First, we used a "real-life" setting of teaching a lecture in a university. We simulated a real classroom as closely as possible, where the main change was that we replaced a human teacher by a robot. The lecture room was familiar to the students, and the lecture content was part of an actual course that they enrolled in. Thus, students might expect the robot to demonstrate teaching skills similar to those of a human or else would not accept the robot as a teacher. Second, in our RoboTutor application, the robot interacts with an audience of about 20 students. This allows us to test whether the robot mood can be effectively communicated to a group of people, and to study the effects of robot mood expression on multiple individuals in a group. Third, this study allows us to test whether the robot mood can be expressed consistently, using body language of the robot over a longer period of time. In order to do so, we generalized our mood expression model [77] to a broad range of robot gestures, which are performed in series during the course of the lecture. We needed such a variety to ensure that the robot's body language would be perceived as more or less natural over a longer period of time (30 min) during the lecture. Forty-one co-verbal gestures were used, each of which was modulated to display mood using our bodily mood expression model [77]. As such, this is the first study looking into the effects of robot mood expression over an extended period of time by means of a large variety of mood-modulated bodily gestures.

In most studies, educational robots have been developed for children. This is probably because robots are more easily accepted by children. Research starts to address educational robots for adults. Abildgaard and Scharfe's study [163] suggested that a Geminoid robot as a lecturer in classroom environment of a university course is acceptable to some extent. Our study is also aimed at adult education, i.e., lectures for master students. As a result, we believe that our findings may be applicable to a broader range of classroom education settings including, e.g., secondary school, high school, and university. We did not use a Geminoid but used a lower-cost widely accessible commercial robot (i.e., the NAO). It is interesting to investigate whether a low-cost robot without sophisticated humanlike features is sufficient for a robotic lecturer role.

6.3. Affective Expression in Educational Robotics

Our approach for improving the learning experience of robot-enhanced education is to enable the RoboTutor to express mood while it is speaking during a lecture. The rationale is twofold. First, mood expression can be used to influence students' affective states that may facilitate learning. The idea here is that 1) a robot mood with positive valence influences a students' mood positively, and therefore improves motivation [157]; and 2) a robot mood with active arousal increases the arousal level of students' mood, which improves learning efficiency according to [167], [168], [169], [170]. In previous work we showed that a human's mood can be influenced by a robot's mood when interacting with the robot in a game setting [81]. Based on these results we came to believe that robot mood also will have an impact on students' mood in a classroom setting. Mood is a less intense form of affective state, compared to emotion. A positive mood usually is accompanied by a moderate arousal. One therefore would expect that a robot mood should not induce a too high arousal of students, which would cause learning performance to decrease [170], [171], [172]. Second, mood expression may improve the students' perception of the RoboTutor and positive attitude towards teachers may increase learning performance. Affective expression is important for social robots to interact with humans naturally and intuitively [26]. Expressive robots are perceived as trustworthy, reliable, and life-like [24]. By controlling the valence and arousal level of mood expression the robot is able to appear as a passionate and enthusiastic teacher. Thus, mood expression may improve students' perception and social acceptance of the robot. Moreover, our mood expression can be used almost all the time during the lecture. We expect that the mood expression have strong effects on the learning.

6.3.1. Positive Mood Improves Learning Motivation and Creative Thinking

Learners' affective states have been shown to influence their motivation and information processing, and ultimately learning outcomes. A positive mood is reported to increase motivation and foster holistic, creative thinking [157]. Our robot mood expression was shown to induce a positive mood to people who interact with the robot in a game [81]. Positive robot mood expression is likely to also induce a positive mood to students in a classroom and thus improves students' motivation. On the other hand, robot mood expression improves life-like quality and social presence of robots, and makes the learning process more entertaining. The robot mood expression thus may reduce the boredom in students, while boredom should be reduced during learning since it was reported to produce negative intrinsic motivation (avoid an action) [157]. Silvestrini and Gendolla also showed that pleasant task valence eliminated motivational deficit caused by negative mood and a difficult task [113]. The robot mood expression may make the learning process more pleasant and thus improve learning outcomes.

6.3.2. Moderate Arousal Optimizes Learning Performance

Maintenance of an optimal arousal level during learning process increases students' learning efficiency. Learning is not a purely cognitive process, but is also mediated by affective processes. The affective state of learners, in particular a moderate level of active arousal, has a positive impact on learning efficiency, since it increases attention and memory [167]. LaBar and Phelps [168] studied arousal-memory interactions in humans using a word recall task. The results showed that arousal improved memory performance by regulating consolidation processes. Studies in neuroscience support the existence of the emotion-memory interaction [169]. However, arousal should be neither too high nor too low, otherwise performance decreases. The well-known Yerkes-Dodson law [170], [171], [172] illustrates the relationship between arousal and performance as an inverted-U curve. The results of the studies on learning experience accord with these principles. Masters et al. [173] showed that positive affective states enhance learning of children. Moreover, their study indicated that even transient mood states may produce lasting changes in behavior. Craig et al. [174] studied the role of affective states in learning. They found that learning gains correlate positively with flow (engagement) and confusion, while correlate negatively with boredom. Shen et al. [175] studied the evolution of learners' emotion during a learning process in a e-learning context. They found that engagement and confusion were important and most common emotions during learning. Note that flow (engagement) and confusion are both affective states with moderate arousal, according to [176]. In addition, Baas et al. [115] extracted the relation between moods and creativity from a range of studies. They found that activating moods enhance creativity, while positive-activating moods produce more creativity than negative-activating moods. The results are generalized across experiment scenarios, populations, and facets of creativity. Therefore, maintaining a moderate arousal level is important to learning efficiency and learning experience. Our previous study also showed that the mood expression of a robot induced an active arousal to people who interacted with the robot in a game [81]. In this study, we aim to use the robot bodily mood expression to induce an active arousal at moderate level to students in a classroom.

6.3.3. Positive Attitudes to Teachers Increases Learning Performance

Learning performance was shown to improve if students have more positive attitudes to their teacher [153]. Several studies have shown that behavior quality of a robot correlates positively with social acceptance. Saerbeck et al. [150] studied social supportive behaviors of a robotic tutor in a language learning application. They modelled social supportiveness in five dimensions: role model, non-verbal feedback, attention guiding, empathy, and communicativeness. Results show that social supportive behaviors improve motivation and learning efficiency of students and improve students' attitude towards robots and towards the learning task, i.e., students considered the learning more like a fun game rather than a tough assignment. Hence, the behavior design of an educational robot has an impact on learning efficiency. Shin and Kim [151] studied students' perception and attitudes to a teaching robot in a classroom environment using three scenarios in which the robot played different roles. They found that students were able to learn from robots and showed positive attitude towards the robot. More importantly, emotion was found to be a vital factor that made the robot perceived as a qualified teacher. Hence, expressive behavior can be used to improve social acceptance of the RoboTutor and consequently improve students' learning performance.

6.4. Mood Expression based on Behavior Modulation

In this chapter, we aim at designing mood expression for robots. Distinctions between affect, emotion, and mood have been discussed in [37], [38], [34], [36], [35]. Here, we highlight the distinctions between mood and emotion that are related to expression: an emotion is a short term, intense affective state, associated with specific expressive behaviors; a mood is a long-term, diffuse affective state, without such specific behaviors. Mood emphasizes a stable affective context, while emotion emphasizes affective responses to events.

We consider that the expression by means of behavior parameter modulation is particularly suitable for expressing mood. First, our mood expression extends over time. We aim to design a generic model that can be applied to a broad range of robot behaviors. By applying the model to multiple behaviors (including task-related behaviors) in a series, the robot mood can be expressed in a more or less continuous fashion. It is suitable to express a long-term affect. Second, our mood expression does not show a particular action tendency. What behaviors should be performed at a particular moment is determined according to the task requirements, but not to the desire of showing mood. The robot mood only changes the "styles" of the existing behaviors. We do not create additional robot body actions for expressing mood. Third, our mood expression is implicit. The expression relies on the behavior cues that result from behavior modulation. Because of this nature, we believe that the expression should not be perceived to have explicit intention of showing mood, but rather an implicit reflection of the mood. We keep the interference caused by the parameter modulation of a behavior with the behavior functions as minimum as possible. The primary function of a behavior is still to fulfill a task, while the mood expression is an additional function. Thus, we believe that the behavior function is more noticeable and the expression by means of the behavior modulation is implicit and less intense. Therefore, we believe that our proposed mood expression is suitable for a diffuse, global, and background affective state of an individual, i.e., mood.

We believe that our mood expression should make the robot more believable and have larger the effects on users compared to other types of bodily expressions. First, because of the implicitness of the expression, users are less likely to perceive the expression as a "show" or making emotional stimuli on purpose, but rather a genius manifestation of the robot internal states. Users may believe more in that the robot truly has the state. That is, the robot will be perceived more believable. Because of the believability of the mood expression, users are more likely to be influenced by the robot mood. Second, the proposed mood expression lasts for a longer time during human robot interactions. The stimuli of the mood expression are presented to users in a more continuous fashion, compared to putting emotion expressions in between functional behaviors of teaching, such as coverbal gestures during the presentation. As a result, the effects of the mood expression on users should be stronger. The robot may also be perceived more expressive because of the long-term mood display. Therefore, we expect that in the RoboTutor study presented in this chapter the mood expression of the Robotuor has larger effects on students in terms of the improvement of students' perception of the robot and the mood induction to the students, compared to the use of other types of expression in a robot enhanced learning process. Our work explores the possibility of using robot bodily expression to improve learning experience. We believe that our mood expression based on behavior modulation can generate better learning outcomes. In addition, the expression also does not break the flow of the coverbal gestures during the speech. The course presentation of the robot thus can be more concurrent. The learning experience should be better.

6

6.5. Research Foci and Hypotheses

6.5.1. Research Questions

The purpose of our study is to explore whether affective robot body language provides an effective tool for improving learning experience of a robot-enhanced education application. We integrated mood expression with the coverbal gestures that the robot performed during the lecture (detailed in Section 6.4). In this study, the gestures were modulated to show either a positive robot mood (the positive condition) or a negative robot mood (the negative condition). We expected that differently modulated gestures should have different effects on the interaction and on the students.

As discussed in Section 6.3.1 and Section 6.3.2, a positive valence strengthens students' motivation in learning, and a moderate active arousal enhances learning performance. We therefore want to evaluate the following:

Q1) Can affective body language of a robotic teacher induce a valence and arousal in students that supports learning?

Moreover, as discussed in Section 6.3.3, positive attitudes of students to teachers improve learning performance. We derived our second research question from this:

Q2) Can body language make students rate a robotic teacher more positively?

The ultimate goal of our study aims at using robot affective body language to improve the students' learning experience. Although improvement learning may be difficult to measure, we still wanted to be able to check whether an immediate effect can be found. We therefore included quiz questions during the lecture that can be used as a measure of learning efficiency. The measure of quiz performance is also used as a behavioral consequential measure for H1 and H2. Our third question therefore is:

Q3) Is students' performance in answering quiz questions influenced by robot body language?

6.5.2. Hypotheses

Mood has been shown to be transferable between persons [97], [165], and from a robot to a person in a dyadic interaction [81]. We also believe that mood transfer can be reproduced during a lecture given by the RoboTutor. The major difference here is that mood may transfer from one robot to multiple individuals (one-to-many interaction).

H1) Participants' affective states are influenced by the robot mood: participants' affective states are significantly more positive in the positive condition than in the negative condition.

Fortunato and Mincy [177] showed that induced positive mood increased students' ratings of teachers. Moreover, the affective body language of the robot enhances the life-like quality of the robot [26], [24] and thus may improve students' attitudes towards a robotic teacher. We therefore expect participants to give higher ratings for lecturing quality and gestures of the robot tutor in the positive condition than in the negative condition, resulting in our second hypothesis:

H2) Participants' ratings of lecturing quality and gestures of the robot are significantly higher in the positive condition than in the negative condition.

As discussed in Section 6.3.1, 6.3.2, and 6.3.3, when students have a positive valence and a moderate active arousal or have a positive attitude to the teacher, their learning performance may be improved. Assuming that the robot body language influenced the mood of the students as hypothesized in H1 or their attitudes were shaped by the robot body language as hypothesized in H2, the students in the positive condition (where the robot displays a positive mood) are expected to answer the quizzes better than the students in the negative condition (where the robot displays a negative mood).

H3) Participants' task performance (correctness of quiz answers) is significantly better in the positive condition than in the negative condition.

6.6. RoboTutor System

6.6.1. RoboTutor Application

We chose to use the humanoid robot NAO and provided the robot with various capabilities that can be used to give a lecture such as using PowerPoint slides, performing coverbal gestures, and asking quiz questions.

One of the ideas behind the RoboTutor application is to design a robot lecturer that takes itself as an example to introduce various aspects (e.g., sensors, effectors, and system) related to robotics. For example, the robot is able to demonstrate how an ultrasonic sensor works by putting its hand in front of the sensor and show the distance detected; it can show that it is able to view the audience by showing a picture of the audience that is taken by its camera on a presentation slide in real-time. The robot can also perform a behavior while talking about it. The robot can illustrate, for example, how many degrees of freedom the NAO has in its arm by moving its arm. A robotic teacher application provides students also with possibilities to interact with the robot in class, for example, by touching the tactile sensors or converse with robot through speech recognition. Students learn better when they actively interact with an environment [178].

A teaching authority that fully controls the learning process is not appreciated [150]. Instead, students' internal control is more desired than external control [179]. Students should have opportunity to actively reflect the content they learned, instead of solely being told all the time. Some interaction may also keep the students attentive. To this end, we enabled the RoboTutor to ask quiz questions related to content just taught: the students are provided a wireless clicker to input answers within about 10∼15 seconds. This also gives them chances to exercise taught knowledge timely. Microsoft PowerPoint 2010 and TurningPoint version 5[1] (a plugin for MS PowerPoint) were used for presenting slides and quizzes. Students used TurningPoint clickers, which communicate wirelessly with the computer, to provide their quiz answers. They were asked to provide their answers within short intervals of time of about 10∼15 seconds, and the time remaining to answer was indicated on the quiz slide. Feedback is essential to effective teaching and students' motivation of learning [179]. The robot responds to answers, and the percentages of students that selected a particular answer is shown on the quiz slide. If most students selected an incorrect answer, the robot provided additional details to explain the correct answer. The robot also nods head (to correct answers) and shakes head (to incorrect answers) with larger amplitude and faster speed in the positive mood condition.

6.6.2. Script Engine

We aimed at creating an authoring system that allows a non-programmer, such as a teacher from a non-technical university, to use it easily. To this end, a script engine was designed to enable course instructors to orchestrate the robot gestures, speech, and slides by editing a text file (script). Users can load, execute, and pause or resume the script using buttons on the GUI.

A script consists of three elements: 1) configurations; 2) commands; and 3) text of speech. Configurations, usually located in the very beginning of a script, include the voice parameters (e.g., speed, volume, and pitch) and behavior parameters like whether the robot will perform random leg movements when ongoing behaviors do not contain leg movements. Commands (blue letters in Figure 6.1) are special control syntax of the system like running a robot behavior, switch a slide, or start a quiz session. Texts are the content of the robot speech. Some built-in syntax of the Text-To-Speech engine of the robot is supported, for example, a pause for a period of time and local voice variation.

[1] http://www.turningtechnologies.com/polling-solutions/turningpoint

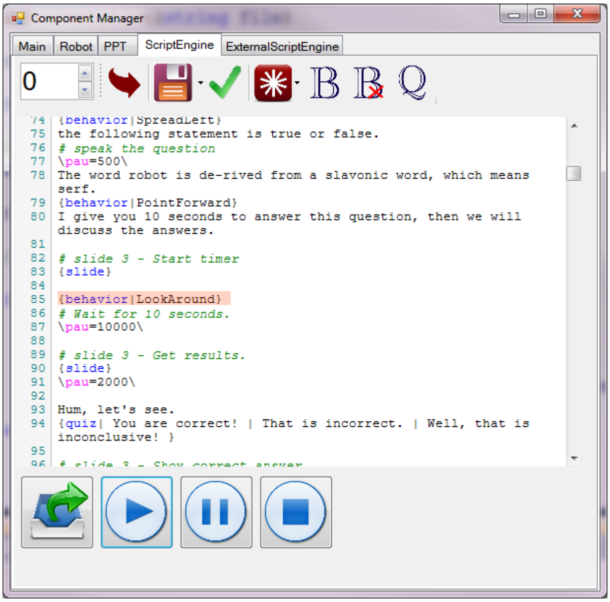


Figure 6.1: The script editor for orchestrating the robot speech and behaviors

A script editor (Figure 6.1) with syntax highlighting and toolbar are provided to users to facilitate editing. For example, users can insert a behavior command by clicking the shortcut on the toolbar and input the behavior name. We also provide some validation functions, such as check whether used behavior names match the behaviors defined in the system. We will also provide spell check for speech texts in the future. More detailed description of the script engine can be found in Appendix B.

The robot speech was generated by a Text-To-Speech engine shipped with the robot. We initially were worried that the voice produced by the standard engine would bore students quickly. However, in a pilot we found this not to be the case. As our focus is on body language here, we kept using the standard speech engine.

We designed a corpus of coverbal gestures, and enabled the script engine to synchronize automatically the starting points of a sentence and its coverbal gestures. Users need to adjust the length of the sentence to guarantee the speech and gestures to finish roughly at the same time if needed. A gesture can be executed by either the left or the right arm. If random leg movement is enabled, the robot selects leg movements from a predefined corpus in real time and performed them between hand gestures, to avoid a long time of no movement.

6.7. BODILY MOOD EXPRESSION

6.7.1. PARAMETERIZED BEHAVIOR MODEL

AMONG the modalities of affective expression, we chose bodily expression because humans understand intuitively the affective state, beliefs, and motives of a robot through nonverbal cues from the robot's expressive body language during human-robot

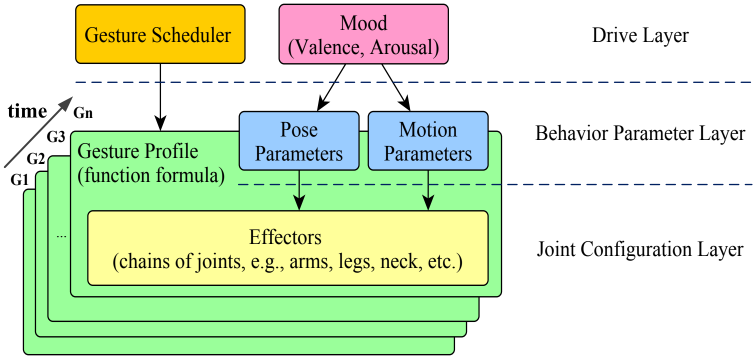


Figure 6.2: The three layer architecture of our parameterized behavior model

interaction (HRI) [31], [150]. Expressive body language also increases the efficiency of human-robot task performance and robustness [58]. Expressive body language also is particularly important for humanoid robots that lack facial features such as the NAO, ASIMO, and QRIO.

Our body language model enables a robot to express mood during the execution of functional behaviors required by tasks. For example, a positive mood can be expressed when a robot shows a direction by pointing or when a robot waves at people for greetings. To this end, our model allows the functional behaviors to be modulated by change behavior parameters.

We briefly discuss our model here. Our model is a parameterized behavior model that consists of three layers: 1) a drive layer; 2) a behavior parameter layer; and 3) a joint configuration layer (Figure 6.2).

The drive layer consists of a function component and an affect component: the function component decides which behaviors should be performed at a specific moment according to the task requirements; the affect component determines the affective state of the robot using an appraisal model, for instance. From the top layer, behavior functions and affect expression are made independent. The affective state of the robot controls the values of the parameters in the behavior parameter layer.

The parameters control spatial extent as well as motion dynamics of a behavior [77], [78], and further changes the behavior appearance. The modulation of movement parameters does not change the function associated with the behavior. Some parameters, such as speed and amplitude of a movement, are generic, and can be used to modulate arbitrary behaviors. Other parameters are associated with a particular body part of the robot such as head, hand palm, and finger. To express mood while performing a specific behavior, one only needs to specify which parameters should be varied. Thus, a range of moods can be expressed, and mood can be displayed throughout a series of behaviors.

The parameters are defined within functional bounds during the construction of the behavior. They serve as interfaces between the affective states and the final configurations of the joint values. Each parameter is associated with one or more joint values using numerical formulas, which are the interpolations between poses. These poses are constrained by the behavior profile of a behavior, which defines how joints depend on each other according to social conventions. For example, we define waving as one hand

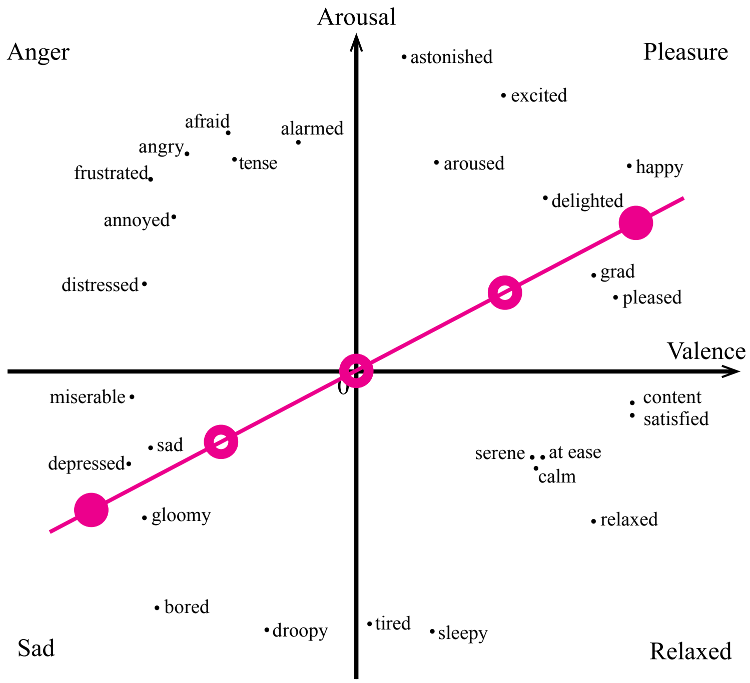


Figure 6.3: Valence (pleasure)-Arousal affect space of Russells' circumplex model [94]. The circles denote roughly the positions of the five mood levels in our previous study. The two solid circles denote the moods we used in the RoboTutor study.

swinging between two horizontally aligned positions repeatedly, and the palm should always face forward. All joints should comply with the definition whenever they are changing.

6.7.2. PLEASURE-AROUSAL AS A BASIS FOR MOOD

One of our main goals with developing a robot body language framework has been to create a generic model of robot behaviors, so that the behaviors can be modulated continuously to express mood that varies in a continuous space. Therefore, we have chosen a dimensional approach to describe mood in theory, although we used discrete levels for experiments. We chose Russell's circumplex model [94] as a basis of the affect space for mood. In this model, valence depicts the negativeness versus positiveness of mood and arousal depicts the activation of mood. Using this model, each mood is modeled as a coordinate in the VA space. For example, the difference between sadness and fear can be represented in a numerical way: fear corresponds with a negative valence and a high-activated arousal, while sadness corresponds with a negative valence and a low arousal.

The VA affect model allows us to build a mapping for each parameter to the VA space, and thus the mood can control these parameters. In this way, it is able to present each behavior parameter as a function of V and A. Initially, linear functions were used for the mapping.

$$P_i = f_i(V, A) = \alpha_i \times V + \beta_i \times A + \gamma_i \tag{6.1}$$

The coefficients α_i and γ_i in the equation above were established empirically in a user study [77] and confirmed in a perceptual task in an additional evaluation study [79]. In the user study, we merely considered the valence dimension in this mapping. Put differently, we set β_i to zero. The reason is that mood mainly varies along the valence axis, but slightly varies along the arousal axis. Only using valence for control also reduces the complexity of the model and reduces the number of conditions of the user study (see details below). It was found in the perceptual task evaluation [79] that the parameters for motion-speed, hold-time (fluency), repetition, and head-vertical correlate with arousal. Moreover, people were able to perceive both valence and arousal of the robot mood from the modulated robot behaviors. This result indicates that each parameter correlates in varying degrees with arousal. However, our previous studies did not allow us to figure out the exact value for the coefficient of arousal (β_i) for each parameter. Although our direct manipulation of the robot mood is to vary valence, the range of the robot mood is from sadness to happiness, i.e., from -A-P to +A+P (see Figure 6.3). In the RoboTutor study, we studied two levels of the valence: negative (very unhappy) and positive (very happy).

6

6.7.3. Mood Expression of the Robotic Teacher

We applied the parameterized behavior model to two behaviors of a NAO robot, and conducted a user study to address which behavior parameters have the potential to express mood and how to modulate these parameters to express a specific mood [77]. The obtained modulation rules are summarized in Table 6.1. The resulting mood expressions were evaluated through a perceptual task without an interaction context and in an interaction game. Although the robot behaviors were modulated solely according to valence, we also asked participants to rate arousal from the behaviors. Results show that participants are able to identify correctly valence and arousal levels of a robot mood in both setups. These results serve as the basis of the study presented in this chapter.

In this study, we parameterized 41 coverbal gestures of the RoboTutor with 12 parameters. The robot showed either a positive or a negative mood during the lecture by modulating the gestures, according to the validated rules in Table 6.1. Decay-speed was used in [77] to control the speed of movements when robot actuators return to their initial poses. In this study, we used motion-speed as decay-speed because decay-speed was found to correlate with motion-speed in [78]. The duration of maintaining a particular pose called hold time was refined into "fluency" hold time and "persistency" hold time [77]. As aforementioned, some parameters were found to correlate with arousal. The modulated gestures thus do not only display the valence of the robot mood but also arousal. Videos of the modulated gestures that show stepwise changed mood and a video recording the robot during the experiment are available from our website[2].

[2] http://ii.tudelft.nl/SocioCognitiveRobotics/index.php/RoboTutorMood

Table 6.1: Design principles for mood expression

Category	Parameters	Modulation	Valence	Arousal
Pose (spatial extent)	Width	outward	positive	/
		inward	negative	/
	Height	high	positive	/
		low	negative	/
	Forward	front	positive	/
		back	negative	/
	Palm Direction	extrovert	positive	/
		introvert	negative	/
	Finger Rigidness	straight	positive	/
		bent	negative	/
	Head Vertical	raised	positive	active
		lowered	negative	passive
	Head Horizontal	follow arm[a]	positive	/
		look forward	negative	/
	Amplitude	large	positive	/
		small	negative	/
Motion (dynamics)	Motion Speed	fast	positive	active
		slow	negative	passive
	Hold Time (fluency)	short	positive	active
		long	negative	passive
	Hold Time (persistency)	long	positive	/
		short	negative	/
	Repetition	repeated	positive	active
		non-repeated	negative	passive

[a]look forward when two arms act.

6.8. EXPERIMENT AND RESULTS

IN this section, we introduce the field study experiment, in which the RoboTutor gave a lecture in a master course about Artificial Intelligence at Delft University of Technology. We first elaborate the experimental design and procedure, then we describe the analysis and results, and finally we interpret the results in a discussion subsection.

6.8.1. EXPERIMENTAL DESIGN

INDEPENDENT VARIABLE

The robot mood was manipulated as an independent variable at two valence levels: positive and negative (see Figure 6.3). Note that the arousal is also different for the two mood levels (discussed in Section 6.7.2). The same lecture was given twice, once for each condition. That is, the script (see Section 6.6.2), the lecture content (presentation and spoken text), and the types of gestures were the same for both conditions. Only the appearance of the gestures was modulated to vary the mood conditions. Slides did not contain too many details to prevent students from paying too much attention to the slides instead of to the robot. Participants were divided into two groups, and were assigned to a lecture in either the positive or the negative condition, making the experiment a between-subject design with one independent variable, the robot mood.

Dependent Variables and Measures

The affective states (valence and arousal) of participants were measured at the beginning of the lecture (T0), during a break in the middle of the lecture (T1), and at the end of the lecture (T2), using Self-Assessment-Manikins (SAM) [117] on 9-point Likert items. The difference between T1 and T0 and between T2 and T0 were taken as measures of the induced affective states (H1). By measuring participants' affect and the perceived robot mood both at T1 and at T2, we obtain a measure for mood change over time. In addition, the lecture of each mood condition was video-recorded. Videos were manually annotated by two annotators (details in Section 6.8.7) to assess the overall valence, arousal (H1), and attention distribution of the audiences.

The post-experiment questionnaires at T2 asked for participants' ratings (H2) about the robot lecturer on 5-point Likert items, using six items about the lecturing quality including 1) maintenance of participants' interests, 2) maintenance of participants' engagement, 3) enthusiasm, 4) friendliness, 5) maintenance of participants' attention, and 6) overall satisfaction. The items were designed based on the aspects investigated in [180]. Moreover, we also asked participants to rate the robot gestures (H2) on 5-point Likert items, using four items including 1) whether the robot was using gestures to communicate information, 2) whether the gestures made the participants to follow the speech more easily, 3) whether the robot organized speech, gestures, and slide switching in a fluent way, and 4) whether the gestures were natural.

6

The task performance was assessed using the answers to the quiz questions (H3). These questions, which are multiple-choice questions, relate to the lecture content taught by the robot just before the questions were asked. Each student was requested to provide answers independently.

We also tested the recognition of the robot mood to verify whether conscious recognition is a precondition for mood induction. Our previous studies showed that people are able to recognize the robot mood from modulated behaviors [79], [81]. In a lecture, although students may pay attention to the slides and may concentrate on thinking about the lecture content, they still pay a considerable amount of attention to the lecturer. We believe that the students should also be able to rate the robot mood as positive/negative when the robot gestures are modulated as positive/negative. Participants were asked to assess the robot mood (valence, arousal, and dominance) using SAM on 9-point Likert items, at T1 and at T2. We took two measures because we wanted to see how the recognition changed over time. The scenario (lecture) lasts for a long time (about 30 minutes) and the robot mood may become clearer to students at the end of the lecture.

In addition, participants were asked to do a self-assessment of the attention they paid to the robot, slides, or something else in percentages, to rate the consistency of the robot mood on a 5-point Likert item, and to answer an open question about the rationale for their ratings of the robot mood in terms of valence, arousal, and dominance separately.

6.8.2. Assignments to Participants

First, participants were requested to listen carefully to the robot. They were informed that the lecture materials used by the robot were prepared by the course instructors, and that the content would be part of the exam. Second, they were requested to answer quiz questions that were posed by the robot and presented on the slides. We encouraged participants to obtain a high quiz score, by telling them beforehand that the first place of each group would receive a Philips LED Rechargeable Candle as a prize.

6.8.3. PARTICIPANTS

Participants were recruited from the students who enrolled in the Artificial Intelligence course at the Delft University of Technology. We asked the students to register, and asked permission from the students for this experiment in advance. They were told that each would receive a bonus course credit. 36 students registered, and all except one were master students. They were randomly assigned to each group, but we ensured that the background of participants (department and master program) was roughly equal within each group. 34 students (28 males and 6 females) whose ages range from 21 to 36 (*Mean*=23.8, *SD*=2.7) participated in the experiment: 18 of them for the positive condition; 16 for the negative condition. They come from 11 different countries, with 18 of them being Dutch. The pre-experiment questionnaire showed that some participants had taken courses related to robotics such as "Humanoid Robots", "Machine Learning", and "Computer Vision". Some participants (12 in each group) attended projects related to robotics during their bachelor. Participants reported that they were open to technology-assisted education (*Mean*=3.941, *SD*=0.736, on a 1 to 5 scale).

6.8.4. MATERIALS AND SETUP

6

A small lecture room that contains about 26 seats (with desks) was selected for the study. This setup has the advantage that participants sit relatively close to the robot so that they were able to notice the details of robot movements more easily and thus more likely to be influenced by the robot mood, even though we did not assign seats to participants (the experiment setup was identical to a usual classroom setup). The seats were aligned in a grid pattern (Figure 6.4), which facilitated the estimation of the distance and angle of a participant to the robot. The shutters of the window were closed. The screen for showing slides was located on the upper part of the wall behind the robot. The course instructor also took part in the experiment and sat in front of the classroom to protect the robot (e.g., from falling down) and to organize the experiment. Other experimenters were seated at the back of the classroom.

A grey NAO robot (NaoQi version 1.14, head version 4.0, body version 3.3) was used with LED lights switched off. The robot was connected with a laptop using cables, via a router and a gigabit switch, to guarantee sufficient speed of data transmission. The robot, which is 58 cm tall, was positioned on a desk (Figure 6.4) while giving the lecture, which ensured that participants could see the robot by looking straight ahead.

Three video cameras were used for video data acquisition. Two cameras were placed on desks at the front of the classroom, on each side of the robot. Each camera recorded half of the classroom. The heights and angles of the two cameras were adjusted to guarantee that participants do not hide each other. The third camera placed at the back of the classroom (Figure 6.4) was used to record the robot.

The course material (see footnote 2 for a link to the slides) was part of the course curriculum and designed by the course instructor. The material is structured in five parts: 1) a general introduction to robotics, 2) a part about robot sensors, 3) a part about robot effectors, and 4) the programming of the NAO robot, and 5) a brief part about the Robo-

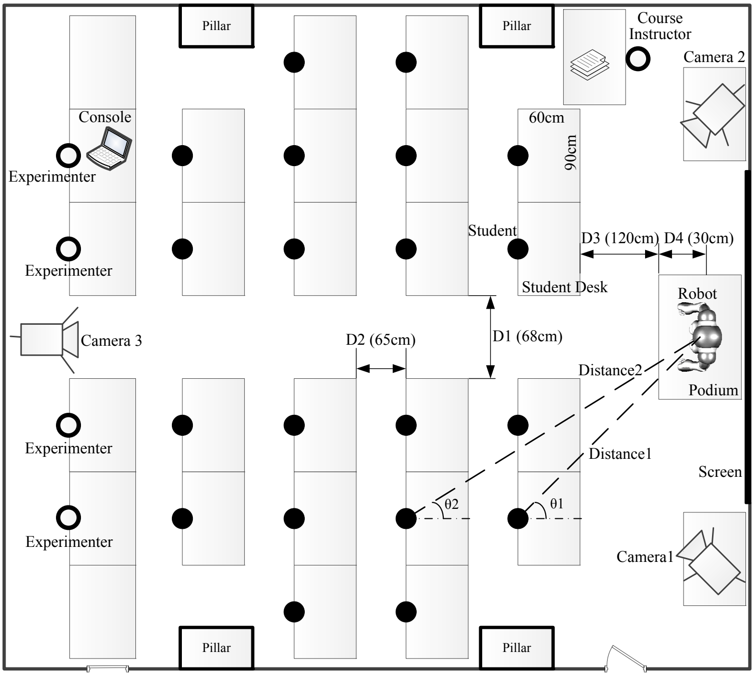


Figure 6.4: The layout of the lecture room and the positions of the robot, students, experimenters, seats, and cameras.

Tutor system itself. The lecture included seven quiz questions. The first one was an easy question, which asked about the origin of the word "robot", used as a warm-up exercise at the beginning of the lecture. The other six were used for assessing participants' performance. The second question about the definition of a robot was asked at the end of the part 1. Three questions about sensors were asked at the end of part 2, just before a short break. The other two were asked at the end of part 3 and 4 each.

6.8.5. PROCEDURE

Before the lecture, experimenters aligned the seats and desks, measured and recorded the dimensions needed (Figure 6.4), and set up the robot, laptop, projector, and cameras. When students arrived, they were allowed to select seats, but were not allowed to rearrange desks. Experimenters gave each participant a description of the experiment and a TurningPoint clicker. Students were requested to fill in a consent form, a demographic form, a general questionnaire about previous experiences with robotics, and a pre-experiment SAM questionnaire to report their own affect (valence, arousal) before the start of the lecture (T0). An explanation sheet for valence, arousal, and dominance was provided to them. The human lecturer briefly described the experiment and answered questions. Students were told that they could not ask the robot questions during the lecture. We did not emphasize the robot mood or gestures to avoid any demand effects (i.e., participants rate what they think we expect).

The experiment started immediately after experimenters collected the pre-experiment forms from all students. Three experimenters started the camera recording manually, and another experimenter started the lecture program. The program started the PowerPoint presentation automatically, and sent the lecture script (see Section 6.6.2 for an example) to the robot. The robot then started to talk and perform gestures.

In the middle of the lecture (after part 2 of the slides), the robot asked participants to take a 5 minute break and to fill in a mid-term questionnaire during the break (T1; see Section 6.8.1). Experimenters handed out the questionnaire, but did not collect the questionnaires during the break to save time. The robot resumed the lecture after 5 minutes.

The whole lecture including the break took about 30 minutes. After the robot finished the lecture, experimenters stopped the cameras. Experimenters first collected the questionnaires that were completed during the break, and then handed out the post-experiment questionnaire (Section 6.8.1). After 10 minutes, experimenters collected all forms and questionnaires. The course instructor provided a brief explanation of the experiment to the participants, and requested them not to tell anything related to the experiment to the second group of participants. Experimenters checked whether all fields had been filled in when they collected questionnaires.

6.8.6. Factors in the Validity of the Results

Here, we discuss other factors that may threat the validity of the results. First, distance and angle between the robot and participant may influence attention paid to the robot and the perception of body language [163], and social distance may influence people's interpretation of, attitude towards, and preferred type of body language [181]. In our case, for example, it might be difficult to see subtle details of the robot body movements like finger or wrist from a distance; waving hands with large amplitude is typically interpreted as a greeting from a certain distance but can be interpreted as drawing someone's attention at a closer distance. In our setup (Figure 6.4), participants sitting in the first two rows are closer (far phase of social distance [182]) to the robot than those sitting in the third or fourth row (close phase of public distance [182]). Hence, the robot mood may influence the participants sitting close to the robot more (H1) and the participants may recognize the robot mood better, than those sitting further away. As a result, distance may also influence the ratings of the lecturing (H2) and the participants' task performances (H3). The distance and angle between robot and each participant was estimated geometrically (Figure 6.4), according to the seat position (row and column) reported by students in the pre-experiment questionnaire. Experimenters aligned the seats in a grid pattern (Figure 6.4) and recorded the dimensions beforehand. The center of the rear edge of the desk (the solid circle in Figure 6.4) was taken as the position of each participant, despite of his/her postures (e.g., leaning back on the chair, leaning forward on the desk).

Second, the attention a participant pays to the robot may mediate the mood contagion process and, as a result, influence task performance [165]. Third, there is evidence showing that social power ("dominance") influences the contagion process [164], [183]. Affect is more likely to transfer from superiors to subordinates. In our case, the contagion effect may be stronger for participants that rate the robot as dominant.

6.8.7. Analysis and Results

Check of Participants' Initial Affective States

As the data are not normally distributed, Mann-Whitney U tests were used to analyze the initial affective states of participants (at T0). The results showed no significant difference in the self-reports of participants' own valence and arousal between mood conditions. We thus may assume that participants in both groups had similar affective states at T0.

Induced Affective States of Participants

The self-reports of participants' own valence and arousal are not normally distributed. Friedman test and Wilcoxon Signed Ranks test were used for each mood condition to analyze whether participants' affective states (H1) were different over time and how the affective states changed from T0 to T1 and from T1 to T2. Results showed the arousal changed over time ($\chi^2(2)$=7.774, p=0.020), and showed a significant increase of arousal at T1 (Med_{T0}=1, Med_{T1}=2, Z=-2.698, p=0.006, two-tailed) and a marginally significant drop at T2 (Med_{T2}=1, Z=-1.931, p=0.066, two-tailed) in the positive condition only and only for arousal (Figure 6.6 left). This shows that there is mood induction in the positive condition.

6

To find out if the induced mood is significantly different between mood conditions, i.e., if positive robot mood induces significantly more arousal than negative robot mood, we calculated two induction measures by subtracting T0 from T1 and T0 from T2 (Figure 6.5 right and Figure 6.6 right). Mann-Whitney U test was used to analyze the induction effect. Results show that the induced arousal at T1 in the positive condition was significantly larger than in the negative condition (Med_{T1neg}=0, Med_{T1pos}=1, U=73.5, Z=-2.486, p=0.012, two-tailed), and the induced arousal at T2 in the positive condition was larger than in the negative condition at a marginally significance level (Med_{T2neg}=-1, Med_{T2pos}=1, U=91.5, Z=-1.857, p=0.064, two-tailed).

The videos of each condition (29 minutes) were annotated by two experienced annotators to assess participants' valence and arousal on a 9-point Likert item, and attention distribution (rank order of robot, slides, and other). We employed the interval coding method: the annotators assessed the overall valence, arousal, and attention of the audiences as a whole from every one minute of the video. Spearman's rho was used to test the inter-coder reliability. Results showed that the correlation is significant and has a large effect size: rho=0.675, p<0.001 for valence, and rho=0.511, p<0.001 for arousal. It indicates a strong consistency between the two coders. We took the average of the ratings of valence and arousal per minute from both coders as final ratings (valence: Med_{neg}=-0.5, Med_{pos}=0.5; arousal: Med_{neg}=-1.0, Med_{pos}=0.5). Mann-Whitney U test was used to analyze the difference of the final ratings between mood conditions. Results showed that both valence and arousal are significantly higher in the positive condition than in the negative condition: U=107.0, Z=-4.962, p<0.001, two-tailed for valence, U=163.5, Z=-4.052, p<0.001, two-tailed for arousal. The results indicate that the robot mood expression had an effect on both the valence and arousal of the audiences. In addition, both coders reported that there was more laughter in the positive condition, and only in the positive condition the participants applauded at the end of the lecture.

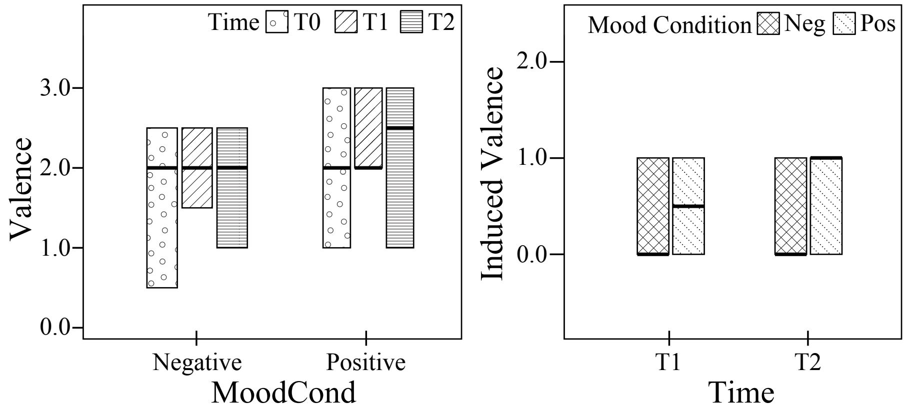


Figure 6.5: Participants' self-reports of their own valence (at T0, T1, T2) and induced valence (at T1, T2): median value and interquartile range (IQR).

PERCEPTION OF LECTURING AND GESTURE QUALITY

The average ratings of the items about lecturing quality of the robot and the items about the robot gesture quality are illustrated in Figure 6.7 and Figure 6.8. There is a trend that the ratings of all items about the lecturing quality are higher in the positive condition than in the negative condition (Figure 6.7). An independent t test shows that the sum of the ratings about the lecturing quality in the positive condition is significantly higher than the negative condition: $t(32)=2.210$, $p=0.034$. That is, the participants believe that the lecturing quality of the robot is higher in the positive condition.

For the ratings of the robot gesture quality, we excluded an outlier (lower than the lower inner fence of the boxplot) from analysis. There is a trend that the ratings of all items about the gesture quality are higher in the positive condition than in the negative condition (Figure 6.8). An independent t test shows that the sum of the ratings about the robot gesture quality in the positive condition is higher than in the negative condition at a marginal significance level: $t(31)=1.920$, $p=0.064$. This suggests that participants believe that the robot gesture quality is higher in the positive condition.

LEARNING PERFORMANCE

As the data of the answers to quiz questions (2-7) is not normally distributed, Mann-Whitney U test was used to analyze the difference between mood conditions. Results showed no significant difference between the positive (Med=4) and negative (Med=4) conditions. That is, we did not observe an effect of robot mood on participants' task performance in terms of question answering (H3).

6.8.8. DISCUSSION

The students' self-reports showed that the positive mood expression of the robot induced a more active arousal to the students than the negative expression. Objective assessment in the form of video annotation also revealed that the positive expression induced both a more positive valence and a more active arousal to the students, compared

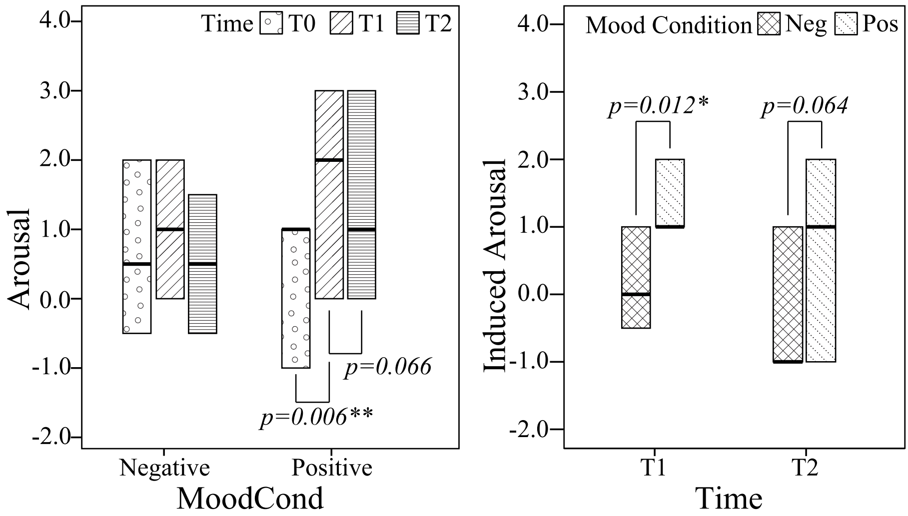


Figure 6.6: Participants' self-reports of their own arousal (at T0, T1, T2) and induced arousal (at T1, T2): median value and interquartile range (IQR).

to the negative expression. This means that the robot body language has an effect on students' affective states. It is known that mood contagion can happen between persons automatically or subconsciously [97], [165]. This study showed that automatic mood contagion could also occur from a robot to audiences. We thus did find support for H1. As demonstrated in Section 6.3, a positive valence and a moderately active arousal may improve students' learning. Therefore, the positive body language of the robotic teacher is possible to improve students' learning by shaping their affective states.

The results support that the ratings of the robot in terms of lecturing quality and the gesture quality are better when the robot displays positive body language. Although each individual item is not significant, which may be due to the small sample size, trends towards perceiving both qualities higher in the positive condition are clear and the sum of those ratings is significant or marginally significant. Thus, there is support for H2. As demonstrated in Section 6.3, a positive attitude of students toward their teacher may improve students' learning. Therefore, the positive body language of the robotic teacher is able to improve students' learning since it is able to improve students' attitudes toward the robot.

We checked for influences of attention, distance, angle, and perceived robot dominance. We did not observe a significant difference of the attention between conditions from t tests based on self-reports. According to these self-reports, participants in the positive mood condition paid attention to the robot for 51.94% (*SD*=15.82%) of the time and 38.61% (*SD*=16.34%) to the slides on average, and participants in the negative mood condition paid attention to the robot for 48.75% (*SD*=18.66%) of the time and 40.00% (*SD*=16.23%) to the slides on average. This is consistent with video annotation of attention distribution. Mann-Whitney U test did not show significant differences between mood conditions for attention focus annotated from videos (inter-coder reliability was strong for attention to robot, rho=0.635, $p<0.001$, and for attention to slides, rho=0.605,

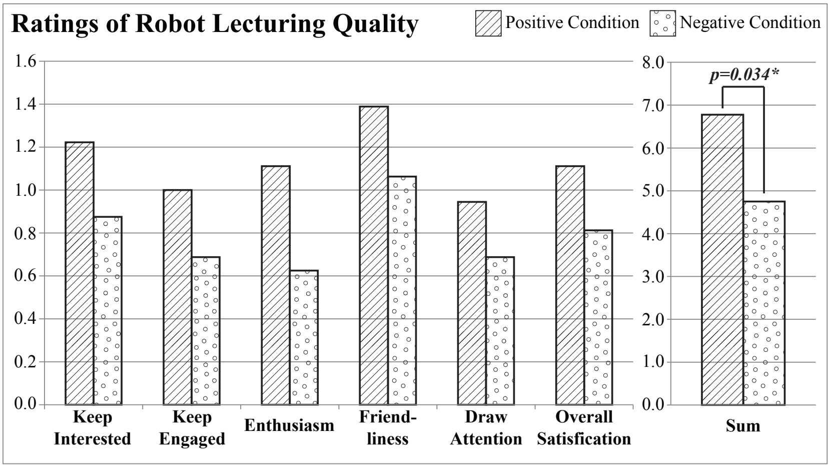


Figure 6.7: Participants' ratings of their course experience at T2: the left side shows each individual items, while the right shows the sum of the six items.

p<0.001). This means that the manipulation of the robot mood is not observed to influence the students' attention. However, the attention paid to the slides may influence the main results. In addition, correlation analyses did not show significant relations between distance, angle, or the perceived robot dominance on the one hand, and the recognition of the robot mood or induced participant mood on the other. This means that the effects of distance, angle, and the perceived robot dominance on the recognition of the robot mood and the mood induction process were not observed.

We did not observe direct effects of robot body language on students' learning. The performances of quiz answering between the positive and negative conditions show no statistically significant difference. H3 is thus rejected. A possible reason could be that the answering to in-class quizzes is primarily course content oriented. The performance of the quiz answering is less influenced by lecturing quality, i.e., in our case, presenting the same course content with different "moody" gestures. Many studies have reported that the improvement in students' learning outcomes caused by involving robots is not guaranteed because many other factors also influence the learning outcomes (see [9] for a review of these studies). Moreover, students paid considerable attention (almost 40%) to the slides, which may hinder the effects of the robot mood expression on the learning performance. This finding is consistent with other studies, e.g., [108], [184]. Another possible explanation is that the improvement in learning can be only observed in a relatively long term [185]. The learning procedure in this experiment is still short-term, although it lasted for 45 minutes. Our measurement of learning performance is based on quick quiz answering and only for once. The effects of the robot body language on students' learning thus may be not big enough be detected by question answering. Even though we did not find significant performance differences, we believe that it is worthwhile to further study the effects of robot body language for improving learning outcomes, because the results show that the robot body language is able to induce affective states that support learning to students and improve students' attitudes to the

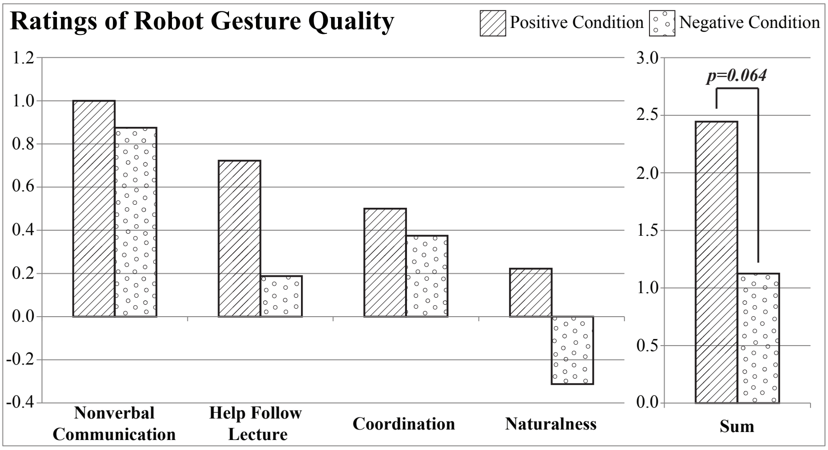


Figure 6.8: Participants' ratings of the robot gestures at T2: the left side shows each individual items, while the right shows the sum of the four items

robotic teacher.

It is not clear whether the students recognized the robot mood consciously from the robot body language. The self-reported SAM ratings about the robot mood did not show a statistically significant difference in the perceived robot mood between conditions. Participants rated the robot valence, arousal, and dominance at T1 and at T2. As the data violated the normal distribution assumption, we compare the ratings of valence, arousal, and dominance between the positive and negative conditions using Mann-Whitney U test. The median values and interquartile range of each variable are illustrated in Figure 6.9. The results did not show significant differences between the positive and negative conditions either at T1 or at T2. It was discussed in [97] that participants would not spontaneously pay attention to another person's expression if they were not required to. In our case, we did not prime the participants to pay attention to the robot mood expression in advance, and the analysis of participants' attention distribution showed that participants paid almost 40% of their attention to the lecture slides in both conditions. This may explain the absence of the significant differentiation of positive and negative mood. Another possible explanation for the absence of a significant difference in reported robot mood is that participants attribute the gesture modulation to teaching quality directly instead of to robot mood. Last, open participant feedback of the university lecture study show that variation in robot mood is attributed to various factors that were not manipulated such as tone and volume of the robot voice, speaking speed, lecture pace, and gaze/eye contact. This may also explain the absence of a significant difference in reported robot mood: these factors may interfere in the conscious recognition of the robot mood through the gesture modulation. Additional work is needed to verify how these factors influence the recognition. Note that the mood transfer between persons occurs automatically and subconsciously [97], [165], i.e., conscious recognition of mood may not be a precondition for mood transfer. This may also be the case for the mood transfer between a robot and people. In this study, we also did not observe significant correlations between the recognition of the robot mood and the self-reported

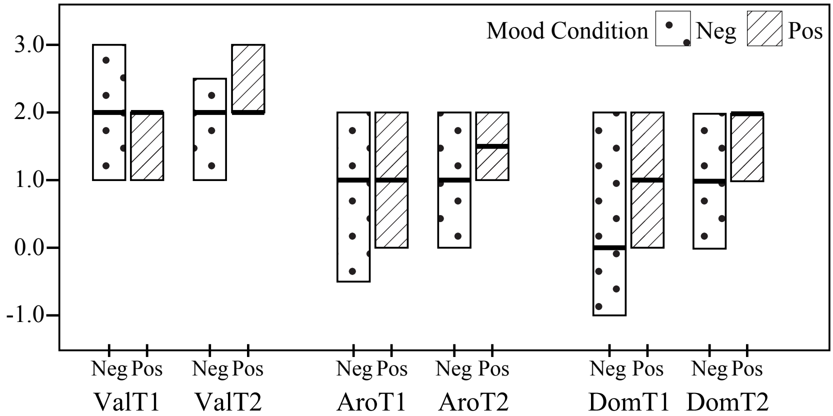


Figure 6.9: Perceived robot mood valence, arousal and dominance at T1 and at T2: median value and interquartile range (IQR).

participants' moods. Thus, the mood induction in this study may have happened subconsciously.

6.9. TEACHERS' PERSPECTIVES

TEACHERS' opinions are useful for improving the RoboTutor. Not only they have plenty of experience as teacher and in lecturing, but also they can provide a perspective on teaching that is different from students and audiences in general. Teachers, researchers, specialists, and students attended an event held in the Netherlands to discuss their own needs in the field of learning and teaching with ICT (Figure 6.10). We seized the opportunity to show our RoboTutor to these teachers and ask for their opinion about the RoboTutor. We used questionnaires as shown in Table 6.2. Fifteen teachers answered our questionnaires.

We asked their perception of the robot mood with respect to the valance, arousal, and dominance dimensions using 9-point Likert items, and their opinions on the statements listed in the table below on a 5-point scale: strongly disagree, disagree, neither agree nor disagree, agree, and strongly agree. In addition, the teachers were also asked to provide suggestions in an open-question section of the questionnaire. Results are illustrated in Figure 6.11.

Results show that the teachers' ratings about whether the body language of the robot makes the robotic teacher more enthusiastic is positive and an one-sample t test shows significance (*Mean*=1.53, *SD*=0.52, $t(14)=11.5$, $p<0.001$, test value 0.00). This suggests that the positively modulated body language is perceived as enthusiastic by teachers. Teachers also consider that the gaze behavior of the robot makes the robot appear enthusiastic (*Mean*=0.71, *SD*=0.83, one-sample $t(13)=3.238$, $p<0.01$, test value 0.00). By asking about this aspect, we intended to check whether teachers considered the eye contact was an issue since the robot is not able to make eye contact with audiences in a natural way (e.g., random scanning the audiences). It appears that the raised head has an already sufficient effect on perceived enthusiasm. A few teachers mentioned in their answers to

Figure 6.10: The RoboTutor is giving a lecture to teachers.

open questions that the robot should look at everyone in the audience from time to time, because by doing so the robot shows awareness of its audience and respect.

The results also show that the perception of whether the robot is too small for teaching in a classroom correlates negatively with the perceived authority (Spearman's *rho*(15)=-0.598, *p*=0.019) and the dominance of the robot (Spearman's *rho*(10)=-0.635, *p*=0.049). This means that teachers who thought the robot is too small for classroom teaching also considered the authority and dominance of the robot to be low. Moreover, the rating of the statement "the robot cannot teach in the classroom" correlates highly with the perceived robot dominance (Spearman's *rho*(10)=-0.664, *p*=0.036). That is, teachers who think that the dominance of the robot is high consider the robot able to teach in a classroom.

Teachers who think that the robot maintains their attention during the lecture also rated the overall satisfaction high (Spearman's *rho*(15)=0.722, *p*<0.005). It seems that whether a robotic teacher can keep students' attention is an important factor that real teachers were concerned about the most. However, there is no agreement on the attention maintenance by the robot. Possible explanations may be that those teachers did not have a learning goal in the lecture and they were listening to the lecture in an open envi-

Table 6.2: Items of the questionnaire

1.	The robot shows sufficient authority for teaching.
2.	I think the robot is too small for teaching in a classroom, even if it stands on a table.
3.	Body language makes the robot more enthusiastic.
4.	The robot lecturer maintains my attention during the presentation.
5.	Overall, I am satisfied with the performance of the robot lecturer.
6.	I like to be taught by a robot about a course related to robotics.
7.	I do NOT think this robot can be used to teach in a classroom.
8.	The gaze behavior of the robot during its speech makes the robot more enthusiastic.

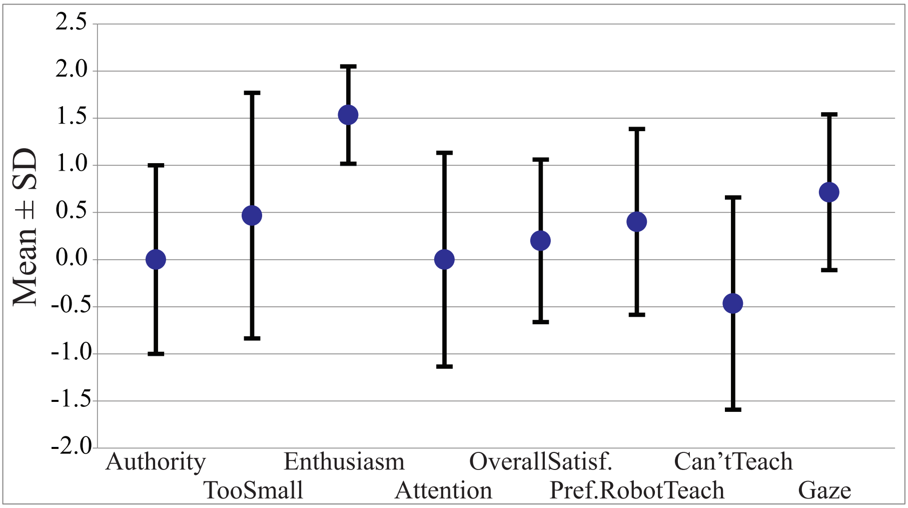


Figure 6.11: Teachers' ratings. The full description of the items is in Table 6.2.

ronment where other events or demos happened nearby. The attention of the teachers was drawn by the other happenings. They thus do not consider that the robot maintain their attention.

6.10. GENERAL DISCUSSION AND FUTURE WORK

THE experiment provides additional insights about a robotic teacher application outside the direct scope of our research. For example, we learned that physical presence is an aspect that both students and teachers are concerned with. The size of the robot is an important aspect of its physical presence. A few students in the university lecture experiment thought that the dominance of the robot is low because "the robot is cute and small". In the ICT event, not all the teachers agreed that the robot has enough authority for teaching, and they did not give a high rating on the robot dominance. Correlation analyses in Section 6.9 show that both the robot teaching authority and dominance correlate with robot size. Two teachers explicitly mentioned in the open questions that the robot should be made bigger. We thus can conclude that one of the physical limitations of the humanoid robot NAO is its child-like size. Putting the robot on a table when it gives a lecture does not change the perception that the robot is too small. The insights that we gained in our study, however, are also useful for bigger sized robots (e.g., ASIMO, ROMEO, and HRP4) and more work is needed to gain a better understanding of the effects of robot size.

Novelty effect is another aspect, which was addressed in many HRI studies through long-term interactions such as [186], [187], [188], [189]. The main concern is whether effects (e.g., attitude, relationship, and mood contagion) of a robot on people in an interaction can be maintained over time or can be reproduced when people get used to the robot. In our university lecture experiment, we observed that participants' arousal increased at T0 but decreased at T2 in the positive condition. The same trend was also observed in the negative condition but less significant. We speculate that this is due to a novelty effect: people's attitudes and preferences to a robot change over time. This effect seems to be stronger when the robot shows positive mood through body language, since the induced arousal at T1 is larger in the positive condition. This effect seems to be able to draw attention from students and increase their arousal. For a less popular course, the novelty effect can also be used to attract students. A long-term study regarding the RoboTutor is necessary to confirm the effects observed in this study. An alternative, more mundane explanation of the reduced arousal in our study, however, may be just due to the time of the course. It is not uncommon that students are less excited when the course is near the end (T2), as they may feel tired and start to imagine about activities after the course.

There are many potential aspects of the RoboTutor that can be improved with the aim of improving learning in the future. In the university lecture study, the robot mood was attributed to various factors related to the speech such as the tone and volume of the robot voice, speaking speed, and lecture pace. Teachers in the ICT event also suggested improvement of the robot voice: for example, "the robot voice should not be monotone". Indeed, the speech is an important channel to communicate mood and other internal states of the robot. Voice can also be made expressive by modulating pitch, volume, and speed, etc. Future work should contribute to a better understanding of multimodal affective communication.

6

Suggestions in the open questions from the teachers in the ICT event also include facial expression. The NAO robot we use in this study does not contain rich facial features and face expression is beyond the scope of our current research. Many other robots [24], [98], [54] have sophisticated facial features. We believe that outcomes of our study on robot body language can be applied to those robots. Combining facial expression with our expressive body language should further enrich the expressiveness of the robot nonverbal communication. Studying the effects of the combined expression on education will be an interesting future work.

Moreover, the need for more interaction between the robotic teacher and the students is suggested by both students and teachers. An effort is needed to make the RoboTutor more responsive, and to provide students with opportunities of active interactions, such as asking questions by raising hands. In addition, behaviors such as gazing at students who are moving and maintaining eye contact with different students in the audience should be added to the robot to show awareness of the environment, which may improve the lifelikeness of the robot. In addition, affective recognition needs to be added to provide a more situated teaching strategy. For example, when students show confusion on their face the robot may provide more detailed explanation on the topic that is being taught at that moment.

Finally, in this study we identified several aspects of the robot body language that we would like to address in future work to improve the RoboTutor. First, as mood is a long-term and stable affective state, expressing a stable mood using a range of behaviors is important. Although students' ratings of the consistency of the robot mood is acceptable (*Mean*=1.1, *SD*=0.9 on a -2 to 2 Likert item), expressing a stable mood remains a challenge. Second, support for the coordination of the modulation of temporal parameters and the synchronization between gestures and speech is needed. In this study, temporal parameters were manually adjusted to align gestures with speech. A model is needed to align the timing of speech and gestures automatically. Third, we deliberately limited the levels of positive and negative mood expression to ensure body language would remain acceptable within the context of a lecture. It is interesting to explore other settings that allow for a broader range of mood expressions.

6.11. CONCLUSION

IN this chapter, we have introduced and discussed a robot that is capable of lecturing and showed that robot body language contributes to the effects of delivering a lecture to an audience. The robot interacts with students during a lecture which is quite different from the more usual application of robots as a passive tool that students can use to complete assignment work for a course. In particular, this study is one of the few that focuses on the quality of the robot teaching behaviors. Mood expression has been integrated with the teaching behaviors (coverbal gestures), i.e., the robot mood is expressed through the robot body language. The focus of our study has been on the effects of the robot mood expression on students' learning.

This study shows that robot mood expression can induce affective states (valence and arousal) in students: their valence and arousal were higher when the robot showed positive mood during the lecture than negative mood. Although we did not observe improvement of learning performance in quiz answering in class, the induced affective states were reported to facilitate learning. Moreover, the ratings of the robot and the learning experience are higher when the robot displays positive mood. These findings signify the value of robot bodily mood expression and also suggest more generally that the quality of the robot teaching behaviors influence learning, when the robot plays an active role in teaching in robot-enhanced education. Future work, however, is needed to provide support for the hypothesis that the mood of a robot teacher may affect content-based learning. Finally, we did not observe the effects of the robot body language on the perception of naturalness, friendliness, or sociability. Further study is also needed for a better understating of these aspects. We also report opinions from real teachers about the RoboTutor. These opinions can be valuable for the design of the RoboTutor.

7

Effects of a Robotic Storyteller's Moody Gestures on Storytelling Perception

This chapter describes our exploration of using the robot bodily mood expression with other modality of affect expression. As multimodal affective communication is common in daily interactions between robots and humans, it is important to study the interaction effects between our mood expression and other modalities.

This chapter is based on J. Xu, J. Broekens, K.V. Hindriks, M.A. Neerincx, *Effects of a Robotic Storyteller's Moody Gestures on Storytelling Perception*, International Conference on Affective Computing and Intelligent Interaction (ACII), pp 449–455, IEEE, 2015.

Abstract

A parameterized behavior model was developed for robots to show mood during task execution. In this study, we applied the model to the coverbal gestures of a robotic storyteller. This study investigated whether parameterized mood expression can 1) show mood that is changing over time; 2) reinforce affect communication when other modalities exist; 3) influence the mood induction process of the story; and 4) improve listeners' ratings of the storytelling experience and the robotic storyteller. We modulated the gestures to show either a congruent or an incongruent mood with the story mood. Results show that it is feasible to use parameterized coverbal gestures to express mood that is evolving over time and that participants can distinguish whether the mood expressed by the gestures is congruent or incongruent with the story mood. In terms of effects on participants we found that mood-modulated gestures (a) influence participants' mood, and (b) influence participants' ratings of the storytelling experience and the robotic storyteller.

Keywords Storytelling, Mood Expression, Nonverbal Cues, Body Language, Social Robots, Human Robot Interaction (HRI).

7.1. Introduction

Bodily expression is important for social robots to naturally communicate affect to humans [26]. Expressive body language of a robot facilitates human understanding of a robot's behavior, rationale, and motives [31], and increases the efficiency of human-robot task performance and robustness [58]. It is known to increase the perception of a robot as trustworthy, reliable, and life-like [24]. Bodily affective expression is in particular important for humanoid robots that lack facial features such as NAO, ASIMO, and QRIO. A model that enables robots to show mood during tasks has been developed [77]. In this study, we applied this model to coverbal gestures of a storytelling scenario to study the mood expression. We have several motivations.

First, in previous studies mood expression based on parameterized behavior has been set to show mood at fixed discrete levels, e.g., a positive and a negative level. It is not clear whether this model is able to show mood that is changing continuously over time. In this study, we apply the model to the coverbal gestures of a storytelling scenario, and we modulate the parameters of coverbal gestures continuously, in order to show an evolving mood that is congruent with the story mood changing with the story line. We evaluate whether people perceive the body language as changing over time and congruent with the story line.

Second, in naturalistic settings people perceive affective information from different channels simultaneously. Interactions between bodily expression and other modalities of expression have been found in people's perception [190], [191], [192], [193], [53]. We would like to investigate the use of the affective body language in a scenario where a robot also communicates affect through other affective channels. We need to guarantee that the robot bodily expression generated by our model can express a congruent mood with other modalities, and we expect that the introduction of bodily expression can improve the recognition and the effects of the overall expression. Speech is an inherent channel of affective communication in storytelling. In this study, we report our exploration of the interaction between body language and speech semantics, while we kept the voice features the same.

Third, we'd like to see whether the affective body language is able to improve storytelling experience. Storytelling is an important application, for example, it supports children's development [8]. Improving storytelling experience may increase acceptance of the robot application. Finally, using the mood expression model in a storytelling context provides more evidence about whether the model is generalizable to different applications.

7.2. RELATED WORK

BODILY expression was found to influence or be influenced by other modalities of expressions. Stock et al. [190] found that bodily expression influenced the recognition of facial expression and emotional tone of a voice. Later, Stock et al. also found that recognition of bodily expression was influenced by nonverbal auditory information (human and animal sounds) [191] or task irrelevant auditory (music) [192]. Meeren et al. [193] studied people's perception of congruent and incongruent integration of facial expression and emotional body language using photographs. They found that people's judgement of facial expression was biased towards the bodily expression. Kret et al. [53] showed that congruency between facial and bodily expression improved recognition. In our case, we explore how the affective body language of robots interacts with affect expressed by semantics of stories.

Gestures influence people's perception of the communication quality between robots and people. Salem et al. studied how gesture influences humans' evaluation of communication quality and the robot using ASIMO [194], [195]. Results showed that the robot was rated more positively when coverbal gestures were used compared to speech alone, even when the gestures did not semantically match the speech. An interesting result is that incongruent gestures were even rated higher across many aspects. Their explanation is that in the incongruent condition the robot is less predictable. In our study, we also include a congruent and incongruent gesture condition, but we focused on affective congruency, i.e., whether the robot gestures show mood that is congruent with story content. In this study gestures are manually coordinated with speech. Automatic coordination is beyond the scope of this study (for an overview see [196]). Gaze of a robot during storytelling is important [197]. In our study, the robot always looks at the listener when the robot does not perform head movement.

Emotional coverbal gestures for storytelling were usually built based on corpora of human behaviors. For example, expressive coverbal gestures of a NAO robot used for a storytelling scenario were constructed using a video corpus of human storytellers [198]. The gestures were shown to improve participants' perception of the expressivity of the robot storyteller [199]. Park et al. developed an expressive robot behavior generation framework based on sentence types and emotions [200]. The behaviors were generated based on movements of actors. In this study, the affective gestures are generated by a parameterized behavior model (Figure 7.1). The principles of parameter modulation were obtained from users [77] and the resulting gestures have been evaluated in [79], [83].

Robot storytelling is an important application. For example, it can be used for children education. Montemayor et al. [201] provided children with a tool to create robotic pets and stories, which then can be acted out by the robots. Emotion expression was argued to be an indispensable feature of a robotic storyteller, as children typically attribute emotions to toys they play with. Storytelling was used as an educational activity to test whether the KindSAR robot can engage children in constructive learning [8]. Bodily expression, alongside with facial expression and vocal expression, was used to show the robot emotion, for example, happiness was shown by raising hands, nodding head, and eye light blinking. Results indicated that the story emotion was efficiently conveyed by the robot and children's emotional involvement was promoted, as the children's emotional responses were significantly correlated with the story emotion. A big difference with our study is that we use mood expression that is expressed using parameterized gestures.

7.3. Mood Expression in Storytelling

Our work focuses on mood. Distinctions between affect, emotion, and mood are explained in [34], [36], [37]. Here, we highlight the distinctions between mood and emotion that are related to expression: emotion is a short-term, intense affective state, associated with specific expressive behaviors; mood is a long-term, diffuse affective state, without such specific behaviors. Mood emphasizes a stable affective context, while emotion emphasizes affective responses to events. We use valence and arousal dimensions to represent mood.

We have used a parameterized behavior model (Figure 7.1) for integrating affect expression with functional behaviors (e.g., task behaviors, communicative gestures, and walking). Using this model, robot movements can be modulated to display the robot mood by changing behavior parameters with respect to both spatial extent and motion dynamics [77], [78]. This model enables a robot to express mood, even during task execution by modulation of the "style" of the behavior. The resulting mood expressions have been evaluated with the NAO in a laboratory setup without context [79] and in a game setting [81].

This model has been applied to 41 coverbal gestures and used in a university lecture scenario [83]. We reused these gestures in the storytelling scenario, in order to express the story mood while the robot is telling stories. The gestures were manually selected for the sentences of the stories and manually aligned with the words in the sentences. In study [83], a script engine was designed to orchestrate the robot gestures, speech, and slides. We reused this engine in the storytelling study. The robot speech was generated by a Text To Speech engine shipped with the robot. The script engine synchronizes the starting points of texts and its coverbal gestures automatically. The robot selected leg movements randomly from a predefined corpus in real time and performed them at the same time as hand gestures. Random leg movements are used to maintain a life-like quality of the robot. Pilot testing showed that a talking robot standing still was perceived unnatural.

7.4. Questions and Hypotheses

Because the parameters of the gestures are controlled by a continuous variable and can be modulated in real time, the gestures can be modulated to show a continu-

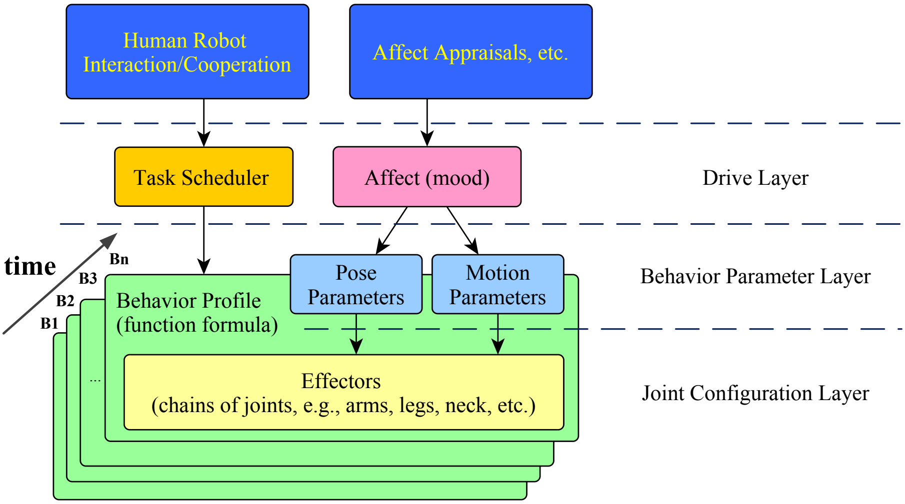


Figure 7.1: General Parameterized Behavior Model

ously changing mood. This study first investigates if the parameterized behavior model can be used to generate behavior that expresses a mood that changes over time. Because story mood changes throughout a story, we chose the storytelling domain. We chose stories in which the mood expressed semantically changes over time. We reasoned that if listeners perceive the mood expressed by the robot as congruent with the story mood, it must have been following the story mood over time as the story mood changes over time. To test this, we hypothesize the following:

- H1. When robot mood is congruent with the story mood, listeners rate the congruency of the robot mood with the story mood to be higher, as compared to a robot mood that is the opposite.

Second, we investigate what perceived effects affective robot body language has on storytelling. The affective communication in storytelling is inherently a multimodal communication, since affect is conveyed through 1) the semantics, i.e., the story content; 2) the voice; and 3) the body language. Body language of humans was shown to influence the recognition of emotions from other modalities [190], [191], [192], [193], [53]. We would like to see if robot body language has similar effects on mood recognition. The difference is that we investigate the effect of robot body language on the affect conveyed by semantics. Here we modulate the robot body language depending on the story mood, and we do not manipulate the robot voice. It was shown that body language reinforced people's recognition of the robot emotions on top of facial expressions [55], [54]. Body language thus may also be able to reinforce other forms of expression, e.g., affect expressed in stories. Specifically, we are interested in whether robot body language can facilitate the understanding of the story mood and make the story mood perceived stronger. We test these aspects based on listeners' self-reports:

- H2. A) When robot mood is congruent with the story mood, listeners perceived the body language as helpful in understanding the story mood, as compared to the incongruent condition.

- H2. B) When robot mood is congruent with the story mood, listeners perceive that the body language makes the story mood stronger, as compared to the incongruent condition.

Third, it is known that stories can induce emotions or moods to listeners [202]. Further, it is well known that mood can be transferred from one person to another [97]. Previous studies also showed that mood can be transferred from a virtual agent displaying facial expressions [107] or a robot displaying affective body language [83], [81] to a person that is interacting with the agent/robot. Body language provides a second channel of mood induction. Moreover, if the perceived story mood is reinforced (H2 and H3) the mood induction may also be stronger. We thus hypothesize:

- H3. When robot mood is congruent with the story mood, listeners report a stronger mood change for their own mood, compared to the incongruent condition.

Finally, it was found in a university lecture study [83] that affective body language was able to influence students' ratings of the robot. Creed and Beale [203] found that inconsistent displays of emotion negatively influenced the perception of an embodied agent. Berry et al. [106] also found that the consistency of the emotion expressions influenced the ratings of the virtual agent. We test the following hypothesis:

- H4. When robot mood is congruent with the story mood it improves listeners' ratings of the storytelling experience and the robotic storyteller, compared to the incongruent mood condition.

7.5. Experimental Setup

7.5.1. Experimental Design

To test the hypotheses, we defined three conditions:

1. Congruent condition: coverbal gestures are modulated to express mood congruent with the mood of the current sentence. The robot also performs random leg movements.

2. Incongruent condition: coverbal gestures are modulated to express mood opposite to the mood of the current sentence. The robot also performs random leg movements.

3. Control condition: the robot performs no coverbal gestures, but random leg movements.

The control condition provides a benchmark, to check for generic effects of gestures. To rule out the possibility that the hypotheses can be verified by arbitrary modulation, we use the incongruent condition as contrast.

We used a between-subject design. Each participant listened to the stories in only one body language condition (RBL condition for short). The dependent variables are 1) the perceived congruency of the coverbal gestures with the story mood; 2) the perceived helpfulness of the coverbal gestures in the understanding of the story mood; 3) the perceived reinforcement of the coverbal gestures on the story mood; 4) listeners' mood; and 5) general ratings of the robotic storyteller.

7.5.2. Materials

Two inspiring stories, one realistic (the ice cream story) and one fantasy (the cracked pot story), were chosen for this study. Both stories were taken from this website[1] and modified. The ice cream story lasts for about 1 minute 45 seconds on our system, and the cracked pot story 3 minutes. The full texts of the stories and the videos of the storytelling can be found in the supplementary materials and our web site[2]. Each story had 2 break points (explained later).

To avoid a ceiling effect (i.e., the mood expressed by the story content is already very strong, so the mood added by the body language is limited), we chose stories with moderate mood or emotions. To avoid confusing mood of different characters in the story, we made the narrative focused on one character. The mood (valence) of the story was annotated sentence-wise by five experienced annotators beforehand. Their annotations are consistent: for the ice cream story Cronbach's $\alpha = 0.736$; for the cracked pot story Cronbach's $\alpha = 0.890$. This annotation was used to drive the gesture-based mood model.

A grey NAO robot (NaoQi version 1.14; head version 4.0; body version 3.3; 58cm tall) with LED lights switched off was used as the storyteller. The robot stands on a table while telling stories and listeners sit in front of the robot while listening.

7.5.3. Measures

We test H1, H2A, H2B, and H4 with the following 11 item post-experiment questionnaire. Each question is measured with a statement to be answered on a 5-point (-2 to 2) Likert scale:

Q1) You did not notice that the robot was performing gestures while it was telling the stories.

Q2) The robot teller was using gestures to communicate the story mood.

Q3) The mood expressed by the robot gestures is congruent with the story mood.

Q4) The gestures of the robot teller helped you to capture the story mood.

Q5) You mainly captured the story mood from the robot speech.

Q6) The gestures of the robot teller made the story mood stronger.

Q7) The robot teller kept you immersed in the stories.

Q8) The robot teller enthusiastically presented the stories.

Q9) The robot teller organized the speech and gestures in a fluent way.

[1] http://rishikajain.com

[2] http://ii.tudelft.nl/SocioCognitiveRobotics/index.php/Storytelling

Q10) The gestures of the robot teller are natural.

Q11) Overall, you are satisfied with the performance of the robot teller.

Questions Q1 and Q2 check if listeners notice the gestures and realize the gestures are used to communicate mood. Q3 tests H1, Q4 and Q5 test H2A, and Q6 tests H2B. Finally, Q7∼Q11 test H4.

The change in listeners' own mood (H3) is measured using the valence and arousal dimensions of SAM (self-assessment manikin) [117] on a 5-point Likert scale. In addition, we asked participants to annotate the story mood during the storytelling in real time in order to get more objective measures of the effects of the modulated gestures on the perception of the story mood (related to H2 and H3). Participants were asked to click the AffectButton whenever they thought the story mood changed.

7.5.4. Participants

66 participants (42 males and 24 females) aged 19 to 48 (Mean = 28.0, SD = 4.8) were recruited from the university campus. They were from 19 different countries: 17 are Dutch; 19 are Chinese; and 7 are Indian. A pre-experiment questionnaire confirms that the participants had little expertise on robotics or virtual agents. Participants had some storytelling experience and they held a positive attitude to reading or listening to stories. Each participant received a gift after the experiment.

7.5.5. Procedure

7

Each participant read the experiment instructions, filled out a consent form, and a general questionnaire about demographics and previous experiences with robots and virtual agents. Participants were told to pay attention to the robot in general when the robot was telling the stories, but we did not emphasize mood or behavior to try to eliminate a demand effect (participants rating what they think we want them to feel / see). Then, a training session of the AffectButton started. The task was to adjust the facial expression on the button to match 32 given affective terms [204]. Just before the start of each story (T0), the current mood of each participant was measured with a SAM self-report. When the robot stopped at break point (T1 and T2) during the storytelling or the end of each story (T3), the mood of the participant was also measured using SAM questionnaires. Participants also filled out a questionnaire about whether they understood the story, whether they heard the story before, the perceived story length in minutes, and their attention distribution at T3 after the mood measurement. Participants were allowed to take a break between the two stories. After the two stories, participants filled out the post-experiment questionnaire. After the experiment, participants were debriefed and thanked for participation. The experiment took 30 minutes.

7.6. Results

7.6.1. Expressing Evolving Mood (H1)

We first check whether participants noticed the robot gestures (Q1) and thought the gestured were used for communication (Q2). Then we test the perceived congruency of the robot gestures (Q3). Kruskal-Wallis tests show a marginal significance for

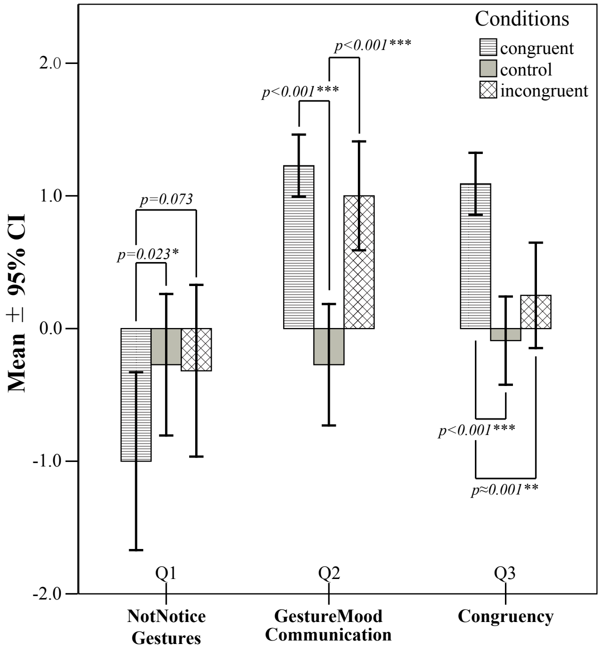


Figure 7.2: Perception check and perceived congruency between the robot body language and the story mood

7

Q1: $\chi^2(2) = 5.568$, p=0.060 and significance for Q2: $\chi^2(2) = 23.447$, p<0.001 and for Q3: $\chi^2(2) = 22.675$, p<0.001. Figure 7.2 shows the means and significances of the post-hoc Mann-Whitney U tests.

These results suggest three things. First, participants noticed gestures more in the congruent condition than in the control condition but not in the incongruent condition. This is a bit odd as participants do indicate that the robot uses gestures to communicate mood in the incongruent condition. Second, participants considered that the robot was using gestures to communicate the story mood in both congruent and incongruent conditions and no significant difference between the two conditions was observed. Apparently gestures made the robot more expressive in general. Third, participants perceived the mood expressed by the gestures in the congruent condition as significantly more congruent than in the incongruent condition or in the control condition. As the story mood changes over time (confirmed by pre-experiment annotation), this confirms the model's ability to express mood that is evolving over time.

In sum, these results support our hypothesis that modulated coverbal gestures can be used for communicating story mood in storytelling continuously and that participants are able to distinguish whether the robot coverbal gestures are congruent or not with the story mood (H1). Further, this confirms the importance of congruent gestures as opposed to incongruent.

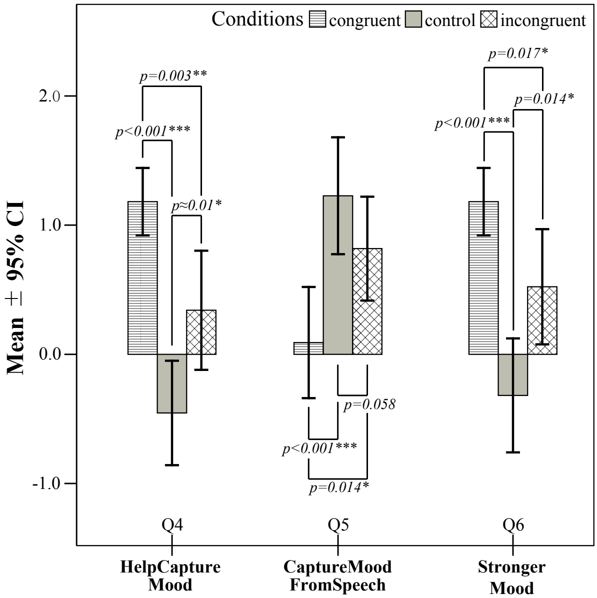


Figure 7.3: Effects of the robot body language on the perception of the story mood

7.6.2. REINFORCEMENT OF STORY MOOD (H2AB)

PARTICIPANTS' PERCEPTION

To test if modulated gestures helped participants to capture mood from the story (Q4), provided an efficient way to capture the story mood in addition to the speech (Q5), and made the perceived story mood stronger (Q6), we performed Kruskal-Wallis tests. These show significant differences for Q4: $\chi^2(2)$=26.979, p<0.001, for Q5: $\chi^2(2)$=15.410, p<0.001, and for Q6: $\chi^2(2)$=22.188, p<0.001. See Figure 7.3 for means and post-hoc Mann-Whitney *U*.

These results suggest two things. First, participants considered coverbal gestures to be helpful for capturing the story mood in general, whether the gestures are congruent with the story or not. However, congruent gestures were considered significantly more helpful (Q4). This is supported by the fact that participants indicated to use the text to capture the story mood in both the control and incongruent conditions (Q5). This indicates that people pay more attention to the mood in the gestures when these are congruent, and otherwise pay more attention to the text. Second, participants indicated that coverbal gestures made the story mood stronger in both congruent and incongruent conditions, with the congruent condition being significantly stronger than the incongruent condition. Apparently, some gesturing is better than none, but mood congruent gestures are better than incongruent gestures.

In sum, we conclude that the affective quality of the gestures influenced these effects: the gestures helped with the understanding the story mood (H2A) and made the story mood stronger to a significantly larger extent, when the gestures expressed mood that is congruent with the story mood (H2B).

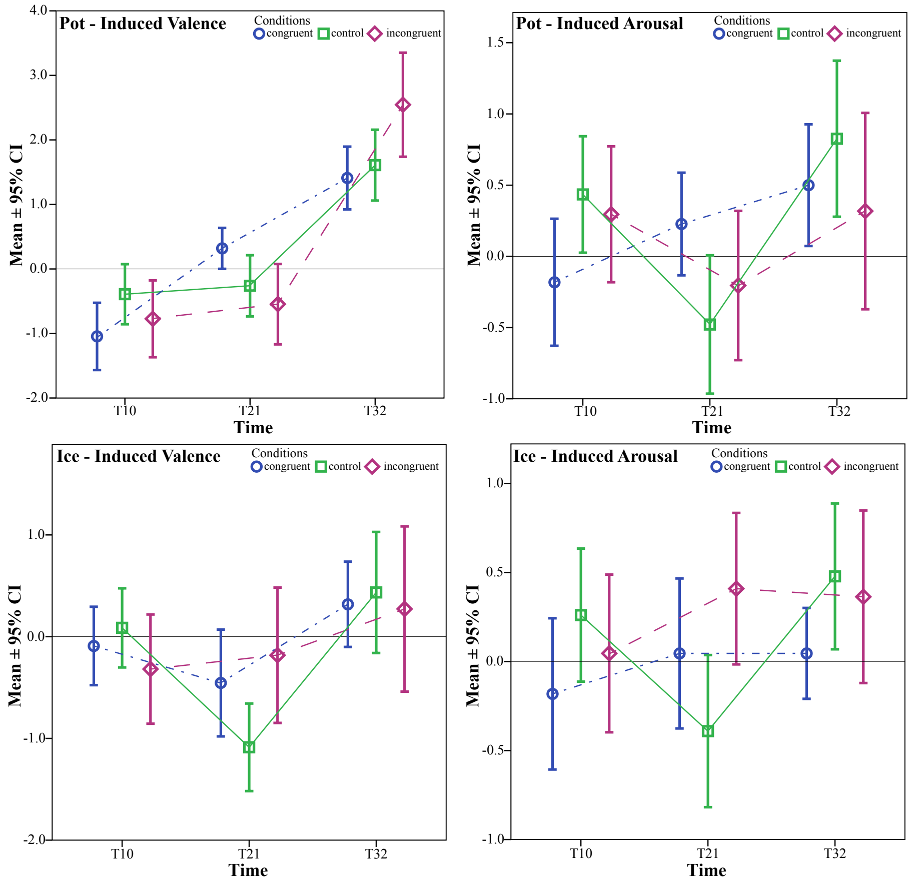


Figure 7.4: Induced mood (valence and arousal) in the period T10: from start to break1, T21: from break1 to break2, and T32 from break2 to end. The story texts and the break positions can be found in the supplement and our web (see footnote 2)

Annotation of the Story Mood

To further study mood enhancement by gestures, we test whether the annotated mood is more positive (valence) and more active (arousal) when the mood of the story is positive and active; more negative and more passive when the mood of the story is negative and passive. All participants' annotations of one story are put together and sorted according to time. Then data points were binned into time periods. ANOVA analyses testing for difference between conditions did not reveal significant differences. This indicates the affect traces are similar between conditions.

7.6.3. Effects on Participants' Moods (H3)

To find out whether the storytelling induced mood to the participants, we first check whether participants' mood changed over time. A mixed model MANOVA with congruency as between-subject factor and time (T0, T1, T2, and T3) as within-subject factor was used to analyze the participants' mood (valence and arousal). The results of the overall tests show that time has an significant effect on the participants' mood, both for the cracked pot story $F(6,58)=20.242$, $p<0.001$, partial $\eta^2=0.677$, and for the ice cream story $F(6,58)=5.371$, $p<0.001$, partial $\eta^2=0.357$. This means that participants' moods were influenced by the storytelling. That is, the mood induction occurred. The cause could be the robot body language, the story content, or something.

To test whether robot body language had an effect on the mood induction process, we calculated induced mood in three periods: from T0 (start) to T1 (the first break), from T1 to T2 (the second break), and from T2 to T3 (end) for each story. The changes of the mood variables during the periods were used as induced mood. Figure 7.4 illustrates the means and confidence intervals of the induced valence and arousal. A mixed model MANOVA, with congruency as between-subject factor, time as within-subject factor, and valence and arousal as two measures, was used.

For the cracked pot story, the effect of the modulated gestures on the mood induction process is evidenced by a significant interaction effect (time*congruency): multivariate test Pillai's Trace $F(8, 122)=2.300$, $p=0.025$, partial $\eta^2=0.131$. The univariate test showed that the interaction effect is on the valence $F(4)=3.193$, $p=0.016$, partial $\eta^2=0.092$. For the ice cream story, an effect of the congruence is observed at a marginal significance level: Pillai's Trace $F(4,126)=2.257$, $p=0.067$, partial $\eta^2=0.067$ (Roy's Largest Root shows significance: $F(2,63)=3.968$, $p=0.024$, partial $\eta^2=0.112$). The univariate test showed that the effect of congruence is on the arousal $F(2)=3.846$, $p=0.027$, partial $\eta^2=0.109$. Post hoc tests with Bonferroni correction showed that the induced arousal in the incongruent condition is significantly larger ($p=0.023$) than in the congruent condition.

Overall, this suggests that robot body language influenced how the participants' mood was evolving over time. Put differently, body language has an effect on the mood induction process. However, a clear effect was shown only for arousal and only for one of the two stories. As such, the results do not support the hypothesis that mood induction was more pronounced in the congruent condition (H3).

7.6.4. Experience of the Storyteller (H4)

In this section, we present the results of how the modulated coverbal gestures influence participants' storytelling experience and their ratings of the robotic teller. The results of Kruskal-Wallis tests of Q7∼Q11 are listed in Table 7.1, and Figure 7.5 shows the result of the post hoc Mann-Whitney U tests.

Table 7.1: The results of Kruskal-Wallis tests for Q7∼Q11

Statistics	Q7 Immerse	Q8 Enthus.	Q9 Fluency	Q10 Natural.	Q11 Overall
$\chi^2(2)$	0.449	14.194	6.379	3.119	2.683
sig.	0.799	<0.001	0.041	0.210	0.261

We did not observe a significant effect of gestures on immersion (Q7). Possible explanation is that the story content already made listeners immersed in the context (or not) and that semantic meaning is therefore more important to immersion.

Participants perceived the robot to be significantly more enthusiastic as long as the robot performs gestures, no matter the mood expressed by the gestures is congruent with

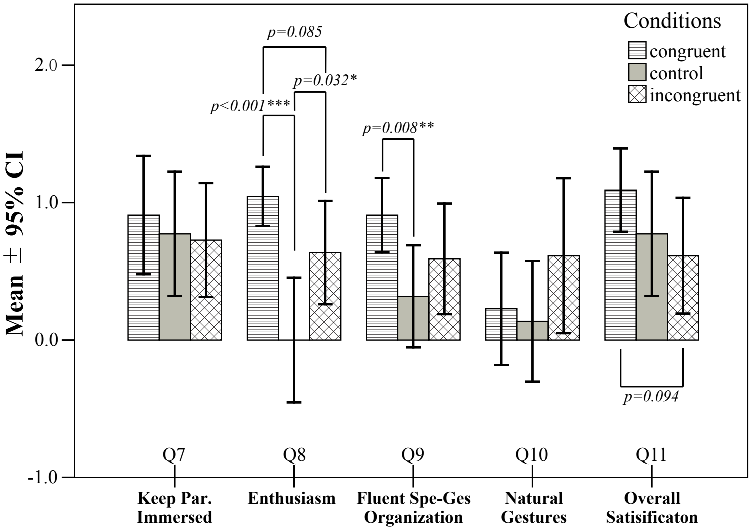


Figure 7.5: Perception of the robot body language and general ratings of the robotic storyteller

the story mood or not (Q8). This may be because that more body movements (gestures vs. no gestures) made the robot appear more active in general. In the congruent condition, the perceived enthusiasm is higher than the incongruent condition at a marginal significance level. This means that in general participants considered a storytelling robot that performs coverbal gestures as enthusiastic and the affective quality of the gestures may have influenced participants' perception of enthusiasm.

We did not observe a significant difference in the fluency of gesture-speech organization between congruent and incongruent conditions (Q9). However, congruent gestures were perceived to be more fluently organized with the speech compared to the control (random leg movements). This provides some evidence that mood-congruent modulation of gestures is important for perceived gesture-speech organization.

We did not observe a significant effect of the gestures on naturalness (Q10).

Finally, the overall satisfaction in the congruent condition is higher than incongruent condition at a marginally significant level (Q11). This is in line with the trends on fluency and enthusiasm.

In sum, there is some evidence to support the hypothesis that story-mood-congruent gestures improve storytelling (H4).

7.7. GENERAL DISCUSSION

OVERALL, our results seem to indicate that the semantic channel takes priority over robot body language. The attention distribution questionnaire showed that participants paid 26% of attention to the robot movements and 52% to the robot speech. The domination of speech seems to be true especially when speech and body language are incongruent. For example, in the incongruent condition, participants indicated that they did not notice the body language (Q1) and that they only captured the story mood from the speech (Q5). This suggests that participants shifted most of their attention to the speech after they perceived little meaning in the incongruent body language. The underlying reason may be that incongruent information adds to cognitive load, which was observed in [106]. The phenomenon that participants following the speech in the incongruent condition can be also explained by cognitive dissonance theory [205], which suggests that people attempt to reduce inconsistency in their perceptions. In our case, participants ignored the mood expressed by the incongruent gestures but followed the mood in the story content.

In addition to the domination effect of speech above, several other reasons may account for the lack of significant effect of the robot body language on the participants' annotation of the story mood. First, using the AffectButton to annotate the story mood and looking at the robot in real time is difficult. Attention distribution showed that participants paid 22% of attention to the laptop during the storytelling, in addition to the amount of attention already taken by the robot speech. This attention occupation might further reduce the effect of the robot body language. Second, it is methodologically difficult to correctly analyze affect traces over time. For example, we cannot decide with 100% certainty to which bin a measurement belongs as participants were free to rate when they wanted, and rating takes some time. So, some inputs might be wrongly classified to belong to a particular sentence. Last, although we considered that the stories chosen are simple, the story mood seems to change too often. This increased complexity and difficulty of annotation. It would be better to do a similar test with a story that clearly changes in mood exactly once.

7.8. Conclusion and Future Work

Our study shows that it is feasible to modulate coverbal gestures in real time, based on the behavior parameterize model, to express a mood that is evolving over time and is congruent with the story line. The results show that participants distinguished whether the mood expressed by the coverbal gestures was congruent with the story mood or not. Results also show that participants perceived the coverbal gestures expressing congruent mood helped them to capture the story mood and made the story mood stronger. In terms of effects on participants we found that mood-modulated robot body language (a) influences participants' mood (but the effect is not entirely clear), and (b) influenced participants' ratings of the storytelling experience and the robotic storyteller.

To the best of our knowledge, this study is one of the very few in which bodily mood expression of robots are studied in a scenario in which another affective communication channel (speech semantics) exists. Some challenges regarding the coexistence of affective robot body language and affective speech content are revealed, which are yet to be explored in the future work. These include speech content domination of affect, the difficulty to rate in real time, and participants' apparent reduction of inconsistency between gesture mood and story mood.

8

Conclusion and Prospects

As one probes into a research field trying to fill in gaps and solve questions, more and more interesting questions and challenges are discovered. One also gets better understanding of particular questions. For example, our goal was initially defined as making the imitation game (see Chapter 5) gestures emotional, so that we can test the effects of this emotion expression. To this end, we actually put more effort than we expected into developing the parameterized behavior model itself and we redefined the expression as mood expression (Chapter 2). Later on, we started to look for generic parameters and attempted to make our model generalizable to more robot behaviors (as we did in Chapter 5, 6, 7).

Some questions that are considered small may become bigger and more meaningful, while some questions become less meaningful and thus be replaced by more significant questions. For example, instead of asking whether parameter modulation can be used to express mood, a better question is what parameters we should use and how we should modulate them to express a mood (Chapter 2); we initially thought an evaluation before using the mood expression in an interaction would be sufficient (Chapter 4), while later on when we considered the impacts of the interaction context on the mood effects, we realized that the interaction context may even influence humans' recognition of the mood expressed by the robot. Many additional factors also emerged, e.g., attention, task difficulty, distance, etc. We have to evaluate the recognition every time to get a complete picture of what is going on (Chapter 5, 6, and 7).

In this chapter, we summarize the main findings of our studies and contributions to the field. We discuss the constraints and limitations of our work, and propose future research directions and potential applications of our mood expression model.

8.1. Answers to Research Questions

One objective of this thesis is to find a way for a robot to express mood during task execution. We propose a parameterized behavior model in which parameters control spatial and temporal characteristics of a robot behavior. Modulating these parameters generates variations in behavior appearance. Different behavior appearances express different robot moods. We have designed the model through a user study, validated the resulting expressions in a recognition experiment, and evaluated the use of the model in three interaction scenarios. In the evaluation within interaction scenarios, we studied the effects of the mood expression on humans. Related to each piece of the work, several research questions have been stated in Chapter 1. In the following paragraphs, we revisit and answer each research question.

Q1. Which parameters of robot behaviors and what modulation principles of these parameters can be used for mood expression?

This question was initially answered by a user study in which a group of participants were asked to design mood expressions by modulating behavior parameters for two robot behaviors (i.e., waving and pointing). Details can be found in Chapter 2. The results showed that the user-designed values of most parameters were significantly different between mood levels, and the settings were generally consistent across participants. The parameters include the height of the hand, the amplitude of the motion, the motion speed and the decay speed, the times of repetition, the vertical movement/posture of the head, the palm orientation, and the straightness of the fingers. The modulation principles participants used were consistent with those from literature and most of the principles are consistent between the two behaviors. Therefore, we conclude that we found parameters that can be modulated to express mood and we obtained general modulation principles. The general modulation rules for each parameter are detailed in Chapter 2. These findings are validated by the recognition experiment (Chapter 4). We applied these parameters and modulation principles to other behaviors in later studies (Chapters 5, 6, and 7), where modulated behaviors are used in different interaction contexts, and we evaluated the recognition in each of the studies. The results showed that people are able to recognize the expressed mood both in a recognition task and in interaction tasks (except for the Robotutor lecture scenario in Chapter 6). The main reason may be that the participants concentrated on the lecture contents so they did not consciously recognize the robot mood (see the detailed discussion in the chapter).

Q2. What is the relative importance of the parameters?

We investigated the relative importance of the parameters statistically (Chapter 3) using the data from the user study (Chapter 2). The results showed that the spatial extent parameters (hand-height and amplitude), the head vertical position, and the temporal parameter (motion-speed) are the most important parameters.

The importance of parameters was validated in the recognition experiment (Chapter 4) by comparing parameters in three importance groups. The results showed that modulating important parameters generates mood expression of better recognition than modulating unimportant parameters and recognizable expressions can still be generated by modulating unimportant parameters. We reasoned that the important parameters are "global" features that shape the overall quality of behaviors and thus are more noticeable. Parameters like finger straightness, palm direction, and hold time only change part of the effector or change the behavior for a short-term. We call them "local" features. That the local parameters are less expressive may be because more attention is required to recognize mood from the modulation of the local parameters. Although the head-vertical parameter also change the movement of only a part of the robot body, the head is a rather important body part that humans pay attention to for most of the time in face-to-face interactions. Thus, this head parameter is also important.

These findings were validated in the imitation game experiment (see Section 5.7.5 of Chapter 5). The resulting importance of parameters is generally consistent with the importance resulted from Chapter 3. The parameters motion speed, amplitude, and head-vertical extent were perceived important, while the parameters finger-straightness and palm direction were perceived less important. Moreover, the parameters hold-time and head-left-right become more important due to the interaction context.

Q3. What are the interrelations between the parameters?

In the study presented in Chapter 3, we investigated the interrelations between parameters from the design rationale provided by participants. The results showed that participants considered several parameters in combination when they were designing a particular expression. The reason of the combination is that the mood cues generated by modulating a parameter may depend on other parameters. Several design patterns were identified from the analyses. As the results are very specific, we refer to Chapter 3 for more details. These design details are still subtle. More dedicated studies are needed for a more confirmative conclusion. Nevertheless, our findings provide more insights in designing mood expression and suggest that modulating a combination of parameters to produce particular affective cues rather than a single parameter may be a significant research direction.

Q4. Is the mood expression based on behavior modulation recognizable?

Across the studies presented in this thesis, we evaluated the recognition of mood expression in two general settings: 1) without an interaction context and 2) within an interaction context. The main differences of recognizing robot mood in an interaction context is that 1) the participants are not explicitly asked to recognize the robot mood and 2) the participants need to perform certain tasks in an interaction context and thus may focus their attention on the tasks. This is important because in real-life use cases of social robots users will not receive an explicit request to recognize the robot mood. The recognition should be spontaneous.

In Chapter 4, we validated the mood expression (i.e., the modulated waving and pointing behavior) of five valence levels resulted from Chapter 2. There was no interaction context. The only task for participants was to compare the difference in valence and arousal presented by several pairs of different modulations of robot behaviors. The results showed that five levels of valence and at least four levels of arousal can be recognized for the two behaviors when the important parameters are modulated. Modulating only the unimportant parameters is promising to express "weak" moods: at least two levels of valence and three levels of arousal for both behaviors can be recognized. These results suggested that mood expression by means of behavior modulation is recognizable in a recognition task.

We validated the recognition in three interaction contexts. In Chapter 5, we applied the modulation model to the gestures of an imitation game. We did not prime the participants to pay attention to the mood expression beforehand, but only asked them to rate valence and arousal of the gestures after the game. The results showed that the participants differentiated the positive and negative mood very well, even when the game difficulty is set to high. Moreover, the post-experiment questions showed that the participants were able to recognize and interpret the behavioral cues generated by most of the parameters. In Chapter 6, we applied the modulation model to the coverbal gestures of a robotic lecturer in a university class setting. This setting is more close to the real-life scenario, as more persons were involved and there was no experiment control over participants. Moreover, we did not prime the participants to pay attention to the mood expression of the robot. Although we did not obtain direct support for the recognition, which may be due to the small sample size of the statistical analysis, the observed mood induction effect provided evidence that the participants had different perception of the mood expression between conditions. In Chapter 7, we modulated the coverbal gestures in a storytelling scenario. During the storytelling, the participants were not primed to recognize the robot mood, but were asked to rate the story mood in a continuous way. The results of the post-experiment questionnaires showed that the participants distinguished whether the mood expressed by the coverbal gestures was congruent with the story mood or not. The successful distinction implied that the participants recognized different moods from different modulations of the robot gestures. In sum, we conclude that people are able to notice and recognize the robot mood from behavior modulation, even if they have to focus on other tasks and they are not explicitly asked to recognize the robot mood.

Q5. Does our mood expression produce mood induction effects on the humans in an interaction context?

8

We observed mood induction effects in the imitation game experiment (Chapter 5) and the Robotutor experiment (Chapter 6). The results showed that participants who interacted with a robot performing behaviors modulated to show a positive mood (positive valence and high arousal) also had a more positive affective state (positive valence and high arousal) according to self-report, compared to who interacted with a robot showing a negative mood. The video annotation used in the Robotutor experiment showed consistent results. We interpreted this mood effect as "mood contagion" [97].

In the storytelling experiment (Chapter 7), the robot body language was shown to have an effect on the mood induction process caused by the stories. We did not observe a clear difference in mood induction caused by robot mood expression conditions, but we observed effects of the mood expression on the evolution of the listeners' moods. That is, how listeners' moods changed with the story line is different between robot mood expression conditions. We conclude that our mood expression is able to induce mood to humans who interact with the robot in an interaction scenario.

Q6. Does our mood expression influence task performance of humans in an interaction context?

Mood expression of the robot induces mood to humans who interact with the robot. Possibly, the induction also influences the humans' task performance. We addressed this by measuring the correction rate of imitations in the imitation game experiment (Chapter 5) and by measuring the correction rate of quiz answering in the Robotutor experiment (Chapter 6). The task of the imitation game is a memory-focused and attention-focused task. The performance of such a task is facilitated by negative mood. We observed that participants who interacted with a robot showing a negative mood via its game gestures performed better in the game. This result answered the question: our mood expression is able to positively influence humans' task performance. In the Robotutor experiment, however, we did not observe effects of the mood expression on the quiz answering. The main reason could be that the change of a learning performance such as the quiz answering performance usually can only be observed after a long time. More discussion can be found in Chapter 6.

Although we cannot rule out the possibility that the effects on the task performance may be caused by other aspects of the robot mood expression instead of mood induction, we can conclude that the robot mood expression influences task performance of humans in the interaction.

Q7. Does our mood expression influence humans' perception of the robot and the interaction experience in an interaction context?

We investigated this question in the Robotutor experiment (Chapter 6) and the storytelling experiment (Chapter 7). We asked the participants to rate about the lecturing quality of the Robotutor (including enthusiasm, engagement, friendliness, etc.) and the quality of the robot gestures (including helpfulness on following the lecture, coordination of the gestures and speech, gesture naturalness, etc.). We also asked the participants in the storytelling experiment to rate about enthusiasm, immersion, fluency, and so on of the robot storyteller. In general, the participants who interacted with a robot showing a positive mood gave better ratings about the interaction experience and the robot, indicating that they had better attitudes towards the robot. We conclude that the (positive) mood expression generated by our model has positive effects on humans' ratings of the robot and interaction experience.

8

Q8. Can our mood expression express a mood that is changing over time?

We addressed this question by applying the behavior modulation to the coverbal gestures of a robot storyteller (Chapter 6). The coverbal gestures were modulated in real time to be either congruent or incongruent with the story mood that is changing over time. Our answer to this question is based on the participants' perception on the congruency of the gestures in the both conditions. The rationale is that if listeners perceive the mood expressed by the robot as congruent with the story mood, the mood must have been following the story mood over time as the story mood changes over time. The results showed that the gestures in the congruent condition were perceived to be significantly more congruent with the story mood. This means that the modulation of the coverbal gestures is able to generate mood expression that is evolving over time in more or less the same way as the mood of the story line evolves.

Q9. Does our mood expression enhance the perceived mood in a spoken story told by the robot?

This question regards multimodal affective communication, which is quite common in daily interactions as people talk, smile, and make gestures, for instance. We addressed the question based on participants' perception in the storytelling experiment (Chapter 6). The results showed that the coverbal gestures, no matter congruent or incongruent with the story mood, 1) helped with the understanding of the story mood and 2) made the story mood stronger. However, compared to the incongruent gestures, the congruent gestures were considered significantly more helpful in capturing the story mood and to make the story mood significantly stronger. We conclude that the mood expression through the robot body language is able to enhance humans' perception of the mood expressed by the semantic content of speech.

8.2. CONTRIBUTIONS

FIRST and foremost, this thesis demonstrated the significance of using behavior modulation to realize robot bodily mood expression. Our approach to robot bodily expression goes beyond the state of the art in the scope of robot bodily affect expressions (e.g., [54–56]), which rely on additional body actions and mostly express emotions, and enables a robot to show mood while executing tasks. The first *scientific contribution* of the thesis is stated as follows.

- SC1. We propose to use behavior modulation to express robot affect via body, which is yet to be largely explored on robots. We point out that behavior-modulation-based expression is suitable for expressing mood. We emphasize the importance of showing affect during task execution and propose to modulate functional behaviors of tasks to express mood.

Based on the outcomes from the study of each chapter, we summarize three aspects that our studies addressed and other contributions of the thesis.

8

8.2.1. THE PARAMETERIZED BEHAVIOR MODEL

The first aspect is the behavior model. We have been aiming at a generic behavior model that can be applied to a broad range of robot behaviors for modulation-based mood expression. We defined a general behavior architecture containing three layers for the parameterized behavior model (see Chapter 2). The general architecture can be specified to accommodate to concrete behaviors. We identified the parameters that can be used for mood expression and the modulation principles for expressing different moods (Q1). By directly taking the perspective of end users (i.e., the designers of mood behaviors in Chapter 2), the obtained modulation principles can be used to generate mood expression that may be more recognizable to general users (i.e., the persons who interact with the robot). Although expert designers (actors/actresses or researchers on human behavior modeling) used in some studies (e.g., [54, 57, 131]) can produce more versatile expressions, sometimes the expressions are not interpreted by general users as intended. The reason might be that general users do not have the same expertise of recognizing (subtle) affective behavioral cues as the experts do. We have applied the behavior model to a broad range of behaviors (Chapter 5, 6, 7). By doing so, we showed the generality of our model to a certain extent.

We provided insights into the parameter modulation by studying the relative importance and the interrelations between behavior parameters in Chapter 3. These findings may be useful for simplifying the model. Moreover, pattens were revealed by our analysis of interrelations between behavior parameters. These patterns can be used to show specific moods.

Our method is similar to existing parameter based approaches in constructing communicative gestures of conversational agents (e.g., [70], [126]). A difference is that our model is a step further in modelling the poses related to behavior functions for more complex (higher degrees of freedom) behaviors such as waving (see Appendix A). We emphasize that our modulation retains the original functions of a robot behavior. Another difference is that we work on robots. Our model has to comply with physical constraints and adapt to limited control interfaces provided by the robot system. These two aspects are integral parts of our behavior model.

The *scientific contributions* of our work on the mood expression model are summarized as follows.

- SC2. We created a parameterized behavior model for behavior-modulation-based mood expression. We identified the parameters that can be modulated to express robot mood and the modulation principles of expressing mood.
- SC3. Our results implied that patterns exist for modulating parameters in combination and correlations exist between the modulation principles of some parameters (detailed in Chapter 3).
- SC4. We showed the generality of our behavior model and the modulation principles by successfully applying them to a range of robot behaviors in different interaction contexts.

8.2.2. THE RECOGNITION OF THE MOOD EXPRESSION BASED ON BEHAVIOR MODULATION

The recognition of the robot mood is a long-term research topic that we have been addressing throughout our studies, since every change in the experiment settings may influence the recognition. For example, as we discussed in Chapter 6, the interaction context may influence the recognition of the robot mood. Apart from the evaluation in Chapter 4, which does not contain an interaction context, we test the recognition when the mood expression is used in interaction scenarios (Chapter 5, 6, and 7). Except for the study of Robotutor in Chapter 6, we obtained direct support for the claim that users can recognize the mood expression in interaction tasks, while mood induction effects observed in all the studies suggest that users had different perceptions of the robot mood expression. Therefore, we conclude that the robot behaviors modulated using our parameters and modulation rules is recognizable to people.

To clarify, our model relies on a dimensional representation of mood (i.e., valence in a scale) as opposed to categorial representations. The "recognition" in this thesis means distinguishing valence and arousal levels (Chapter 4) or give ratings in scales of valence and arousal (Chapter 5, 6, and 7). Testing the recognition of underlying affect dimensions goes beyond the recognition of categorial emotions seen in the majority of other studies (e.g., [54–56]). It is a step further to investigating the recognition accuracy.

One of the key interests is to test whether people can recognize mood spontaneously. That is, people should not be primed to pay attention to the robot expressions. Affective communication between humans is spontaneous by nature. People recognize emotions or mood of others automatically. We believe that this nature of interaction should also apply for the recognition of robot mood or emotion. We argue that it is important to design robot expressions that can be recognized by people automatically in order to achieve natural interaction between humans and robots. We have kept this in mind across all of our studies.

The parameter importance resulted from Chapter 3 was further verified in the recognition experiment in Chapter 4. From the differences in the perception of the parameters, we identified the "global" and "local" parameters. We envision that behaviors with more "global" parameters are more expressive. This result supports, from a perception point of view, that the expressiveness of parameters differ from each other.

We identified valence-oriented and arousal oriented behavior parameters. Although in current model only valence is used to control the behavior parameters, users indeed can recognize differences in arousal according to the results in Chapter 4. Correlation analysis showed that speed parameters, repetition, and head-up-down correlate with arousal. The recognition of the arousal dimension also implies that some of the parameters correlate with both valence and arousal. More insights were obtained from the imitation game study (Chapter 5). The users' descriptions of the behavioral cues showed which parameters are more related to valence, which more to arousal, and which to both. From the rationale of how the participants recognized the robot mood from the given behavior parameters, we found that parameters like the motion-speed and the hold-time that control the dynamics of a behavior, parameters like finger-straightness that present the force or stiffness of a body part, and parameters like head-left-right (movement interpretation) that change the overall intensity of movement are usually interpreted as showing arousal; parameters like amplitude, head-up-down, finger-straightness, and head-left-right (posture interpretation) that control the posture and spatial extent of a behavior are usually interpreted as showing valence. These results provide the foundations for the independent control of the valence and arousal of mood expression, and show the possibility of using our model to express a broad range of moods.

Our work on evaluating the recognizability of the robot mood expression by means of behavior modulation has the following contributions.

- SC5. We showed that the robot bodily expression of mood by means of behavior modulation is recognizable without priming, indicating the feasibility of using behavior modulation to express robot mood in daily interactions.

- SC6. We validated the parameterized behavior model we propose and the modulation principles we employ.

- SC7. We found that the parameters that control the overall quality of behaviors are more expressive and more salient than those that only control parts of the effectors or control behaviors for a short time.

8.2.3. THE EFFECTS OF MOOD EXPRESSION IN INTERACTIONS

The third aspect is the effects of our robot mood expression on the affective state, experience, and performance of the users who are interacting with the robots. We investigated three types of effects of the robot mood expression: *a*) *mood induction* - effects on users' affective states; *b*) *behavioral impact* - effects on users' responses and behavior, i.e., task performance; and *c*) *ratings* - effects on users' ratings of the robot and the interaction that include many items depending on the specific interaction scenario.

The mood induction effect was investigated in both dyadic settings (Chapter 5 and 7) and group settings (Chapter 6). The differences are elaborated in Chapter 6. In general, the group formation will possibly influence the mood induction process. The results of these studies showed that our robot mood expression is effective in mood induction. Although it is possible that participants had a more positive affective states just because they liked the robot with positive mood expression more, still the mood expression had a positive effect.

Positive effects on the task performance was observed in the imitation game experiment (Chapter 5). Although we did not observe the effects on learning performance in the Robotutor experiment (Chapter 6), we did observe significant effects of the robot mood expression on students' arousal during the lecture, while arousal was shown to be an important component that supports learning. In addition, listeners of the storytelling robot (Chapter 7) rated the robot body language to be helpful in capturing the story mood and to make the story mood stronger. In sum, our robot bodily mood expression is promising to have positive effects on humans in an interaction scenario.

We tested participants' rating of the robot and the interaction experience in the Robotutor study and the storytelling study. In general, the results of both studies showed that participants' gave better ratings when the robot's behaviors were modulated to show a positive mood. This suggests that modulating the robot behavior in a more or less positive way will improve the acceptance of the robot. This shows the importance of robot mood expression for the design of a user-friendly robot.

In sum, the contributions of our work on the effects of the mood expression are the following.

- SC8. Our work provides evidence that the robot behaviors modulated to show positive mood are able to induce more positive affect to users than those modulated to show negative mood.
- SC9. Our work provides evidence that the modulated robot behaviors are able to positively influence the users' task performance. This effect depends on task context: our study showed that the behaviors showing negative robot mood improve users' performance in a memory focused task, while the behaviors showing positive robot mood may improve users' performance in creative tasks. We provide an explanation that this effect is likely to result from the mood induction effect (SC8).
- SC10. Our work showed that mostly the robot behaviors modulated to show positive mood are able to improve users' ratings of the robot while sometimes even the behaviors showing negative mood are also able to improve some of the ratings.

We believe that our work not only contributes to the field of robotics, but also contributes to the field of virtual agents. There are scenarios in which virtual agents perform body actions that are constrained by functional requirements and dimensions of the virtual environment. For example, the virtual agents in training system need to demonstrate standard operations (e.g., [127], [128], [129]). Our model can be used to parameterize these behaviors for modulation based expressions, while also modelling the functional and spatial constraints of these behaviors.

8.2.4. TECHNICAL CONTRIBUTIONS

In addition to the scientific contributions, our work also include the following *technical contributions.*

- TC1. We implemented the behavior modulation model on a set of behaviors of the NAO humanoid robots.
- TC2. We created a script engine that can be used to schedule the robot behaviors and synchronize with the robot speech. The robot mood can be set in the script and the behaviors will be modulated according to the mood.

More details can be found in the appendices.

8.3. LIMITATIONS AND OUTLOOK

IN this section, we discuss potential improvements of our model, as well as the things in our experiments that need further investigation and the things we have not focused on but may influence the generalization of our findings. Also we discuss the challenges remained that can be interesting to investigate in the future.

8.3.1. IMPROVEMENTS OF THE PARAMETERIZED BEHAVIOR MODEL

First, there is still room for improving our parameterized behavior model for mood expression. It is not possible yet to control the valence and arousal of the expression independently. Another variable that controls arousal can be added to the model. However, while our model succeeds to display positive-valence high-arousal and negative-valence low-arousal moods, it is not easy to display negative-valence high-arousal and positive-valence low-arousal moods, for example, the anger displayed in the pointing behavior (Chapter 4). The reason is that most parameters of our model correlate positively with both valence and arousal. That is, the increase of those parameter results in the increase of both displayed valence and arousal. The independent control of valence and arousal is important for being able to show any mood across the valence-arousal space. One feasible approach to the independent control is to quantify the valence and arousal displayed by each parameter in a more or less precise way and then compute the value for each parameter mathematically according to the valence-arousal "coordinates" of a mood. This requires full factor analysis of all parameters, i.e., modulating a single parameter at one time while keeping others constant and testing the change of expressed valence and arousal. Performing such an analysis is challenging when the number of parameters becomes large. Our study on parameter importance (Chapter 3 and 4) and parameter "orientation" (Chapter 4 and 5) may simplify the method. The results showed that some parameters relate more to the arousal while some parameters relate more to valence. Then one can use those valence-oriented parameters as prime parameters to control the expressed valence and those arousal-oriented parameters as prime parameters to control the expressed arousal. The parameters that are less related to either valence or arousal, e.g., the unimportant parameters, can be used as tuning factors. This way, less parameters require the full factor analysis. For example, it is not necessary to accurately quantify, for example, the amount of arousal expressed by a valence-oriented parameter. Another aspect of the quantification is the noticeable change of each parameter in expressed valence and arousal. Our study on the recognition of valence and arousal from modulated behaviors (Chapter 4) showed the promise of using paired comparison to obtain perceived valence and arousal in interval scales. It may be possible to find the minimum change for each parameter to produce recognizable change in expressed valence and arousal.

The second direction to improve the model is to use additional parameters to achieve more detailed modulation of a behavior. Our spatial parameters were designed mainly to control the hand positions (e.g., hand height and amplitude) and its shape (e.g., finger straightness and palm direction). Additional parameters can be designed to control, for example, the position of elbow. An outward elbow position may show the expansiveness of an arm, while an inward elbow position may show the narrowness of an arm. More spatial parameters usually require more complex mathematical calculations to compute each joint. Our temporal parameters control every stroke of a motion, while individual parameters can be used to control different strokes to generate variations in the motion flow. For example, the motion speed of different strokes may be different. When more temporal parameters are applied to coverbal gestures, complex temporal control requires a more sophisticated synchronization model to coordinate the gestures and speech. Speech-gesture synchronization has been an active field (e.g., [89, 206, 207]). It would be interesting to bridge the synchronization models and the behavior modulation models.

The third direction of improving the model would be additional layers consisting of higher level parameters. We have found in Chapter 3 that several parameters should be modulated in combination in order to display a certain style of the behavior. For example, small amplitude combined with slow motion speed and long hold time makes a behavior appear sluggish and thus can be used to display a sad mood, while small amplitude combined with fast motion speed and short hold time makes a behavior appear rapid and thus can be used to show excitement. Hence, a higher level parameter that presents the extent of sluggishness/rapidness of the motion can be used to control the amplitude, motion speed, and hold time in combination. It is more intuitive to establish the relations between such high level parameters and the mood variables, because the high level parameters have semantic meaning (e.g., sluggish vs. rapid) that is closer to mood. Moreover, when our model can control expressed valence and arousal independently, the settings for parameters may not be unique. Our study on interrelations between parameters (Chapter 3) suggested that patterns exist in the modulation. The patterns provide more constraints to the parameter settings and make it easier to determine the parameter settings. The high level parameters can be used to control the patterns. For example, the sluggishness parameter controls the relations of the amplitude and speed parameters. Further exploration and investigation are needed on the modulation patterns. Moreover, how to integrate the patterns and high level parameters in the control mechanism of our behavior model remains an interesting question to us.

8.3.2. Future work on the Perception and Effects of the Expression in HRI

In this section, we discuss the aspects that need further investigation when using the behavior-modulation-based expression in HRI scenarios. We found across all our HRI studies (Chapter 5, 6, and 7) that participants' appraisal of the robot mood is a comprehensive affective appraisal over all aspects including the robot (including body movements, speech, appearance, etc.), participants' own states and performance, and the other events in the HRI, etc. We categorize their appraisals into two different types: *1*) *By looking at what mood the robot appears to have*: Participants perceive the robot mood by the *appearance* of its physical body, voice, facial expression, and body movements. *2*) *By judging what mood the robot should have*: Participants put themselves in the shoes of the robot and think what mood they should have according to the current situation of the interaction, even though the robot does not display that mood.

Our work aims to investigate how people perceive the robot mood displayed by the body language. We expect participants to use the first type of appraisal to recognize the robot mood. However, even so, people may have attributed the mood to other aspects that the robot showed but we did not modulate, such as the robot voice and facial expression. It is difficult to exclude such factors from the experiment, especially when we want to keep the experiment setting as natural as possible. That is, affective interaction is multimodal by nature. People tend to gather affective information from different channels. On the other hand, people may attribute the behavior modulation to other aspects instead of mood. For example, participants in the Robotutor experiment (Chapter 6) might have attributed the gesture modulation to teaching quality directly instead of to robot mood. It is interesting to explore this conscious attribution of mood and its causes in a more detailed way in future work.

8

Second, it is also difficult to make sure that participants do not use the second type of appraisal. For example, one participant in the imitation game experiment (Chapter 5) said "the robot's mood was negative because I always made mistakes." This participant thought the robot should have a negative mood according to the participant's performance. Another participant in the imitation game experiment indicated that the robot was happy because the robot did not display a negative mood even when she made many mistakes, whereas another participant indicated that the robot was not so happy because the robot did not praise and encourage him when he made a correct imitation. These two participants had expectations of what the robot should respond to them and then inferred the robot mood from what the robot actually did. Further studies may be conducted to separate these two appraisals in order to gain a clear map of how people perceive the robot mood. For example, the displayed mood can be made congruent or incongruent with what mood the robot should have in certain situations. By comparing the perception of the robot mood under these congruent and incongruent conditions, we may get some clues about how people make their appraisals of the robot mood.

We believe that it makes more sense for HRI researchers to investigate the perception of affective expressions in certain contexts. Cognitive dissonance theory [205] suggests that people attempt to reduce the inconsistency of inconsistent things in their perceptions. We believe that people tend to interpret an expression to be consistent with the context. We have obtained evidence in the storytelling experiment (Chapter 7): people are capable to correct incongruent expression. Assuming the robot expresses mood that is consistent with the context, the context narrows the possible interpretations of an expression. It is thus easier for people to recognize the mood that a robot intends to display within a context. Several studies (e.g., [54, 208]) have reported low recognition rate of certain emotion expressions. There might not be any problem with the expressions themselves. The recognition rate might be sufficiently high when using these expressions in a suitable context.

We attempted to make the behavior modulation not interfere with the behavior functions. This does not mean that the modulation introduces no effects on the behavior or on the users. For example, we observed effects of the gesture modulation in the imitation game (Chapter 5) on the user task performance: the use of head movements was reported as something that distracted attention and the slow speed of the gestures in the negative mood condition was reported as something that increased the duration of the gesture sequence. These made it more difficult for participants to remember the gesture sequence. The slow speed of movement also made the Robotutor lecture (Chapter 6) of the negative condition and the storytelling (Chapter 7) of the negative condition slightly longer. These might influence the user experience. We consider that more precisely defined behavior profile and more strict regulations on the parameter range may be helpful to reduce the unexpected effects of modulation. For example, a suitable range may be found for the speed parameter, within which the modulation of motion speed will not make the flow of movements (e.g., a gesture sequence) perceived significant slower or faster. Additional study is needed to figure out the range. Moreover, the regulations of a parameter may depend on the behavior. As we discussed in Chapter 4, the same parameter may play different roles in different behaviors. For example, the hold-time means smoothness for the waving behavior but persistence for the pointing behavior. The regulations on the hold time parameter are thus different for these two behaviors.

We also consider that the regulations may also depend on the task context. For example, one may wave hand with a small amplitude at a person standing close, but wave with a large amplitude at a person far away. Thus, a small range can be used for amplitude for the first context, while a large range for the second context. Another example is that in the imitation game experiment (Chapter 5) the head left right movement can be interpreted as either looking away (thus showing negative mood) or following the arm movement (thus showing more excitement). The interpretation of the mood depends on individual's judgment of the current interaction context. Here, the context influences parameter ranges in terms of the behavior function.

The context may also influence the naturalness of a behavior. An interesting topic related to improving the model concerns the balance between behavior expressiveness and behavior naturalness. Expressive behaviors often require some exaggeration. However, in certain contexts exaggerated behaviors may be perceived as unnatural. For example, in a game setting (Chapter 5) exaggerated behaviors were more acceptable than in a lecture setting (Chapter 6). We deliberately limited the levels of positive and negative mood expression to ensure body language would remain acceptable within the context of a lecture (Chapter 6). A formal model can be built to classify contexts and then adapt the bounds of the parameter modulation.

8.3.3. Potential Applications

Our parameterized behavior model makes mood expression an integral part of the ongoing tasks. It gives the robot more flexibility in time to show its affective states. We believe that this type of expression can be applied to many applications and it is interesting to explore the use of the mood expression in different applications.

First, the mood expression can be used in applications in which a robot is required to communicate affective information. The expressed mood is not necessarily the mood of the robot. For example, in the applications of the storytelling robots in Chapter 7 and robotic theater (e.g., [209]), the expressed mood is the mood of the story or the drama. Behaviors of a robotic actor in a theater are supposed to be expressive. Currently, expressions of a robotic actor are mainly based on facial expression and a few specific body actions that are exaggerated to be expressive. These body actions can hardly be used in another drama or in other occasions where these body actions should not be exaggerated. Our behavior modulation model provides flexibility for adjusting the expressiveness of robot behaviors. A robot behavior can be easily switched from emotional or exaggerated form to a relatively neutral form by only changing the behavior parameters or changing the affective variables that are mapped to the parameters. Moreover, using our model, the design of the behaviors and the design of the drama procedures are separated, since the behavior modulation does not require the change of the order of behaviors. One can envision that the meaning conveyed by a drama can be completely different by only modulating the behaviors to show different moods while keeping the same drama procedures.

Second, our mood expression can be applied to robots that are supposed to "live" together and interact with humans on a daily basis. Examples of these robots are elderly care robots, nursing robots, personal companion, and service robots, etc. These applications more or less require the robot to perform emotional labor, e.g., showing empathy and sympathy. The aim of showing expression here is to bring good feelings to human users. We believe that it is important for robots to show mood for a longer time, because showing mood continuously makes the expression more believable and also sustains the good feelings in humans. Our approach to mood expression enables a robot to show mood during service tasks, and thus the robot can show mood more in a continuous fashion.

Third, another interesting application is to use the body language to indicate the robot internal states during task execution. From the indication, people can understand how the task is going and the current work load of the robot. For example, our mood expression can be used to show the stage of goal achievement in a robot learning scenario, in which a human teaches a robot to perform a certain task, such as learning by demonstration. The human needs to guide the robot to go through certain steps in order to achieve the final goal and needs to adapt the guidance from time to time according to the robot learning progress. The robot mood can be coupled with the rewarding system of the learning mechanism: the robot shows a positive mood when receiving rewards and shows a negative mood when receiving punishments. From the mood expressed through the task behavior, the human teacher can determine the learning progress of the robot. It is interesting to see whether the mood simultaneously expressed during the task will make the learning more efficient. Similarly, our mood expression can be used in human robot teamwork applications. For example, the robot can show mood to indicate whether it is busy/overloaded or available to receive more requests from the human teammates. Since the mood expression is integrated with the task behaviors, no additional communication is needed for human teammates to understand the robot states. This way, the coordination between the robots and humans is more efficient.

Appendix A - Parameterized Behavior Modelling Framework

One advantage of modeling modulation while constructing the behavior is that the physical constraints can be modelled at the same time. Figure A.1 shows the structure of the right arm of NAO and the degree range of each joint. The left arm is symmetric to the right arm. Besides the degree constraints of each joints, constraints also come from the fact that the arm should not bump into the body and other effectors (e.g., legs, the other arm, and the head). The following examples demonstrate how a behavior profile is formulated within the physical constraints and how the parameters are defined.

Constructing Imitation Gestures

The concrete model of imitation gestures, which embodies the general model (Figure 5.1), is shown in Figure A.2. There are four gestures in this game: Left-Up, Right-Up, Left-Down, Right-Down (Figure 5.2). The left and right gestures are symmetric, so we take the left gestures (the right arm gestures) as examples. The hand position should be higher and further away than the shoulder for the left-up gesture, while lower and more outward than the shoulder for the left-down gesture. The following equation thus should be met:

$$\begin{cases} -90 \leq J_{ShoulderPitch} \leq 0, & upgestures \\ 90 \leq J_{S}houlderPitch \leq 115, & downgestures \end{cases} \tag{1}$$

$$J_{ShoulderRoll} \leq 0 \tag{2}$$

The bounds of above conditions are obtained from extreme positions of the robot arm. We define two parameters amplitudever and amplitudehor to control the vertical and horizontal spatial extent of the (upper) arm. Linear functions were used as below:

$$J_{ShoulderPitch} = \begin{cases} -9 \times AmpVer, & upgestures \\ -2.5 \times AmpVer + 115, & downgestures \end{cases} \tag{3}$$

$$J_{ShoulderRoll} = \begin{cases} -4 \times AmpHor, & upgestures \\ -3 \times AmpHor - 10, & downgestures \end{cases} \tag{4}$$

We define the parameter palm-direction to control the direction of the palm. For the down gesture, the palm faces more up/forward when the mood is more positive, while

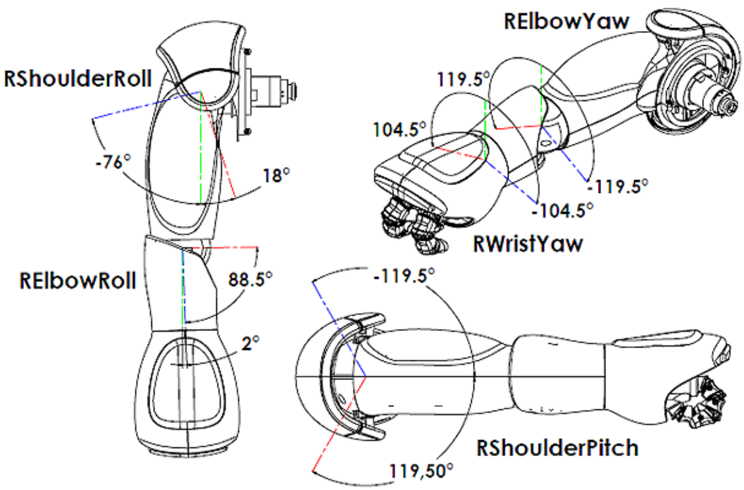


Figure A.1: A diagram about NAO arm (joints) from Aldebaran website

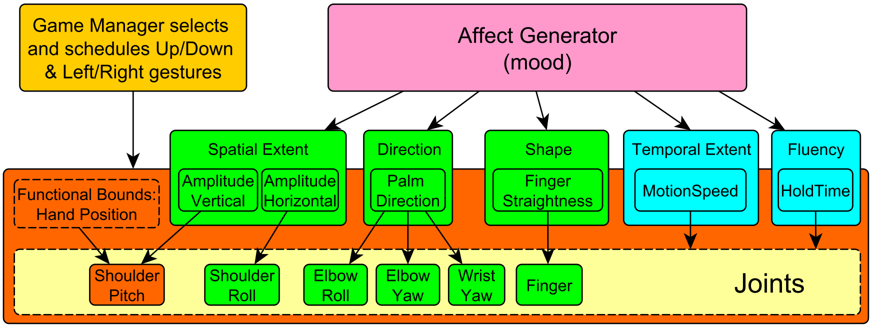


Figure A.2: The concrete model for the imitation (arm) gestures with specific parameters

faces more down/backward when the mood is more negative.

$$PalmDirection(indegree) = \begin{cases} 80 - 16 \times PalmDir, & upgestures \\ -90 + 18 \times PalmDir, & downgestures \end{cases} \tag{5}$$

The values of joints ElbowRoll, ElbowYaw, WristYaw are computed using forward kinematics and gradient decent optimization, with given values of joints ShoulderPitch, ShoulderRoll, and the expected palm-direction. The finger-rigidness controls the straightness of the fingers.

$$J_{hand} = 1.0 \times FingerStraightness \tag{6}$$

The numerical functions were obtained by interpolation between extreme positions of the joints, which is bounded by physical constraints. This shows how we handled the physical constraints of the robot when constructing these behaviors.

CONSTRUCTING WAVING BEHAVIOR

We define waving as one hand swinging between two horizontally aligned positions repeatedly, and the palm should always face forward. The concrete parameterized behavior model of waving (Figure A.3) embodies the general model (Figure 5.1). The two end poses of arm-swings – the maximum inward and outward poses (Figure A.4) – are determined by the pose parameters including a) hand-height, b) finger-rigidness, and c) amplitude. To keep the palm facing forward at the two end poses, the joints need to meet the following condition

$$Vector_{PalmDirection} = R_{shoulderPitch} \bullet R_{shoulderRoll} \bullet R_{elbowYaw} \quad (7)$$

$$\bullet R_{elbowRoll} \bullet R_{wrist} \bullet [0 \;\; 0 \;\; -1]^T \quad (8)$$

$$\theta = cos^{-1}\left(\frac{Vector_{PalmDirection} \bullet [1 \;\; 0 \;\; 0]^T}{\|Vector_{PalmDirection}\|}\right) = 0 \quad (9)$$

R_{joint} is a rotation along the joint; $[0 \;\; 0 \;\; -1]^T$ is the vector when all joints are 0 degree in the robot coordinate space; θ is the angle between the palm direction and a unit vector along X-axis. The behavior profile constrains the joints according to the definition of waving, while affective variations can be generated by modifying pose and motion parameters.

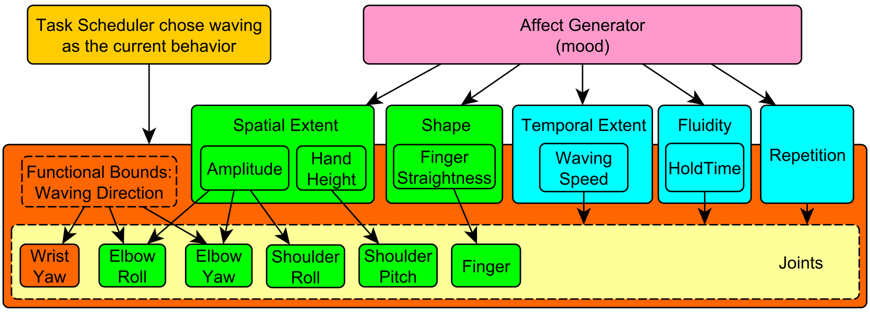
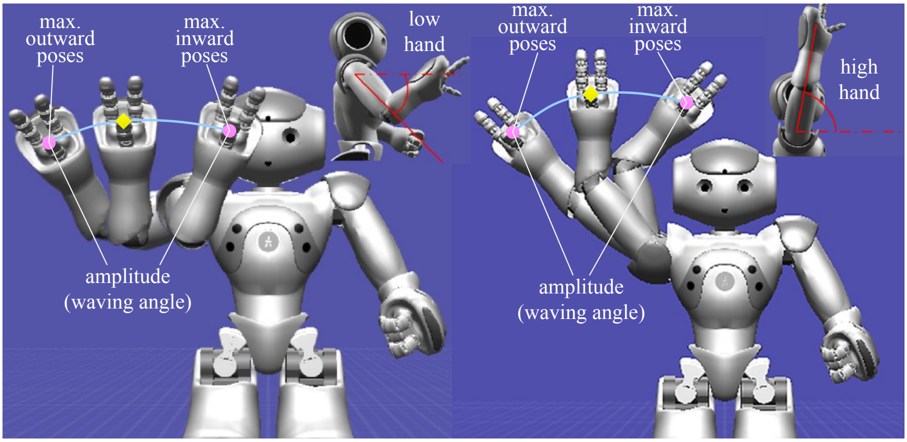


Figure A.3: The concrete model for the arm movement of the waving behavior with specific parameters

Since the palm needs to face forward and NAO's arm does not have wrist-roll joint, the pose of the forearm is fixed. Hence, the hand-height can be controlled only by the shoulder-pitch joint, which controls the inclination of the upper-arm (see top-right figures in Figure A.4).

$$J_{shoulderPitch} = -130.0 \times HandHeight + 57.14 \quad (10)$$

The waving of a human mainly relies on the movement of elbow joint (the corresponding joint of NAO is elbow-roll). However, it is impossible for NAO to generate a natural waving with enough amplitude merely by the elbow-roll joint, due to its angle range (-2deg to 88.5deg). In our model, therefore, waving has two general modes that are switched according to the hand-height: arm-swings are realized by controlling elbow-yaw and



(a) Waving mode 1 (b) Waving mode 2

Figure A.4: The pose parameters of the waving behavior

shoulder-roll joints when hand-height is low (Figure A.4a), and by controlling elbow-roll and shoulder-roll joints when hand-height is high (Figure A.4b). The amplitude specifies the waving angle, and in practice the angle is allocated to the elbow and shoulder. Here we do not model the two end poses directly. Instead we coupled the parameter amplitude with the movement (ΔJ) between the two end poses and a virtual middle pose.

$$J^{outward}_{shoulderRoll} = J^{mid}_{shoulderRoll} - \Delta J_{shoulderRoll} \tag{11}$$

$$J^{inward}_{shoulderRoll} = J^{mid}_{shoulderRoll} + \Delta J_{shoulderRoll} \tag{12}$$

For the low hand-height $0 \leq handheight \leq 0.8$. When amplitude (the swinging angle) is small, we mainly change ElbowYaw to present the increment of amplitude. When amplitude (the swinging angle) becomes large, the arm is likely to bump into the body if the ElbowYaw is too large. Thus, we capped the range of the ElbowYaw, and uses ShoulderRoll instead.

$$J^{mid}_{shoulderRoll} = -20.0 \tag{13}$$

$$\Delta J_{shoulderRoll} = \begin{cases} 10.0, & 0 < Amplitude < 0.82 \\ 50.0 \times Amplitude - 31.0, & 0.82 \leq Amplitude \leq 1 \end{cases} \tag{14}$$

$$J^{outward}_{elbowYaw} = J^{mid}_{elbowYaw} + \Delta J_{elbowYaw} \tag{15}$$

$$J^{inward}_{elbowYaw} = J^{mid}_{elbowYaw} - \Delta J_{elbowYaw} \tag{16}$$

$$J^{mid}_{elbowYaw} = \begin{cases} 88.0, & 0 < HandHeight < 0.5 \\ -40.0 \times HandHeight + 108.0, & 0.5 \leq HandHeight \leq 1 \end{cases} \tag{17}$$

$$\Delta J_{elbowYaw} = \begin{cases} 50.0 \times Amplitude - 10.0, & 0 < Amplitude < 0.82 \\ 31.0, & 0.82 \leq Amplitude \leq 1 \end{cases} \tag{18}$$

The values of joints ElbowRoll, WristYaw are computed to minimize the θ using gradient decent, given the values of joints ShoulderPitch, ShoulderRoll, and ElbowYaw as inputs. For the high hand-height (*handheight* ≥ *0.8*), the amplitude is presented by both ShoulderRoll and ElbowRoll as they move in the same direction in this arm configuration. When amplitude (the swinging angle) becomes large, the arm is likely to bump into the head if ElbowRoll continue to increase. Thus, we increase ShoulderRoll more but capped the ElbowRoll.

$$J^{mid}_{shoulderRoll} = \begin{cases} -20.0, & 0 < Amplitude \leq 0.4 \\ -20.0 \times HandHeight - 12.0, & 0.4 < Amplitude \leq 1 \end{cases} \tag{19}$$

$$\Delta J_{shoulderRoll} = \begin{cases} 16.67 \times Amplitude + 3.33, & 0 < Amplitude \leq 0.7 \\ 36.67 \times Amplitude - 10.67, & 0.7 < Amplitude \leq 1 \end{cases} \tag{20}$$

$$J^{outward}_{elbowRoll} = J^{mid}_{elbowRoll} - \Delta J^{outward}_{elbowRoll} \tag{21}$$

$$J^{inward}_{elbowRoll} = J^{mid}_{elbowRoll} + \Delta J^{inward}_{elbowRoll} \tag{22}$$

$$J^{mid}_{elbowRoll} = 30.0 \tag{23}$$

$$\Delta J^{outward}_{elbowRoll} = \begin{cases} 33.33 \times Amplitude - 3.33, & 0 < Amplitude \leq 0.7 \\ 26.67 \times Amplitude + 1.33, & 0.7 < Amplitude \leq 1 \end{cases} \tag{24}$$

$$\Delta J^{inward}_{elbowRoll} = \begin{cases} 33.33 \times Amplitude - 3.33, & 0 < Amplitude \leq 0.7 \\ 20.0, & 0.7 < Amplitude \leq 1 \end{cases} \tag{25}$$

$$J^{outward}_{elbowYaw} = J^{inward}_{elbowYaw} = 0.0 \tag{26}$$

$$J^{outward}_{wristYaw} = J^{inward}_{wristYaw} = 0.0 \tag{27}$$

$$\tag{28}$$

The finger-rigidness controls the straightness of the fingers.

$$J_{hand} = 1.0 \times FingerStraightness \tag{29}$$

The numerical functions were obtained by interpolation between extreme positions of the joints, which is bounded by physical constraints.

Appendix B - Script Engine

The script engine is an authoring system that allows a non-programmer, such as a teacher from a non-technical university, to easily create a script that contains sequence of robot actions (including gestures, speech, leg movements, and eye-LED movements) and slides operations. A GUI based script editor (Figure B.1) with syntax highlighting is provided for users to edit scripts and control procedures. Users can load, execute, and pause or resume the script using buttons on the GUI.

A script consists of three elements: 1) configurations; 2) commands; and 3) text of speech. Configurations, usually located in the very beginning of a script, include the voice parameters (e.g., speed, volume, and pitch) and behavior parameters like whether the robot will perform random leg movements when ongoing behaviors do not contain leg movements.

```
# reset configurations
\rst\
# Speech speed
\rspd=95\
# Speech volume
\vct=100\
# Enable leg random move
{idle_leg}
# Enable random gaze
{idle_head}
```

Commands (blue letters in Figure B.1) are special syntax of the system control like executing a robot behavior, switching a slide, or starting a quiz session. We designed a corpus of coverbal gestures, and enabled the script engine to synchronize automatically the starting points of a sentence and its coverbal gestures. Users need to adjust the length of the sentence to guarantee the speech and gestures to finish roughly at the same time if needed. A gesture can be executed by either the left or the right arm. If random leg movement is enabled, the robot selects leg movements from a predefined corpus in real time and performed them between hand gestures, to avoid a long time of no movement.

```
{behavior|PushAside} # Robot behavior
I will also say a few things about, how you can
write programs for controlling my behavior.          # Robot speech

{behavior|HandOverLeft} # Robot behavior
Finally, I will introduce the robot tutor project,
\pau=300\and \rmw=1\how the scenario is created\rmw=0\. # Robot speech
```

Plain texts are the content of the robot speech. The robot speech was generated by a Text-To-Speech (TTS) engine shipped with the robot. Some built-in syntax of the TTS engine of the robot is supported, for example, a pause for a period of time and local voice variation.

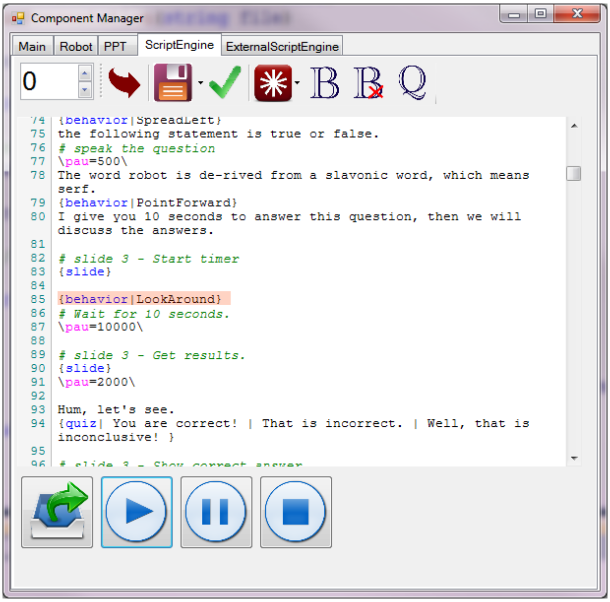


Figure B.1: The script editor for orchestrating the robot speech and behaviors

```
# slide 2
{behavior|Twinkle} # Eye LED simulated blink
{slide}            # Switch to next slide
\pau=1000\         # Pause for a certain number of milliseconds
```

The current system only works with quiz slides designed using the Turningpoint[1] plugin. The Turningpoint clickers are provided to audiences to input answers. A quiz is started by PowerPoint slide operation (i.e., the next slide command). The script engine system sends the command to the PowerPoint program, when the script command {slide} is executed.

```
# The current slide contains a quiz
# Speak the question
{behavior|MeAndYou}
Using the clicker that we provided to you,
please indicate whether you think,
{behavior|SpreadLeft}
the following statement is true or false.
\pau=500\
The word robot is derived from a slavonic word, which means serf.
{behavior|PointForward}
I give you 10 seconds to answer this question,
then we will discuss the answers.

# Start quiz timer
{slide}
# Wait for 10 seconds
{behavior|LookAround}
```

[1] http://www.turningtechnologies.com/polling-solutions/turningpoint

```
\pau=10000\
# Get results
{slide}
\pau=2000\
Hum, let's see.
# Quiz responses
{quiz|You are correct!|That is incorrect.|Well, that is inconclusive!}
```

The robot can choose different responses according to the answers given by audiences. The response sentences are predefined in the script.

A toolbar (on top of the editor; see Figure B.1) is provided to users to facilitate editing. For example, users can insert a behavior command by clicking the shortcut on the toolbar and input the behavior name. We also provide some validation functions, such as check whether used behavior names match the behaviors defined in the system. We will also provide spell check for speech texts in the future. The RoboTutor script engine software is open source and available at the GitHub repository[2].

The script engine can be used for creating different human-robot interaction scenarios. To make the syntax set expandable, the syntax parser is designed using the Interpreter Design Pattern. The script syntax can be easily modified or expanded by simply adding new syntax classes to the code. A template is provided below. The code is written in C#.

```
// Send-out message
public delegate void ehNewSyntax();

// Syntax Class
class NewSyntaxExpression : AbstractExpression
{
    private NewSyntaxExpression(){}

    // Interpret method
    public static IExpression Interpret(string line)
    {
        // Add how the syntax should interpreted. Below is an exmaple.
        if (line.StartsWith("new syntax"))
        {
            IExpression new_syntax_expr = new NewSyntaxExpression();
            return interruptexpr;
        }
        else return null;
    }

    // Execute method
    public static event ehNewSyntax evNewSyntax;
    public override void Execute()
    {
        // Add what actions are followed by the syntax

        evNewSyntax();
    }
}
```

[2]The source code is available in https://github.com/RoboTutor/Mood-Expression-Behavior-Engine

The user has to define how a syntax should be interpreted and what are the follow-up actions (e.g., robot behaviors, slide operations, or other system actions). This is usually the only thing one needs to do for the expansion.

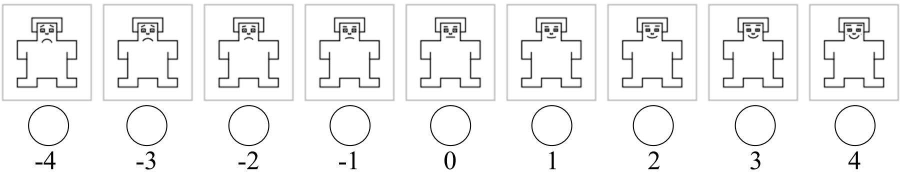
Appendix C - SAM Questionnaires Used in the Experiment

The questionnaires I and II were used after two sessions of the game (see Section 5.6.6). The images from [210] were used. We provided an explanation sheet for participants to refer to for the meaning of valence and arousal.

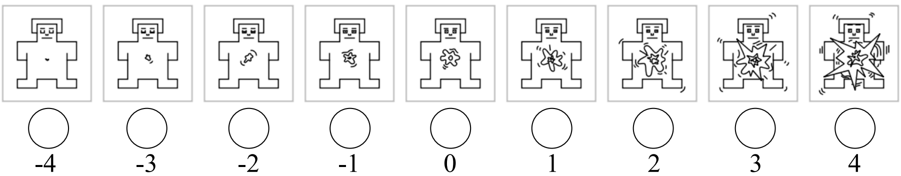
Questionnaire I: What was the robot mood during the game?

Session I

Valence (Negative - Positive; Displeasure - Pleasure)



Arousal (Activation; Calm - Excited)



Session II

The same SAM scales and prompts as Session I were used.

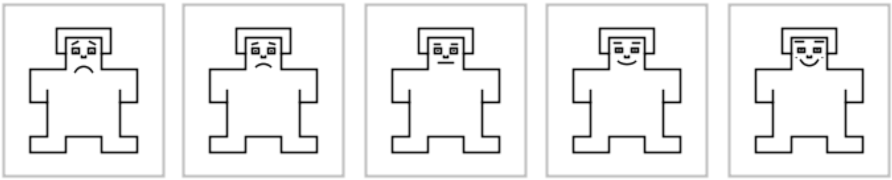
Questionnaire II: What did you feel when you were playing with the robot?

The same SAM scales and prompts as Questionnaire I were used for two sessions.

Explanation Sheet

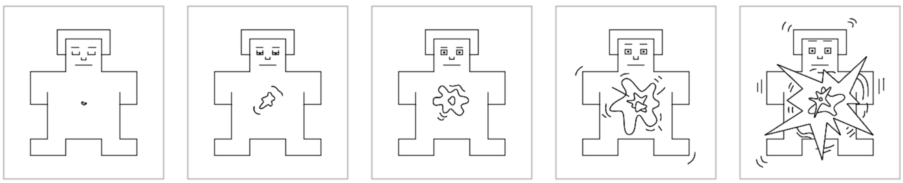
Valence

Dimension	Low score	High score
Positive versus negative affective states.	Negative affective states, e.g., sad, angry, and bored.	Positive affective states, e.g., happy, excited, and relaxed.



Arousal

Dimension	Low score	High score
Level of mental alertness and physical activity.	Low level of mental alertness and physical activity, e.g., sleepy, bored, and relaxed.	High-level of mental alertness and physical activity, e.g., wakeful, excited, and alarmed.



SUMMARY

Robots will be increasingly integrated with daily activities of humans. The robots will cooperate with us, assist us, and accompany us. Social abilities are important for such robots to interact with us harmoniously and to be accepted by us. The expression of affect is one of the social abilities. The expression facilitates human understanding of a robot's behavior, rationale, and motives, and increases the perception of a robot as trustworthy, reliable, and life-like. Most of the current approaches focus on categorial emotional expressions, often with a focus on facial expressions. A few studies addressed bodily emotion expressions that are separate body actions. For enduring human-robot interactions, there is a lack of models and methods for bodily mood expressions that the robot can show during execution of functional behaviors. In this thesis, we develop body language for humanoid robots to express mood at an arbitrary time, even while executing a task, and the mood is represented in dimensional scales. We create a model for robot mood expression, validate the model, and investigate users' perception of the robot mood and effects of the mood expression on users in dyadic and group settings.

To enable a robot to express mood, even during task execution, we have developed a model for integrating mood expression with functional behaviors (e.g., task behaviors, communicative gestures, and walking). Our approach is to "stylize" behaviors by modulating behavior parameters, rather than using additional body movements. In our model, a particular functional behavior is parameterized, and by varying these parameters, the "style" or "appearance" of the behavior is modified, while the function of that behavior is not changed. We developed a parameterized behavior model that consists of three layers. From the top to the bottom, the robot mood controls behaviors parameters and the parameters control the behavior style.

Our research questions are: 1) Which behavior parameters have the potential to express mood when modulated, and how should these parameters be modulated to express a specific mood? 2) How well do people, while interacting with a robot, recognize mood from robot behaviors that are modulated to express positive or negative moods? and 3) what are the effects of robot mood on someone who is interacting with that robot? For example, it is well known that mood can be transferred between persons, and thus, it is useful to gain insights into the possible transfer and effects of mood from a robot to an individual.

To figure out which behavior parameters have the potential to express mood and how to modulate these parameters to express specific moods, we conducted a user study in which participants were asked to modulate behaviors to match given valence levels by adjusting the parameters. We evaluated the resulting "moody" behaviors in a recognition task. The results show that mood levels can be well recognized. Not only valence but also arousal can be recognized. We also found that the spatial extent parameters (hand-height and amplitude), the head vertical position, and the temporal parameter (motion-speed) are the most important parameters. They are "global" features that shape the

overall quality of behaviors. This provides us the user perspective of how a behavior should be like to show a certain mood.

Eventually, the expression will be used during interactions with humans in a daily scenario. We then evaluated our model and modulation principles in human robot interaction scenarios. These scenarios include two dyadic interactions and a one-to-multiple interaction.

We first integrated our mood expression with the gestures used in an imitation game, in which a human player imitates the gestures performed by the robot in a laboratory environment. The results not only confirmed that people can recognize robot mood from the body language in an interaction context, even when they were not primed to pay attention to the expression, but also shows evidence of a "mood contagion" effect: participants' own mood matches with the mood of the robot in the easy task condition. Moreover, the robot mood had an effect on game performance: in the negative mood condition participants performed better on difficult tasks than in the positive mood condition. As a behavior measure, this result further supports the contagion effect.

Second, we investigated the mood expression in a real-life scenario, in which the robot gave a lecture and interacted with audiences using quiz questions in a university classroom. Our mood expression model was applied to 41 coverbal gestures. The robot gave the same lecture to two groups of audiences in either a positive or a negative mood condition. We observed that participants' own valence and arousal are higher in the positive mood condition compared to the negative condition, which suggests that the mood expression can be used to shape the interaction affectively. The audiences' ratings of the lecturing quality and gesture quality of the robot are higher in the positive condition, which suggests mood expression of a robotic teacher is important for the rating of the robot's teaching quality.

Third, we investigated the mood expression in a storytelling scenario, where there is an additional modality of affect communication, the semantic content of the stories. As the affective communication in our daily interaction is multimodal by nature (e.g., voice, semantic information, facial expression, body language, etc.), it is interesting to investigate how the mood expression by means of body language interacts with other modalities. Moreover, we tested whether the robot body language can express mood evolving over time and its effects on storytelling experience. The expressed mood (i.e., the modulation of the coverbal gestures) followed the mood of the story line. The results show that the robot affective body language is able to express mood that is evolving over time. Moreover, when the expressed mood is consistent with the story mood, the body language was perceived to help capture story mood and make the story mood stronger. We also found evidence that the robot affective body language influences mood induction process. Last but not least, the body language that is consistent with the story mood improves the listeners' experience.

In sum, we have developed mood expression by means of behavior modulation for humanoid robots. The results of several experiments show that the expression is recognizable and can have (positive) effects on the interaction in many aspects.

SAMENVATTING

Robots zullen steeds meer worden geïntegreerd met de dagelijkse activiteiten van de mens. Robots zullen met ons samenwerken, ons assisteren en ons gezelschap houden. Sociale vaardigheden zijn belangrijk voor dergelijke robots om harmonieus met ons te interacteren en om door ons geaccepteerd te worden. Het tonen van emoties is één van die sociale vaardigheden. Het tonen van emoties ondersteunt het menselijk begrip van robotgedrag, de beweegredenen en motieven, en verhoogt de geloofwaardigheid, betrouwbaarheid en levensechtheid van de robot. Het merendeel van de huidige benaderingen richt zich op het vertonen van concrete emoties, vaak gefocust op gezichtsuitdrukkingen. Een paar studies hebben zich gericht op het uitdrukken van emoties via het lichaam met behulp van extra bewegingen. Voor langdurige mens-robot interacties is er een gebrek aan modellen en methodes voor het lichamelijk uitdrukken van gemoedstoestanden tijdens het uitvoeren van functioneel gedrag door een robot.

In dit proefschrift ontwikkelen we lichaamstaal voor humanoïde robots om op willekeurige momenten gemoedstoestanden uit te drukken, zelfs tijdens het uitvoeren van een taak. De gemoedstoestanden worden uitgedrukt op een 3-dimensionele schaal. We creëren en valideren een model voor het tonen van gemoedstoestanden door de robot. Het gecreëerde model is een geparametriseerd gedragsmodel bestaande uit drie lagen. De gemoedstoestand van de robot stuurt gedragsparameters aan, en de parameters bepalen op hun beurt de "stijl"van het gedrag. Daarnaast onderzoeken we de gebruikersperceptie van de robot zijn gemoedstoestanden en de gevolgen van het tonen van gemoedstoestanden op gebruikers in één-op-één situaties en groepsverband.

Om een robot in staat te stellen om gemoedstoestanden uit te drukken, zelfs tijdens het uitvoeren van de taak, hebben we een model ontwikkeld voor de integratie van het tonen van gemoedstoestanden en functioneel gedrag (bijvoorbeeld het uitvoeren van een taak, communicatieve gebaren en wandelen). Onze aanpak is om gedrag te "stileren"door gedragsparameters te gebruiken, in plaats van extra lichaamsbewegingen toe te voegen. In ons model wordt een bepaald functioneel gedrag geparametriseerd en door het variëren van deze parameters wordt de stijl van het gedrag aangepast, terwijl de functie van het gedrag niet wordt gewijzigd.

Onze onderzoeksvragen zijn: 1) Welke gedragsparameters hebben het potentieel om gemoedstoestanden uit te drukken, en hoe moeten deze parameters worden ingesteld om bepaalde gemoedstoestanden uit te drukken? 2) Hoe goed kunnen mensen tijdens de interactie met een robot gemoedstoestanden van de robot herkennen aan geparametriseerde gedragingen die positieve of negatieve gemoedstoestanden uitdrukken? en 3) Wat zijn de effecten van de gemoedstoestanden van de robot op iemand die interacteert met die robot? Het is bijvoorbeeld bekend dat gemoedstoestanden kunnen worden overgedragen tussen personen. Het is dus nuttig om het inzicht in de mogelijke overdracht en effecten van gemoedstoestanden van een robot naar een individu te vergroten.

Om erachter te komen welke gedragsparameters het potentieel hebben om gemoedstoestanden uit te drukken en hoe deze parameters gemodificeerd kunnen worden om specifieke gemoedstoestanden uit te drukken, hebben we een gebruikersstudie uitgevoerd. In deze studie werd de deelnemers gevraagd om het gedrag van de robot te modificeren met behulp van de parameters, zodat de gemoedstoestand van de robot overeenkwam met de gegeven 'valence' (valence geeft aan hoe positief of negatief een emotie wordt gezien). Vervolgens hebben we de gedragingen van de robot geëvalueerd in een herkenningstaak. De resultaten daarvan tonen aan dat de gemoedstoestanden herkend worden. Naast valence wordt ook 'arousal' (arousal geeft aan hoe stimulerend een emotie is) herkend. Verder vonden we dat de ruimtelijke parameters (handhoogte en amplitude van bewegingen), de verticale hoofdpositie, en de tijdelijke parameter bewegingssnelheid de belangrijkste parameters zijn. Dit zijn globale eigenschappen die de karakteristieken van gedrag vormen. Dit geeft ons het gebruikersperspectief van hoe gedrag gestileerd zou moeten zijn om een bepaalde gemoedstoestand uit te drukken.

Uiteindelijk zal het uitdrukken van gemoedstoestanden worden gebruikt tijdens interacties met mensen in dagelijkse scenario. Vervolgens hebben we ons model en principes om gemoedstoestanden geparametriseerd te modificeren in verschillende mens-robot interactie scenario's geëvalueerd. Deze scenario's omvatten twee één-op-één interacties en een één-op-veel interactie.

Eerst hebben we het uitdrukken van gemoedstoestanden geïntegreerd met de gebaren die gebruikt worden in een imitatiespel. In dit imitatiespel imiteert een menselijke speler de bewegingen van een robot in een laboratorium. De resultaten bevestigen dat mensen de gemoedstoestanden van de robot kunnen herkennen aan de lichaamstaal van de robot, zelfs wanneer ze niet waren geïnstrueerd om aandacht te besteden aan de gemoedstoestand. Ook vonden we bewijs van een "stemmings-besmettingseffect": de gemoedstoestand van de deelnemers kwam overeen met de gemoedstoestand van de robot in de gemakkelijke taak conditie. Bovendien had de gemoedstoestand van de robot effect op de spelprestaties. In de negatieve gemoedstoestand conditie presteerden de participanten beter op moeilijke taken dan in de positieve gemoedstoestand conditie. Dit effect bevestigt het stemmings-besmettingseffect.

Ten tweede hebben we het uitdrukken van gemoedstoestanden in een real-life scenario onderzocht. In het scenario gaf de robot een lezing en interacteerde met het publiek door middel van quizvragen in een collegezaal. Ons model werd toegepast op 41 co-verbale gebaren. De robot gaf dezelfde lezing voor twee groepen, voor één groep in positieve gemoedstoestand en voor de andere groep in een negatieve gemoedstoestand. We zagen dat de eigen valence en arousal van deelnemers hoger waren in de positieve gemoedstoestand dan in de negatieve gemoedstoestand conditie. Dit suggereert dat het uitdrukken van een gemoedstoestand kan worden gebruikt om interactie te beïnvloeden. De kwaliteit van de lezing en de gebaren van de robot werden door de participanten hoger gewaardeerd in de positieve conditie, hetgeen suggereert dat het uitdrukken van gemoedstoestanden door een robotleraar van belang is voor de waardering van de robot zijn lesvaardigheid.

Ten derde, onderzochten we het uitdrukken van gemoedstoestanden in de context van verhalen vertellen. Het vertellen van verhalen brengt een extra modaliteit met zich mee, namelijk de communicatie van emoties, ofwel de semantische inhoud van de verhalen. Omdat de affectieve communicatie in onze dagelijkse interactie multimodaal van aard is (bijvoorbeeld: stem, semantische informatie, gezichtsuitdrukking, lichaamstaal, etc.), is het interessant om te onderzoeken hoe de expressie van gemoedstoestanden door middel van lichaamstaal interacteert met de andere modaliteiten. Daarnaast hebben we onderzocht of de lichaamstaal van de robot gemoedstoestanden kan uitdrukken veranderend over de tijd en wat de effecten daarvan zijn op de ervaring tijdens het verhalen vertellen. De getoonde gemoedstoestand (d.w.z. de modificatie van de co-verbale gebaren) volgde de sfeer van de verhaallijn. De resultaten laten zien dat de affectieve lichaamstaal van de robot in staat is om ontwikkelingen in gemoedstoestanden over tijd te tonen. Wanneer de getoonde gemoedstoestand consistent was met de sfeer in het verhaal, dan werd de lichaamstaal gezien als ondersteuning voor de sfeer in het verhaal en de sfeer als sterker. We vonden ook bewijs dat de affectieve lichaamstaal van de robot de overdracht van gemoedstoestanden tussen mensen en/of objecten beïnvloedt. Ook niet onbelangrijk is dat lichaamstaal die in overeenstemming is met de sfeer in het verhaal de ervaring van de luisteraars verbetert.

Samengevat hebben we een model en bijbehorende principes voor het uitdrukken van gemoedstoestanden door middel van het modificeren van het gedrag van humanoïde robots ontwikkelt. De resultaten van diverse experimenten tonen aan dat de gemoedstoestanden herkenbaar zijn, en het uitdrukken daarvan (positieve) effecten op de interactie kan hebben.

ACKNOWLEDGEMENT

This four-year PhD life is the most precious experience in my life so far. Beside the fun of living in a completely new environment, the PhD life enhanced my scientific competence, broadened my view, and made me more international. I would not enjoy the PhD life as much as I do, without the help from the people around me.

Everything was new, the place, the people, and the weather, when I first arrived in this "low land" (Netherlands). I would like to thank Franca Post, who settled me down and introduced the university to me. Thanks to the warm welcome from Willem-Paul Brinkman. He got me introduced to every member of the group. I felt less stressed after seeing that people here are friendly and are willing to help.

The beginning of my PhD life was difficult. I was exhausted after a day talking and hearing English for almost all conversations. I am grateful to my copromotor Koen Hindriks and promotor Mark Neerincx; they were patient to explain things to me. My group members tried to speak English as much as possible when I was there. This was quite helpful. Without a good English speaking environment, my English was not able to improve as quickly as it did. No one laughed at me when I was puzzled during conversations. This brought me confidence and comfort to exercise English in daily conversations. I give special thanks to Claire Taylor, my first English teacher in the TUD. She taught me that I should "think in English".

I thank my copromotor Koen Hindriks, promotor Mark Neerincx, and group leader Caitholijn Jonker for the opportunities to go to the ECCE 2011 and ICSR 2011 conferences. I was struggling for deciding the focus of my PhD research. Human robot interaction is such a broad and heavily interdisciplinary field. Communications with peers at conference inspired me a lot. I appreciate the contributions my (co)promotors made to my research. We worked as a team. My promotor, Mark Neerincx, steered us toward the right direction. My second copromotor, Joost Broekens, refined my ideas using his creativity. My first copromotor, Koen Hindriks, consolidated the theory of my research and the papers with his cautiousness.

Academic activities in our group are well supported. I appreciate the help from Ruud de Jong, Bart Vastenhouw, Anita Hoogmoed, and Helen de Roo. I give great thanks to Ruud and Bart for participating in my experiment as "Wizards", and to Anita for arranging gifts for my participants. Moreover, I would like to give special thanks to Ruud. More than only solving technical issues, he always tries to help with my research proactively and provide constructive advices. I also would like to thank Bert Bierman for his contribution to the software that I used for experiment. Acknowledgement is also given to Willem-Paul Brinkman, Judith Redi, and Ingrid Heynderickx for sharing their knowledge of statistical analysis. Special acknowledgement is given to Chinese Scholarship Council for financial support. Importantly, I would like to thank the people who participated in my experiments. Without them I would not have finished my studies.

Last but not least, I thank my parents and other family members for their wishes and encouragement from the other side of the earth, China. I give great thanks to my wife Ni Kang. She spent much time taking care of our little boy, Kangning Xu. Of course, I have to thank my son, a special gift during my PhD life. He brought us quite a lot of joy and prolonged my PhD life.

Junchao XU
Delft, July 2015

Curriculum Vitæ

Junchao XU

16-01-1986	Born in Nanjing, China.

Education

2004–2008	Undergraduate in Measuring Control Technique & Instrumentation Southeast University (formerly Nanjing Institute of Technology), China
2008–2010	Graduate in Instrumentation Science & Technology Southeast University (formerly Nanjing Institute of Technology), China
2010–2015	PhD. Computer Science Delft University of Technology, the Netherlands *Thesis:* Affective Body Language of Humanoid Robots: Perception and Effects in Human Robot Interaction *Promotor:* Prof. dr. M. A. Neerincx

References

[1] K. Dautenhahn, *Socially intelligent robots: dimensions of human-robot interaction,* Philosophical Transactions of the Royal Society of London - Series B: Biological Sciences **362**, 679 (2007).

[2] A. Zelinsky, ed., *Springer Handbook of Robotics* (Springer, 2008) pp. 959–1301.

[3] E. Torta, F. Werner, D. O. Johnson, J. F. Juola, R. H. Cuijpers, M. Bazzani, J. Oberzaucher, J. Lemberger, H. Lewy, and J. Bregman, *Evaluation of a small socially-assistive humanoid robot in intelligent homes for the care of the elderly,* Journal of Intelligent & Robotic Systems **76**, 57 (2014).

[4] R. Looije, M. A. Neerincx, and F. Cnossen, *Persuasive robotic assistant for health self-management of older adults: Design and evaluation of social behaviors,* International Journal of Human Computer Studies **68**, 386 (2010).

[5] O. A. B. Henkemans, B. P. Bierman, J. Janssen, M. A. Neerincx, R. Looije, H. van der Bosch, and J. A. van der Giessen, *Using a robot to personalise health education for children with diabetes type 1: A pilot study,* Patient education and counseling **92**, 174 (2013).

[6] C. Plaisant, A. Druin, C. Lathan, K. Dakhane, K. Edwards, J. M. Vice, and J. Montemayor, *A storytelling robot for pediatric rehabilitation,* in *Proceedings of the fourth international ACM conference on Assistive technologies* (ACM, 2000) pp. 50–55.

[7] K. Dautenhahn, C. L. Nehaniv, M. L. Walters, B. Robins, H. Kose-Bagci, N. A. Mirza, and M. Blow, *KASPAR – a minimally expressive humanoid robot for human–robot interaction research,* Applied Bionics and Biomechanics **6**, 369 (2009).

[8] M. Fridin, *Storytelling by a kindergarten social assistive robot: A tool for constructive learning in preschool education,* Computers & Education **70**, 53 (2014).

[9] F. B. V. Benitti, *Exploring the educational potential of robotics in schools: A systematic review,* Computers & Education **58**, 978 (2012).

[10] B. Robins, E. Ferrari, K. Dautenhahn, G. Kronreif, B. Prazak-Aram, G.-j. Gelderblom, B. Tanja, F. Caprino, E. Laudanna, and P. Marti, *Human-centred design methods: Developing scenarios for robot assisted play informed by user panels and field trials,* International Journal of Human-Computer Studies **68**, 873 (2010).

[11] E. I. Barakova and T. Lourens, *Expressing and interpreting emotional movements in social games with robots,* Personal and ubiquitous computing **14**, 457 (2010).

[12] H. Kozima, M. P. Michalowski, and C. Nakagawa, *Keepon,* International Journal of Social Robotics **1**, 3 (2009).

[13] C. D. Kidd, W. Taggart, and S. Turkle, *A sociable robot to encourage social interaction among the elderly,* in *Proceedings IEEE International Conference on Robotics and Automation (ICRA)* (IEEE, 2006) pp. 3972–3976.

[14] G. Hoffman, O. Zuckerman, G. Hirschberger, M. Luria, and T. Shani-Sherman, *Design and evaluation of a peripheral robotic conversation companion, Human Robot Interaction,* (2015), 10.1145/2696454.2696495.

[15] G. Hoffman and K. Vanunu, *Effects of robotic companionship on music enjoyment and agent perception,* in *ACM/IEEE International Conference on Human-Robot Interaction (HRI)* (IEEE, 2013) pp. 317–324.

[16] P. Rane, V. Mhatre, and L. Kurup, *Study of a home robot: Jibo,* in *International Journal of Engineering Research and Technology*, Vol. 3 (ESRSA Publications, 2014).

[17] T. Kanda, M. Shiomi, Z. Miyashita, H. Ishiguro, and N. Hagita, *An affective guide robot in a shopping mall,* in *Proceedings of the 4th ACM/IEEE international conference on Human robot interaction* (ACM, 2009) pp. 173–180.

[18] W. Burgard, A. B. Cremers, D. Fox, D. Hähnel, G. Lakemeyer, D. Schulz, W. Steiner, and S. Thrun, *Experiences with an interactive museum tour-guide robot,* Artificial intelligence **114**, 3 (1999).

[19] M. Bennewitz, F. Faber, D. Joho, M. Schreiber, and S. Behnke, *Towards a humanoid museum guide robot that interacts with multiple persons,* in *IEEE-RAS International Conference on Humanoid Robots* (IEEE, 2005) pp. 418–423.

[20] Y. Kuno, K. Sadazuka, M. Kawashima, K. Yamazaki, A. Yamazaki, and H. Kuzuoka, *Museum guide robot based on sociological interaction analysis,* in *Proceedings of the SIGCHI conference on Human factors in computing systems* (ACM, 2007) pp. 1191–1194.

[21] T. Hashimoto, S. Hiramatsu, T. Tsuji, and H. Kobayashi, *Realization and evaluation of realistic nod with receptionist robot saya,* in *International Symposium on Robot and Human interactive Communication (RO-MAN)* (IEEE, 2007) pp. 326–331.

[22] M. K. Lee, S. Kiesler, and J. Forlizzi, *Receptionist or information kiosk: how do people talk with a robot?* in *Proceedings of the 2010 ACM conference on Computer supported cooperative work* (ACM, 2010) pp. 31–40.

[23] K. Dautenhahn, *The Art Of Designing Socially Intelligent Agents: Science, Fiction, And The Human In The Loop, Applied Artificial Intelligence,* **12**, 573 (1998).

[24] C. Breazeal, *Designing Sociable Robots* (MIT Press, 2002).

[25] C. Breazeal, *Toward sociable robots,* Robotics and Autonomous Systems **42**, 167 (2003).

[26] T. Fong, I. Nourbakhsh, and K. Dautenhahn, *A survey of socially interactive robots,* Robotics and Autonomous Systems **42**, 143 (2003).

[27] C. Bartneck and J. Forlizzi, *A design-centred framework for social human-robot interaction,* in *IEEE International Workshop on Robot and Human Interactive Communication (RO-MAN)* (2004) pp. 591–594.

[28] C. Breazeal and J. Velasquez, *Robot in society: friend or appliance,* in *Proceedings of the 1999 Autonomous Agents Workshop on Emotion-Based Agent Architectures* (1999) pp. 18–26.

[29] C. Breazeal, A. Brooks, J. Gray, G. Hoffman, C. Kidd, H. Lee, J. Lieberman, A. Lockerd, and D. Mulanda, *Humanoid robots as cooperative partners for people,* International Journal of Humanoid Robots **1**, 2004 (2004).

[30] A. Tapus, M. Maja, and B. Scassellatti, *The grand challenges in socially assistive robotics,* IEEE Robotics and Automation Magazine **14**, 35 (2007).

[31] C. Breazeal, A. Takashini, and T. Kobayashi, *Social Robots that Interact with People,* in *Springer Handbook of Robotics*, edited by B. Sicilano and O. Khatib (Springer Verlag, 2008) pp. 1349–1369.

[32] C. Breazeal, *Role of expressive behaviour for robots that learn from people,* Philosophical Transactions of the Royal Society B: Biological Sciences **364**, 3527 (2009).

[33] C. Breazeal, *Emotion and sociable humanoid robots,* International Journal of Human-Computer Studies **59**, 119 (2003).

[34] N. H. Frijda, *The emotions*, Studies in Emotion and Social Interaction (Cambridge University Press, 1986).

[35] J. R. Kelly and S. G. Barsade, *Mood and Emotions in Small Groups and Work Teams,* Organizational Behavior and Human Decision Processes **86**, 99 (2001).

[36] J. A. Russell, *Core affect and the psychological construction of emotion.* Psychological review **110**, 145 (2003).

[37] C. Beedie, P. Terry, and A. Lane, *Distinctions between emotion and mood,* Cognition & Emotion **19**, 847 (2005).

[38] P. Ekkekakis, *Affect, mood, and emotion,* Measurement in sport and exercise psychology , 321 (2012).

[39] J. Bates *et al.*, *The role of emotion in believable agents,* Communications of the ACM **37**, 122 (1994).

[40] B. R. Duffy, *Anthropomorphism and the social robot,* Robotics and Autonomous Systems **42**, 177 (2003).

[41] S. R. Fussell, S. Kiesler, L. D. Setlock, and V. Yew, *How people anthropomorphize robots,* Proceedings of the 3rd international conference on Human robot interaction - HRI '08 , 145 (2008).

[42] R. Gockley, J. Forlizzi, and R. Simmons, *Interactions with a Moody Robot,* in *Proceedings of ACM SIGCHI/SIGART conference on Human-robot interaction* (2006) pp. 186–193.

[43] Q. Le, J. Huang, and C. Pelachaud, *A Common Gesture and Speech Production Framework for Virtual and Physical Agents,* in *ACM International Conference on Multimodal Interaction* (2012).

[44] I. Leite, G. Castellano, and A. Pereira, *Modelling empathic behaviour in a robotic game companion for children: an ethnographic study in real-world settings,* international conference on Human-Robot Interaction , 367 (2012).

[45] M. Tielman, M. Neerincx, J. Meyer, and R. Looije, *Adaptive emotional expression in robot-child interaction,* in *Proceedings of the ACM/IEEE international conference on Human-robot interaction* (2014).

[46] J. Kessens, M. Neerincx, R. Looije, M. Kroes, and G. Bloothooft, *Facial and vocal emotion expression of a personal computer assistant to engage, educate and motivate children,* in *Affective Computing and Intelligent Interaction and Workshops (ACII)* (2009) pp. 1–7.

[47] B. Robins, *From isolation to communication: a case study evaluation of robot assisted play for children with autism with a minimally expressive humanoid robot,* in *International Conferences on Advances in Computer-Human Interactions* (IEEE, 2009) pp. 205–211.

[48] I. Leite, C. Martinho, A. Pereira, and A. Paiva, *iCat: an affective game buddy based on anticipatory mechanisms,* Proceedings of international joint conference on Autonomous agents and multiagent systems , 1229 (2008).

[49] A. Mehrabian, *Silent Messages* (Wadsworth, 1971).

[50] A. Mehrabian, *Nonverbal communication* (Transaction Publishers, 1977).

[51] D. McNeill, *Hand and mind: What gestures reveal about thought* (University of Chicago Press, 1992).

[52] R. M. Krauss, P. Morrel-Samuels, and C. Colasante, *Do conversational hand gestures communicate?* Journal of personality and social psychology **61**, 743 (1991).

[53] M. Kret, J. Stekelenburg, K. Roelofs, and B. De Gelder, *Faces and bodies: perception and mimicry of emotionally congruent and incongruent facial and bodily expressions,* Frontiers in Psychology **4** (2013), 10.3389/fpsyg.2013.00028.

[54] M. Zecca, Y. Mizoguchi, K. Endo, F. Iida, Y. Kawabata, N. Endo, K. Itoh, and A. Takanishi, *Whole body emotion expressions for kobian humanoid robot - preliminary experiments with different emotional patterns -,* in *RO-MAN, IEEE* (2009) pp. 381–386.

[55] J. Hirth, N. Schmitz, and K. Berns, *Towards social robots: Designing an emotion-based architecture,* International Journal of Social Robotics **3**, 273 (2011).

[56] M. Häring, N. Bee, and E. Andre, *Creation and evaluation of emotion expression with body movement, sound and eye color for humanoid robots,* in *RO-MAN, IEEE* (2011) pp. 204–209.

[57] A. Beck, B. Stevens, K. A. Bard, and L. Cañamero, *Emotional body language displayed by artificial agents,* ACM Transactions on Interactive Intelligent Systems **2**, 1 (2012).

[58] C. Breazeal, C. Kidd, A. Thomaz, G. Hoffman, and M. Berlin, *Effects of nonverbal communication on efficiency and robustness in human-robot teamwork,* in *IROS* (2005) pp. 708–713.

[59] I. Cohen, R. Looije, and M. Neerincx, *Child's perception of robot emotions: effects of platform, Context and experience,* International Journal of Social Robotics (2014), 10.1007/s12369-014-0230-6.

[60] S. Kajita, K. Kaneko, F. Kaneiro, K. Harada, M. Morisawa, S. Nakaoka, K. Miura, K. Fujiwara, E. S. Neo, I. Hara, *et al.*, *Cybernetic human hrp-4c: A humanoid robot with human-like proportions,* in *Robotics Research* (Springer, 2011) pp. 301–314.

[61] T. M. Glomb and M. J. Tews, *Emotional labor: A conceptualization and scale development,* Journal of Vocational Behavior **64**, 1 (2004).

[62] J. Fast, *Body language* (Simon and Schuster, 1970).

[63] B. Parkinson, *Changing moods: the psychology of mood and mood regulation* (Longman, 1996).

[64] A. P. Atkinson, W. H. Dittrich, A. J. Gemmell, and A. W. Young, *Emotion perception from dynamic and static body expressions in point-light and full-light displays,* Perception **33**, 717 (2004).

[65] H. Wallbott, *Bodily expression of emotion,* European J. Social Psychology **28**, 879 (1998).

[66] R. Laban and L. Ullmann, *The mastery of movement.* (ERIC, 1971).

[67] C. Rose, M. Cohen, and B. Bodenheimer, *Verbs and adverbs: multidimensional motion interpolation,* Computer Graphics and Applications, IEEE **18**, 32 (1998).

[68] K. Amaya, A. Bruderlin, and T. Calvert, *Emotion from motion,* in *Graphics Interface* (1996) pp. 222–229.

[69] D. Chi, M. Costa, L. Zhao, and N. Badler, *The emote model for effort and shape,* in *SIGGRAPH* (ACM, 2000) pp. 173–182.

[70] C. Pelachaud, *Studies on gesture expressivity for a virtual agent,* Speech Communication **51**, 630 (2009).

[71] M. Mancini, G. Castellano, C. Peters, and P. W. McOwan, *Evaluating the communication of emotion via expressive gesture copying behaviour in an embodied humanoid agent,* in *Affective Computing and Intelligent Interaction* (Springer, 2011) pp. 215–224.

[72] Q. A. Le, S. Hanoune, and C. Pelachaud, *Design and implementation of an expressive gesture model for a humanoid robot,* in *IEEE-RAS International Conference on Humanoid Robots (Humanoids)* (2011) pp. 134–140.

[73] A. Yamaguchi, Y. Yano, S. Doki, and S. Okuma, *A study of emotional motion description by motion modification rules using adjectival expressions,* in *SMC*, Vol. 4 (2006) pp. 2837–2842.

[74] A. Yamaguchi, Y. Yano, Y. Doki, and S. Okuma, *A study of emotional motion description by motion modification and adjectival expressions,* in *IEEE Conf. Cybern. and Intelligent Syst.* (2006) pp. 1–6.

[75] Y.-H. Lin, C.-Y. Liu, H.-W. Lee, S.-L. Huang, and T.-Y. Li, *Evaluating emotive character animations created with procedural animation,* in *Intelligent Virtual Agents* (Springer-Verlag, 2009) pp. 308–315.

[76] A. Brooks and R. Arkin, *Behavioral overlays for non-verbal communication expression on a humanoid robot,* Autonomous Robots **22**, 55 (2007).

[77] J. Xu, J. Broekens, K. Hindriks, and M. A. Neerincx, *Mood expression through parameterized functional behavior of robots,* in *Proceedings of IEEE International Symposium on Robot and Human Interactive Communication* (IEEE, Gyeongju, 2013) pp. 533–540.

[78] J. Xu, J. Broekens, K. Hindriks, and M. A. Neerincx, *The relative importance and interrelations between behavior parameters for robots' mood expression,* in *Proceedings of International Conference on Affective Computing and Intelligent Interaction, ACII 2013* (2013) pp. 558–563.

[79] J. Xu, J. Broekens, K. Hindriks, and M. A. Neerincx, *Bodily mood expression: Recognize moods from functional behaviors of humanoid robots,* in *International Conference on Social Robotics* (2013) pp. 511–520.

[80] J. Xu, J. Broekens, K. Hindriks, and M. A. Neerincx, *Mood contagion of robot body language in human robot interaction,* Autonomous Agents and Multi-Agent Systems **29**, 1216 (2015).

[81] J. Xu, J. Broekens, K. Hindriks, and M. A. Neerincx, *Robot Mood is Contagious: Effects of Robot Body Language in the Imitation Game,* in *Autonomous Agents and Multi-Agent Systems (AAMAS)* (2014) pp. 973–980.

[82] J. Xu, J. Broekens, K. Hindriks, and M. A. Neerincx, *Robotic Lecturer with Affective Body Language, Journal of Computer & Education,* (submitted, 2015).

[83] J. Xu, J. Broekens, K. Hindriks, and M. Neerincx, *Effects of Bodily Mood Expression of a Robotic Teacher on Students,* in *International Conference on Intelligent Robots and Systems (IROS)* (IEEE, Chicago, 2014) pp. 2614–2620.

[84] J. Xu, J. Broekens, K. Hindriks, and M. A. Neerincx, *Effects of a robotic storyteller's moody gestures on storytelling perception,* in *ACII 2015* (IEEE, 2015) pp. 449–455.

[85] A. Kleinsmith, N. Bianchi-Berthouze, and A. Steed, *Automatic recognition of non-acted affective postures,* IEEE Trans. Syst. Man Cybern. B, Cybern. **41**, 1027 (2011).

[86] M. Masuda and S. Kato, *Motion rendering system for emotion expression of human form robots based on laban movement analysis,* in *RO-MAN, IEEE* (2010) pp. 324–329.

[87] E. I. Barakova and T. Lourens, *Expressing and interpreting emotional movements in social games with robots,* Personal and Ubiquitous Computing **14**, 457 (2010).

[88] A. Beck, L. Cañamero, and K. Bard, *Towards an affect space for robots to display emotional body language,* in *RO-MAN, IEEE* (2010) pp. 464–469.

[89] S. Kopp, B. Krenn, S. Marsella, A. Marshall, C. Pelachaud, H. Pirker, K. Thórisson, and H. Vilhjálmsson, *Towards a common framework for multimodal generation: The behavior markup language,* in *Intelligent Virtual Agents*, Vol. 4133 (2006) pp. 205–217.

[90] E. A. Crane, *Measures of emotion: how feelings are expressed in the body and face during walking,* Ph.D. thesis, The University of Michigan (2009).

[91] K. Bergmann, S. Kopp, and F. Eyssel, *Individualized gesturing outperforms average gesturing–evaluating gesture production in virtual humans,* in *Intelligent Virtual Agents* (Springer Berlin Heidelberg, 2010) pp. 104–117.

[92] P. G. Engeldrum, *Psychometric scaling: a toolkit for imaging systems development* (Imcotek Press, 2000).

[93] R. Rajae-Joordens and J. Engel, *Paired comparisons in visual perception studies using small sample sizes,* Displays **26**, 1 (2005).

[94] J. A. Russell, *A circumplex model of affect.* Journal of personality and social psychology **39**, 1161 (1980).

[95] P. J. Lang, M. M. Bradley, and B. N. Cuthbert, *International affective picture system (iaps): Technical manual and affective ratings,* (1999).

[96] T. Belpaeme, P. E. Baxter, R. Read, R. Wood, H. Cuayáhuitl, B. Kiefer, S. Racioppa, I. Kruijff-Korbayová, G. Athanasopoulos, V. Enescu, *et al.*, *Multimodal child-robot interaction: Building social bonds,* Journal of Human-Robot Interaction **1**, 33 (2012).

[97] R. Neumann and F. Strack, *"Mood contagion": the automatic transfer of mood between persons.* Journal of personality and social psychology **79**, 211 (2000).

[98] C. Bartneck, J. Reichenbach, and v. A. Breemen, *In your face, robot! the influence of a character's embodiment on how users perceive its emotional expressions,* in *Proceedings of the Design and Emotion* (2004) pp. 32–51.

[99] S. Kopp, B. Jung, N. Leßmann, and I. Wachsmuth, *Max - a multimodal assistant in virtual reality construction,* Künstliche Intelligenz (KI) **4**, 11 (2003).

[100] R. Beale and C. Creed, *Affective interaction: How emotional agents affect users,* International Journal of Human-Computer Studies **67**, 755 (2009).

[101] H. Prendinger and M. Ishizuka, *The empathic companion: A character-based interface that addresses users' affective states,* Applied Artificial Intelligence **19**, 267 (2005).

[102] J. Klein, Y. Moon, and R. W. Picard, *This computer responds to user frustration: Theory, design, and results,* Interacting with computers **14**, 119 (2002).

[103] K. Hone, *Empathic agents to reduce user frustration: The effects of varying agent characteristics,* Interacting with computers **18**, 227 (2006).

[104] W. Burleson and R. W. Picard, *Gender-specific approaches to developing emotionally intelligent learning companions,* Intelligent Systems, IEEE **22**, 62 (2007).

[105] H. Maldonado, J.-E. R. Lee, S. Brave, C. Nass, H. Nakajima, R. Yamada, K. Iwamura, and Y. Morishima, *We learn better together: enhancing elearning with emotional characters,* in *Proceedings of th 2005 conference on Computer support for collaborative learning: learning 2005: the next 10 years!* (International Society of the Learning Sciences, 2005) pp. 408–417.

[106] D. C. Berry, L. T. Butler, and F. De Rosis, *Evaluating a realistic agent in an advice-giving task,* International Journal of Human-Computer Studies **63**, 304 (2005).

[107] J. Tsai, E. Bowring, S. Marsella, W. Wood, and M. Tambe, *A study of emotional contagion with virtual characters,* in *Intelligent Virtual Agents* (Springer, 2012) pp. 81–88.

[108] C. Okonkwo and J. Vassileva, *Affective pedagogical agents and user persuasion.* in *HCI* (2001) pp. 397–401.

[109] L. Gong, *Is happy better than sad even if they are both non-adaptive? effects of emotional expressions of talking-head interface agents,* International Journal of Human-Computer Studies **65**, 183 (2007).

[110] M. E. Glickman, *Parameter estimation in large dynamic paired comparison experiments,* Journal of the Royal Statistical Society: Series C (Applied Statistics) **48**, 377 (1999).

[111] J. L. Tracy and R. W. Robins, *The automaticity of emotion recognition.* Emotion **8**, 81 (2008).

[112] L. Jefferies, D. Smilek, E. Eich, and J. Enns, *Emotional valence and arousal interact in attentional control,* Psychological Science **19**, 290 (2008).

[113] N. Silvestrini and G. H. Gendolla, *The joint effect of mood, task valence, and task difficulty on effort-related cardiovascular response and facial emg,* International Journal of Psychophysiology **73**, 226 (2009).

[114] K. Gasper and G. Clore, *Attending to the big picture: Mood and global versus local processing of visual information,* Psychological Science (2002), 10.1111/1467-9280.00406.

[115] M. Baas, C. K. De Dreu, and B. A. Nijstad, *A meta-analysis of 25 years of mood-creativity research: Hedonic tone, activation, or regulatory focus?* Psychological bulletin **134**, 779 (2008).

[116] M. R. Basso, B. K. Schefft, M. D. Ris, and W. N. Dember, *Mood and global-local visual processing.* Journal of the International Neuropsychological Society : JINS **2**, 249 (1996).

[117] M. M. Bradley and P. J. Lang, *Measuring emotion: the self-assessment manikin and the semantic differential,* Journal of behavior therapy and experimental psychiatry **25**, 49 (1994).

[118] M. de Meijer, *The contribution of general features of body movement to the attribution of emotions,* Journal of Nonverbal behavior **13**, 247 (1989).

[119] F. E. Pollick, H. M. Paterson, A. Bruderlin, and A. J. Sanford, *Perceiving affect from arm movement,* Cognition **82**, B51 (2001).

[120] H. M. Patterson, F. E. Pollick, and A. J. Sanford, *The role of velocity in affect discrimination, Proceedings of the Twenty-Third Annual Conference of the Cognitve Science Society,* , 756 (2001).

[121] W. James, *What is an emotion?* Mind **9**, 188 (1884).

[122] J. D. Laird, *Self-attribution of emotion: the effects of expressive behavior on the quality of emotional experience.* Journal of personality and social psychology **29**, 475 (1974).

[123] S. E. Duclos, J. D. Laird, E. Schneider, M. Sexter, L. Stern, and O. Van Lighten, *Emotion-specific effects of facial expressions and postures on emotional experience.* Journal of Personality and Social Psychology **57**, 100 (1989).

[124] M. Sonnby-Borgström, P. Jönsson, and O. Svensson, *Emotional empathy as related to mimicry reactions at different levels of information processing,* Journal of Nonverbal behavior **27**, 3 (2003).

[125] E. J. Moody and D. N. McIntosh, *Mimicry of dynamic emotional and motor-only stimuli,* Social Psychological and Personality Science , 1948550611406741 (2011).

[126] J. Lee and S. Marsella, *Nonverbal behavior generator for embodied conversational agents,* in *Intelligent virtual agents* (Springer, 2006) pp. 243–255.

[127] W. L. Johnson and J. Rickel, *Steve: An animated pedagogical agent for procedural training in virtual environments,* ACM SIGART Bulletin **8**, 16 (1997).

[128] L. Ieronutti and L. Chittaro, *Employing virtual humans for education and training in x3d/vrml worlds,* Computers & Education **49**, 93 (2007).

[129] C. Buche, R. Querrec, P. De Loor, and P. Chevaillier, *Mascaret: pedagogical multi-agents systems for virtual environment for training,* in *International Conference on Cyberworlds* (IEEE, 2003) pp. 423–430.

[130] P. Ekman and W. V. Friesen, *Constants across cultures in the face and emotion.* Journal of personality and social psychology **17**, 124 (1971).

[131] A. Kleinsmith, P. R. D. Silva, and N. Bianchi-Berthouze, *Cross-cultural differences in recognizing affect from body posture,* Interacting with Computers **18**, 1371 (2006), special Issue: Symbiotic Performance between Humans and Intelligent Systems.

[132] A. Kleinsmith and N. Bianchi-Berthouze, *Affective body expression perception and recognition: A survey,* Affective Computing, IEEE Transactions on **4**, 15 (2013).

[133] C. Bartneck, T. Suzuki, T. Kanda, and T. Nomura, *The influence of people's culture and prior experiences with aibo on their attitude towards robots,* Ai & Society **21**, 217 (2006).

[134] D. J. Howard and C. Gengler, *Emotional contagion effects on product attitudes,* Journal of Consumer research **28**, 189 (2001).

[135] E. Smeets, *Does ict contribute to powerful learning environments in primary education?* Computers & Education **44**, 343 (2005).

[136] T. A. Mikropoulos and A. Natsis, *Educational virtual environments: A ten-year review of empirical research (1999–2009),* Computers & Education **56**, 769 (2011).

[137] P. Marshall, Y. Rogers, and M. Scaife, *Puppet: playing and learning in a virtual world,* International Journal of Continuing Engineering Education and Life Long Learning **14**, 519 (2004).

[138] W. Swartout, D. Traum, R. Artstein, D. Noren, P. Debevec, K. Bronnenkant, J. Williams, A. Leuski, S. Narayanan, D. Piepol, *et al.*, *Ada and grace: Toward realistic and engaging virtual museum guides,* in *Intelligent Virtual Agents* (Springer, 2010) pp. 286–300.

[139] A. Gulz, *Benefits of virtual characters in computer based learning environments: Claims and evidence,* International Journal of Artificial Intelligence in Education **14**, 313 (2004).

[140] J. Wainer, D. J. Feil-Seifer, D. Shell, M. J. Matarić, *et al.*, *The role of physical embodiment in human-robot interaction,* in *IEEE International Symposium on Robot and Human Interactive Communication (ROMAN), 2006* (IEEE, 2006) pp. 117–122.

[141] J. Wainer, D. J. Feil-Seifer, D. Shell, M. J. Mataric, *et al.*, *Embodiment and human-robot interaction: A task-based perspective,* in *IEEE International Symposium on Robot and Human interactive Communication (RO-MAN)* (IEEE, 2007) pp. 872–877.

[142] A. Powers, S. Kiesler, S. Fussell, and C. Torrey, *Comparing a computer agent with a humanoid robot,* in *ACM/IEEE International Conference on Human-Robot Interaction (HRI)* (IEEE, 2007) pp. 145–152.

[143] C. D. Kidd, *Sociable robots: The role of presence and task in human-robot interaction*, Ph.D. thesis, Massachusetts Institute of Technology (2003).

[144] A. Pereira, C. Martinho, I. Leite, and A. Paiva, *icat, the chess player: the influence of embodiment in the enjoyment of a game,* in *Proceedings of the 7th international joint conference on Autonomous agents and multiagent systems-Volume 3* (International Foundation for Autonomous Agents and Multiagent Systems, 2008) pp. 1253–1256.

[145] C.-W. Chang, J.-H. Lee, C.-Y. Wang, and G.-D. Chen, *Improving the authentic learning experience by integrating robots into the mixed-reality environment,* Computers & Education **55**, 1572 (2010).

[146] R. Mitnik, M. Recabarren, M. Nussbaum, and A. Soto, *Collaborative robotic instruction: A graph teaching experience,* Computers & Education **53**, 330 (2009).

[147] C. Bartneck, *EMuu: An Embodied Emotional Character for the Ambient Intelligent Home* (Technische Universiteit Eindhoven, 2002).

[148] H. Ryu, S. S. Kwak, and M. Kim, *A study on external form design factors for robots as elementary school teaching assistants,* in *IEEE International Symposium on Robot and Human interactive Communication (RO-MAN)* (IEEE, 2007) pp. 1046–1051.

[149] D. Feil-Seifer and M. J. Matarić, *Defining socially assistive robotics,* in *International Conference on Rehabilitation Robotics (ICORR)* (IEEE, 2005) pp. 465–468.

[150] M. Saerbeck, T. Schut, C. Bartneck, and M. D. Janse, *Expressive robots in education: varying the degree of social supportive behavior of a robotic tutor,* in *CHI* (2010) pp. 1613–1622.

[151] N. Shin and S. Kim, *Learning about, from, and with Robots: Students' Perspectives,* in *IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)* (IEEE, 2007) pp. 1040–1045.

[152] C. Chang, J. Lee, P.-Y. Chao, C.-Y. Wang, and G.-D. Chen, *Exploring the Possibility of Using Humanoid Robots as Instructional Tools for Teaching a Second Language in Primary School.* Educational Technology & Society **13**, 13 (2010).

[153] J. L. Abrantes, C. Seabra, and L. F. Lages, *Pedagogical affect, student interest, and learning performance,* Journal of Business Research **60**, 960 (2007).

[154] A. Cruz-Martín, J. Fernández-Madrigal, C. Galindo, J. González-Jiménez, C. Stockmans-Daou, and J. Blanco-Claraco, *A LEGO Mindstorms NXT approach for teaching at Data Acquisition, Control Systems Engineering and Real-Time Systems undergraduate courses,* Computers & Education **59**, 974 (2012).

[155] A. Araújo, D. Portugal, M. S. Couceiro, and R. P. Rocha, *Integrating Arduino-based educational mobile robots in ROS,* Journal of Intelligent & Robotic Systems (2013), 10.1007/s10846-013-0007-4.

[156] F. Tanaka and S. Matsuzoe, *Children Teach a Care-Receiving Robot to Promote Their Learning: Field Experiments in a Classroom for Vocabulary Learning,* Journal of Human-Robot Interaction **1**, 78 (2012).

[157] R. Pekrun, *The impact of emotions on learning and achievement: Towards a theory of cognitive/motivational mediators,* Applied Psychology (1992).

[158] M. Fridin, *Kindergarten social assistive robot: First meeting and ethical issues,* Computers in Human Behavior **30**, 262 (2014).

[159] L. D. Riek, *Wizard of oz studies in hri: a systematic review and new reporting guidelines,* Journal of Human-Robot Interaction **1** (2012).

[160] A. Weiss, R. Bernhaupt, M. Tscheligi, D. Wollherr, K. Kuhnlenz, and M. Buss, *A methodological variation for acceptance evaluation of human-robot interaction in public places,* in *IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)* (IEEE, 2008) pp. 713–718.

[161] S. Sabanovic, M. P. Michalowski, and R. Simmons, *Robots in the wild: Observing human-robot social interaction outside the lab,* in *IEEE International Workshop on Advanced Motion Control* (IEEE, 2006) pp. 596–601.

[162] A. Weiss, J. Igelsböck, M. Tscheligi, A. Bauer, K. Kühnlenz, D. Wollherr, and M. Buss, *Robots asking for directions: the willingness of passers-by to support robots,* in *Proceedings of the 5th ACM/IEEE international conference on Human-robot interaction* (IEEE Press, 2010) pp. 23–30.

[163] J. Abildgaard and H. Scharfe, *A geminoid as lecturer,* in *International Conference on Social Robotics* (2012) pp. 408–417.

[164] R. Coenen and J. Broekens, *Modeling emotional contagion based on experimental evidence for moderating factors,* in *EAS* (2012) pp. 4–8.

[165] S. G. Barsade, *The Ripple Effect: Emotional Contagion and Its Influence on Group Behavior,* Administrative Science Quarterly **47**, 644 (2002).

[166] S. Kiesler and J. N. Cummings, *What do we know about proximity and distance in work groups? a legacy of research,* Distributed work **1**, 57 (2002).

[167] D. Kahneman, *Attention and effort* (Englewood Cliffs, NJ: Prentice-Hall, 1973).

[168] K. LaBar and E. Phelps, *Arousal-Mediated Memory Consolidation: Role of the Medial Temporal Lobe in Humans,* Psychological Science **9**, 490 (1998).

[169] E. A. Phelps, *Human emotion and memory: interactions of the amygdala and hippocampal complex,* Current opinion in neurobiology **14**, 198 (2004).

[170] R. M. Yerkes and J. D. Dodson, *The relation of strength of stimulus to rapidity of habit-formation,* Journal of comparative neurology and Psychology **18**, 459 (1908).

[171] R. M. Yerkes and J. Dodson, *The relation of strength of stimulus to rapidity of habit-formation,* in *Punishment: Issues and experiments* (Appleton-Century-Crofts New York, 1968) pp. 27–41.

[172] K. H. Teigen, *Yerkes-dodson: A law for all seasons,* Theory & Psychology **4**, 525 (1994).

[173] J. Masters, R. Barden, and M. Ford, *Affective states, expressive behavior, and learning in children.* Journal of Personality and Social Psychology **37**, 380 (1979).

[174] S. Craig, A. Graesser, J. Sullins, and B. Gholson, *Affect and learning: An exploratory look into the role of affect in learning with AutoTutor,* Journal of Educational Media **29**, 241 (2004).

[175] L. Shen, M. Wang, and R. Shen, *Affective e-Learning: Using "Emotional" Data to Improve Learning in Pervasive Learning Environment Related Work and the Pervasive e-Learning Platform,* Educational Technology & Society **12**, 176 (2009).

[176] A. Mehrabian, *Basic dimensions for a general psychological theory implications for personality, social, environmental, and developmental studies,* (1980).

[177] V. J. Fortunato and M. D. Mincy, *The interactive effects of dispositional affectivity, sex, and a positive mood induction on student evaluations of teachers,* Journal of Applied Social Psychology **33**, 1945 (2003).

[178] S. Linder, B. Nestrick, S. Mulders, and C. L. Lavelle, *Facilitating active learning with inexpensive mobile robots,* Journal of Computing Sciences in Colleges **16**, 21 (2001).

[179] R. G. Tiberius and J. M. Billson, *The social context of teaching and learning,* New directions for teaching and learning **1991**, 67 (1991).

[180] P. Spooren, B. Brockx, and D. Mortelmans, *On the Validity of Student Evaluation of Teaching The State of the Art,* Review of Educational Research **83**, 598 (2013).

[181] C. Bethel and R. Murphy, *Survey of non-facial/non-verbal affective expressions for appearance-constrained robots,* IEEE Transactions On Systems, Man, & Cybernetics—Part C: Applications & Reviews **38**, 83 (2008).

[182] E. T. Hall, *The hidden dimension* (New York: Anchor Books, 1969).

[183] C. K. Hsee, E. Hatfield, J. G. Carlson, and C. Chemtob, *The effect of power on susceptibility to emotional contagion,* Cognition & Emotion **4**, 327 (1990).

[184] S. van Mulken, E. André, and J. Müller, *The persona effect: how substantial is it,* People and computers XIII: Proceedings of HCI **98**, 53 (1998).

[185] Y. Kim, *Empathetic virtual peers enhanced learner interest and self-efficacy,* in *Workshop on Motivation and Affect in Educational Software, in conjunction with the 12th International Conference on Artificial Intelligence in Education* (2005) pp. 9–16.

[186] I. Leite, C. Martinho, A. Pereira, and A. Paiva, *As time goes by: Long-term evaluation of social presence in robotic companions,* in *IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)* (IEEE, 2009) pp. 669–674.

[187] T. Kanda, T. Hirano, D. Eaton, and H. Ishiguro, *Interactive robots as social partners and peer tutors for children: A field trial,* Human-Computer Interaction **19**, 61 (2004).

[188] J. Sung, H. Christensen, R. E. Grinter, *et al.*, *Robots in the wild: understanding long-term use,* in *ACM/IEEE International Conference on Human-Robot Interaction (HRI)* (IEEE, 2009) pp. 45–52.

[189] R. Gockley, A. Bruce, J. Forlizzi, M. Michalowski, A. Mundell, S. Rosenthal, B. Sellner, R. Simmons, K. Snipes, A. C. Schultz, *et al.*, *Designing robots for long-term social interaction,* in *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)* (IEEE, 2005) pp. 1338–1343.

[190] J. Van den Stock, R. Righart, and B. De Gelder, *Body expressions influence recognition of emotions in the face and voice,* Emotion **7**, 487 (2007).

[191] J. Van den Stock, J. Grèzes, and B. de Gelder, *Human and animal sounds influence recognition of body language,* Brain research **1242**, 185 (2008).

[192] J. Van den Stock, I. Peretz, J. Grezes, and B. de Gelder, *Instrumental music influences recognition of emotional body language,* Brain topography **21**, 216 (2009).

[193] H. K. Meeren, C. C. van Heijnsbergen, and B. de Gelder, *Rapid perceptual integration of facial expression and emotional body language,* Proceedings of the National Academy of Sciences of the United States of America **102**, 16518 (2005).

[194] M. Salem, K. Rohlfing, S. Kopp, and F. Joublin, *A friendly gesture: Investigating the effect of multimodal robot behavior in human-robot interaction,* in *RO-MAN, 2011 IEEE* (IEEE, 2011) pp. 247–252.

[195] M. Salem, S. Kopp, I. Wachsmuth, K. Rohlfing, and F. Joublin, *Generation and evaluation of communicative robot gesture,* International Journal of Social Robotics **4**, 201 (2012).

[196] P. Wagner, Z. Malisz, and S. Kopp, *Gesture and speech in interaction: an overview,* Speech Communication **57**, 209 (2014).

[197] B. Mutlu, J. Forlizzi, and J. Hodgins, *A storytelling robot: Modeling and evaluation of human-like gaze behavior,* in *IEEE-RAS International Conference on Humanoid Robots* (IEEE, 2006) pp. 518–523.

[198] C. Pelachaud, R. Gelin, J.-C. Martin, and Q. A. Le, *Expressive gestures displayed by a humanoid robot during a storytelling application,* New Frontiers in Human-Robot Interaction (AISB), Leicester, GB (2010).

[199] Q. A. Le and C. Pelachaud, *Evaluating an expressive gesture model for a humanoid robot: experimental results,* in *Submitted to 8th ACM/IEEE International Conference on Human-Robot Interaction* (2012).

[200] J.-C. Park, H. Song, S. Koo, Y.-M. Kim, and D.-S. Kwon, *Robot's behavior expressions according to the sentence types and emotions with modification by personality,* in *IEEE Workshop on Advanced Robotics and its Social Impacts (ARSO)* (IEEE, 2010) pp. 105–110.

[201] J. Montemayor, *Pets: A personal electronic teller of stories,* Robots for kids: Exploring new technologies for learning , 73 (2000).

[202] S. Keen, *A theory of narrative empathy,* Narrative **14**, 207 (2006).

[203] C. Creed and R. Beale, *Psychological responses to simulated displays of mismatched emotional expressions,* Interacting with Computers **20**, 225 (2008).

[204] J. Broekens and W.-P. Brinkman, *Affectbutton: Towards a standard for dynamic affective user feedback,* in *International Conference on Affective Computing and Intelligent Interaction and Workshops (ACII)* (IEEE, 2009) pp. 1–8.

[205] E. Aronson, *Back to the Future: Retrospective Review of Leon Festinger's" A Theory of Cognitive Dissonance",* The American Journal of Psychology **110**, 127 (1997).

[206] H. Welbergen, D. Reidsma, Z. M. Ruttkay, and J. Zwiers, *Elckerlyc: A BML Realizer for continuous, multimodal interaction with a Virtual Human,* (2009).

[207] V. Ng-Thow-Hing, P. Luo, and S. Okita, *Synchronized gesture and speech production for humanoid robots,* in *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)* (IEEE, 2010) pp. 4617–4624.

[208] A. Beck, A. Hiolle, A. Mazel, and L. Cañamero, *Interpretation of emotional body language displayed by robots,* in *Proc. 3rd Int. workshop Affective interaction in natural environments*, AFFINE '10 (ACM, New York, NY, USA, 2010) pp. 37–42.

[209] C. Y. Lin, L. C. Cheng, C. C. Huang, L. W. Chuang, W. C. Teng, C. H. Kuo, H. Y. Gu, K. L. Chung, and C. S. Fahn, *Versatile humanoid robots for theatrical performances,* International Journal of Advanced Robotic Systems **10** (2013), 10.5772/50644.

[210] H.-J. Suk, *Color and Emotion-a study on the affective judgment across media and in relation to visual stimuli,* Ph.D. thesis (2006).

SIKS Dissertation Series

A list of SIKS dissertations published between 1998 and 2008 can be found at SIKS website[3].

====
2009
====

2009-01 Rasa Jurgelenaite (RUN)
Symmetric Causal Independence Models

2009-02 Willem Robert van Hage (VU)
Evaluating Ontology-Alignment Techniques

2009-03 Hans Stol (UvT)
A Framework for Evidence-based Policy Making Using IT

2009-04 Josephine Nabukenya (RUN)
Improving the Quality of Organisational Policy Making using Collaboration Engineering

2009-05 Sietse Overbeek (RUN)
Bridging Supply and Demand for Knowledge Intensive Tasks - Based on Knowledge, Cognition, and Quality

2009-06 Muhammad Subianto (UU)
Understanding Classification

2009-07 Ronald Poppe (UT)
Discriminative Vision-Based Recovery and Recognition of Human Motion

2009-08 Volker Nannen (VU)
Evolutionary Agent-Based Policy Analysis in Dynamic Environments

2009-09 Benjamin Kanagwa (RUN)
Design, Discovery and Construction of Service-oriented Systems

2009-10 Jan Wielemaker (UVA)
Logic programming for knowledge-intensive interactive applications

2009-11 Alexander Boer (UVA)
Legal Theory, Sources of Law & the Semantic Web

2009-12 Peter Massuthe (TUE, Humboldt-Universitaet zu Berlin)
perating Guidelines for Services

2009-13 Steven de Jong (UM)
Fairness in Multi-Agent Systems

2009-14 Maksym Korotkiy (VU)
From ontology-enabled services to service-enabled ontologies
(making ontologies work in e-science with ONTO-SOA)

2009-15 Rinke Hoekstra (UVA)
Ontology Representation - Design Patterns and Ontologies that Make Sense

[3] http://www.siks.nl/dissertations.php

2009-16 Fritz Reul (UvT)
New Architectures in Computer Chess

2009-17 Laurens van der Maaten (UvT)
Feature Extraction from Visual Data

2009-18 Fabian Groffen (CWI)
Armada, An Evolving Database System

2009-19 Valentin Robu (CWI)
Modeling Preferences, Strategic Reasoning and Collaboration in Agent-Mediated Electronic Markets

2009-20 Bob van der Vecht (UU)
Adjustable Autonomy: Controling Influences on Decision Making

2009-21 Stijn Vanderlooy (UM)
Ranking and Reliable Classification

2009-22 Pavel Serdyukov (UT)
Search For Expertise: Going beyond direct evidence

2009-23 Peter Hofgesang (VU)
Modelling Web Usage in a Changing Environment

2009-24 Annerieke Heuvelink (VUA)
Cognitive Models for Training Simulations

2009-25 Alex van Ballegooij (CWI)
"RAM: Array Database Management through Relational Mapping"

2009-26 Fernando Koch (UU)
An Agent-Based Model for the Development of Intelligent Mobile Services

2009-27 Christian Glahn (OU)
Contextual Support of social Engagement and Reflection on the Web

2009-28 Sander Evers (UT)
Sensor Data Management with Probabilistic Models

2009-29 Stanislav Pokraev (UT)
Model-Driven Semantic Integration of Service-Oriented Applications

2009-30 Marcin Zukowski (CWI)
Balancing vectorized query execution with bandwidth-optimized storage

2009-31 Sofiya Katrenko (UVA)
A Closer Look at Learning Relations from Text

2009-32 Rik Farenhorst (VU) and Remco de Boer (VU)
Architectural Knowledge Management: Supporting Architects and Auditors

2009-33 Khiet Truong (UT)
How Does Real Affect Affect Affect Recognition In Speech?

2009-34 Inge van de Weerd (UU)
Advancing in Software Product Management: An Incremental Method Engineering Approach

2009-35 Wouter Koelewijn (UL)
Privacy en Politiegegevens; Over geautomatiseerde normatieve informatie-uitwisseling

2009-36 Marco Kalz (OUN)
Placement Support for Learners in Learning Networks

2009-37 Hendrik Drachsler (OUN)
Navigation Support for Learners in Informal Learning Networks

2009-38 Riina Vuorikari (OU)
Tags and self-organisation: a metadata ecology for learning resources in a multilingual context

2009-39 Christian Stahl (TUE, Humboldt-Universitaet zu Berlin)
Service Substitution – A Behavioral Approach Based on Petri Nets

2009-40 Stephan Raaijmakers (UvT)
Multinomial Language Learning: Investigations into the Geometry of Language

2009-41 Igor Berezhnyy (UvT)
Digital Analysis of Paintings

2009-42 Toine Bogers
Recommender Systems for Social Bookmarking

2009-43 Virginia Nunes Leal Franqueira (UT)
Finding Multi-step Attacks in Computer Networks using Heuristic Search and Mobile Ambients

2009-44 Roberto Santana Tapia (UT)
Assessing Business-IT Alignment in Networked Organizations

2009-45 Jilles Vreeken (UU)
Making Pattern Mining Useful

2009-46 Loredana Afanasiev (UvA)
Querying XML: Benchmarks and Recursion

====
2010
====

2010-01 Matthijs van Leeuwen (UU)
Patterns that Matter

2010-02 Ingo Wassink (UT)
Work flows in Life Science

2010-03 Joost Geurts (CWI)
A Document Engineering Model and Processing Framework for Multimedia documents

2010-04 Olga Kulyk (UT)
Do You Know What I Know? Situational Awareness of Co-located Teams in Multidisplay Environments

2010-05 Claudia Hauff (UT)
Predicting the Effectiveness of Queries and Retrieval Systems

2010-06 Sander Bakkes (UvT)
Rapid Adaptation of Video Game AI

2010-07 Wim Fikkert (UT)
Gesture interaction at a Distance

2010-08 Krzysztof Siewicz (UL)
Towards an Improved Regulatory Framework of Free Software.
Protecting user freedoms in a world of software communities and eGovernments

2010-09 Hugo Kielman (UL)
A Politiele gegevensverwerking en Privacy, Naar een effectieve waarborging

2010-10 Rebecca Ong (UL)
Mobile Communication and Protection of Children

2010-11 Adriaan Ter Mors (TUD)
The world according to MARP: Multi-Agent Route Planning

2010-12 Susan van den Braak (UU)
Sensemaking software for crime analysis

2010-13 Gianluigi Folino (RUN)
High Performance Data Mining using Bio-inspired techniques

2010-14 Sander van Splunter (VU)
Automated Web Service Reconfiguration

2010-15 Lianne Bodenstaff (UT)
Managing Dependency Relations in Inter-Organizational Models

2010-16 Sicco Verwer (TUD)
Efficient Identification of Timed Automata, theory and practice

2010-17 Spyros Kotoulas (VU)
Scalable Discovery of Networked Resources: Algorithms, Infrastructure, Applications

2010-18 Charlotte Gerritsen (VU)
Caught in the Act: Investigating Crime by Agent-Based Simulation

2010-19 Henriette Cramer (UvA)
People's Responses to Autonomous and Adaptive Systems

2010-20 Ivo Swartjes (UT)
Whose Story Is It Anyway? How Improv Informs Agency and Authorship of Emergent Narrative

2010-21 Harold van Heerde (UT)
Privacy-aware data management by means of data degradation

2010-22 Michiel Hildebrand (CWI)
End-user Support for Access to Heterogeneous Linked Data

2010-23 Bas Steunebrink (UU)
The Logical Structure of Emotions

2010-24 Dmytro Tykhonov
Designing Generic and Efficient Negotiation Strategies

2010-25 Zulfiqar Ali Memon (VU)
Modelling Human-Awareness for Ambient Agents: A Human Mindreading Perspective

2010-26 Ying Zhang (CWI)
XRPC: Efficient Distributed Query Processing on Heterogeneous XQuery Engines

2010-27 Marten Voulon (UL)
Automatisch contracteren

2010-28 Arne Koopman (UU)
Characteristic Relational Patterns

2010-29 Stratos Idreos(CWI)
Database Cracking: Towards Auto-tuning Database Kernels

2010-30 Marieke van Erp (UvT)
Accessing Natural History - Discoveries in data cleaning, structuring, and retrieval

2010-31 Victor de Boer (UVA)
Ontology Enrichment from Heterogeneous Sources on the Web

2010-32 Marcel Hiel (UvT)
An Adaptive Service Oriented Architecture: Automatically solving Interoperability Problems

2010-33 Robin Aly (UT)
Modeling Representation Uncertainty in Concept-Based Multimedia Retrieval

2010-34 Teduh Dirgahayu (UT)
Interaction Design in Service Compositions

2010-35 Dolf Trieschnigg (UT)
Proof of Concept: Concept-based Biomedical Information Retrieval

2010-36 Jose Janssen (OU)
Paving the Way for Lifelong Learning; Facilitating competence development through a learning path specification

2010-37 Niels Lohmann (TUE)
Correctness of services and their composition

2010-38 Dirk Fahland (TUE)
From Scenarios to components

2010-39 Ghazanfar Farooq Siddiqui (VU)
Integrative modeling of emotions in virtual agents

2010-40 Mark van Assem (VU)
Converting and Integrating Vocabularies for the Semantic Web

2010-41 Guillaume Chaslot (UM)
Monte-Carlo Tree Search

2010-42 Sybren de Kinderen (VU)
Needs-driven service bundling in a multi-supplier setting - the computational e3-service approach

2010-43 Peter van Kranenburg (UU)
A Computational Approach to Content-Based Retrieval of Folk Song Melodies

2010-44 Pieter Bellekens (TUE)
An Approach towards Context-sensitive and User-adapted Access to Heterogeneous Data Sources, Illustrated in the Television Domain

2010-45 Vasilios Andrikopoulos (UvT)
A theory and model for the evolution of software services

2010-46 Vincent Pijpers (VU)
e3alignment: Exploring Inter-Organizational Business-ICT Alignment

2010-47 Chen Li (UT)
Mining Process Model Variants: Challenges, Techniques, Examples

2010-48 Milan Lovric (EUR)
Behavioral Finance and Agent-Based Artificial Markets

2010-49 Jahn-Takeshi Saito (UM)
Solving difficult game positions

2010-50 Bouke Huurnink (UVA)
Search in Audiovisual Broadcast Archives

2010-51 Alia Khairia Amin (CWI)
Understanding and supporting information seeking tasks in multiple sources

2010-52 Peter-Paul van Maanen (VU)
Adaptive Support for Human-Computer Teams:
Exploring the Use of Cognitive Models of Trust and Attention

2010-53 Edgar Meij (UVA)
Combining Concepts and Language Models for Information Access

====
2011
====

2011-01 Botond Cseke (RUN)
Variational Algorithms for Bayesian Inference in Latent Gaussian Models

2011-02 Nick Tinnemeier(UU)

Organizing Agent Organizations. Syntax and Operational Semantics of
an Organization-Oriented Programming Language

2011-03 Jan Martijn van der Werf (TUE)
Compositional Design and Verification of Component-Based Information Systems

2011-04 Hado van Hasselt (UU)
Insights in Reinforcement Learning; Formal analysis and empirical evaluation
of temporal-difference learning algorithms

2011-05 Base van der Raadt (VU)
Enterprise Architecture Coming of Age - Increasing the Performance of an Emerging Discipline.

2011-06 Yiwen Wang (TUE)
Semantically-Enhanced Recommendations in Cultural Heritage

2011-07 Yujia Cao (UT)
Multimodal Information Presentation for High Load Human Computer Interaction

2011-08 Nieske Vergunst (UU)
BDI-based Generation of Robust Task-Oriented Dialogues

2011-09 Tim de Jong (OU)
Contextualised Mobile Media for Learning

2011-10 Bart Bogaert (UvT)
Cloud Content Contention

2011-11 Dhaval Vyas (UT)
Designing for Awareness: An Experience-focused HCI Perspective

2011-12 Carmen Bratosin (TUE)
Grid Architecture for Distributed Process Mining

2011-13 Xiaoyu Mao (UvT)
Airport under Control. Multiagent Scheduling for Airport Ground Handling

2011-14 Milan Lovric (EUR)
Behavioral Finance and Agent-Based Artificial Markets

2011-15 Marijn Koolen (UvA)
The Meaning of Structure: the Value of Link Evidence for Information Retrieval

2011-16 Maarten Schadd (UM)
Selective Search in Games of Different Complexity

2011-17 Jiyin He (UVA)
Exploring Topic Structure: Coherence, Diversity and Relatedness

2011-18 Mark Ponsen (UM)
Strategic Decision-Making in complex games

2011-19 Ellen Rusman (OU)
The Mind ' s Eye on Personal Profiles

2011-20 Qing Gu (VU)
Guiding service-oriented software engineering - A view-based approach

2011-21 Linda Terlouw (TUD)
Modularization and Specification of Service-Oriented Systems

2011-22 Junte Zhang (UVA)
System Evaluation of Archival Description and Access

2011-23 Wouter Weerkamp (UVA)
Finding People and their Utterances in Social Media

2011-24 Herwin van Welbergen (UT)

Behavior Generation for Interpersonal Coordination with Virtual Humans
On Specifying, Scheduling and Realizing Multimodal Virtual Human Behavior

2011-25 Syed Waqar ul Qounain Jaffry (VU)
Analysis and Validation of Models for Trust Dynamics

2011-26 Matthijs Aart Pontier (VU)
Virtual Agents for Human Communication - Emotion Regulation and Involvement-Distance Trade-Offs in Embodied Conversational Agents and Robots

2011-27 Aniel Bhulai (VU)
Dynamic website optimization through autonomous management of design patterns

2011-28 Rianne Kaptein(UVA)
Effective Focused Retrieval by Exploiting Query Context and Document Structure

2011-29 Faisal Kamiran (TUE)
Discrimination-aware Classification

2011-30 Egon van den Broek (UT)
Affective Signal Processing (ASP): Unraveling the mystery of emotions

2011-31 Ludo Waltman (EUR)
Computational and Game-Theoretic Approaches for Modeling Bounded Rationality

2011-32 Nees-Jan van Eck (EUR)
Methodological Advances in Bibliometric Mapping of Science

2011-33 Tom van der Weide (UU)
Arguing to Motivate Decisions

2011-34 Paolo Turrini (UU)
Strategic Reasoning in Interdependence: Logical and Game-theoretical Investigations

2011-35 Maaike Harbers (UU)
Explaining Agent Behavior in Virtual Training

2011-36 Erik van der Spek (UU)
Experiments in serious game design: a cognitive approach

2011-37 Adriana Burlutiu (RUN)
Machine Learning for Pairwise Data, Applications for Preference Learning and Supervised Network Inference

2011-38 Nyree Lemmens (UM)
Bee-inspired Distributed Optimization

2011-39 Joost Westra (UU)
Organizing Adaptation using Agents in Serious Games

2011-40 Viktor Clerc (VU)
Architectural Knowledge Management in Global Software Development

2011-41 Luan Ibraimi (UT)
Cryptographically Enforced Distributed Data Access Control

2011-42 Michal Sindlar (UU)
Explaining Behavior through Mental State Attribution

2011-43 Henk van der Schuur (UU)
Process Improvement through Software Operation Knowledge

2011-44 Boris Reuderink (UT)
Robust Brain-Computer Interfaces

2011-45 Herman Stehouwer (UvT)
Statistical Language Models for Alternative Sequence Selection

2011-46 Beibei Hu (TUD)
Towards Contextualized Information Delivery: A Rule-based
Architecture for the Domain of Mobile Police Work

2011-47 Azizi Bin Ab Aziz(VU)
Exploring Computational Models for Intelligent Support of Persons with Depression

2011-48 Mark Ter Maat (UT)
Response Selection and Turn-taking for a Sensitive Artificial Listening Agent

2011-49 Andreea Niculescu (UT)
Conversational interfaces for task-oriented spoken dialogues:
design aspects influencing interaction quality

====
2012
====

2012-01 Terry Kakeeto (UvT)
Relationship Marketing for SMEs in Uganda

2012-02 Muhammad Umair(VU)
Adaptivity, emotion, and Rationality in Human and Ambient Agent Models

2012-03 Adam Vanya (VU)
Supporting Architecture Evolution by Mining Software Repositories

2012-04 Jurriaan Souer (UU)
Development of Content Management System-based Web Applications

2012-05 Marijn Plomp (UU)
Maturing Interorganisational Information Systems

2012-06 Wolfgang Reinhardt (OU)
Awareness Support for Knowledge Workers in Research Networks

2012-07 Rianne van Lambalgen (VU)
When the Going Gets Tough: Exploring Agent-based Models
of Human Performance under Demanding Conditions

2012-08 Gerben de Vries (UVA)
Kernel Methods for Vessel Trajectories

2012-09 Ricardo Neisse (UT)
Trust and Privacy Management Support for Context-Aware Service Platforms

2012-10 David Smits (TUE)
Towards a Generic Distributed Adaptive Hypermedia Environment

2012-11 J.C.B. Rantham Prabhakara (TUE)
Process Mining in the Large: Preprocessing, Discovery, and Diagnostics

2012-12 Kees van der Sluijs (TUE)
Model Driven Design and Data Integration in Semantic Web Information Systems

2012-13 Suleman Shahid (UvT)
Fun and Face: Exploring non-verbal expressions of emotion during playful interactions

2012-14 Evgeny Knutov(TUE)
Generic Adaptation Framework for Unifying Adaptive Web-based Systems

2012-15 Natalie van der Wal (VU)
Social Agents. Agent-Based Modelling of Integrated Internal and
Social Dynamics of Cognitive and Affective Processes

2012-16 Fiemke Both (VU)

Helping people by understanding them - Ambient Agents supporting
task execution and depression treatment

2012-17 Amal Elgammal (UvT)
Towards a Comprehensive Framework for Business Process Compliance

2012-18 Eltjo Poort (VU)
Improving Solution Architecting Practices

2012-19 Helen Schonenberg (TUE)
What's Next? Operational Support for Business Process Execution

2012-20 Ali Bahramisharif (RUN)
Covert Visual Spatial Attention, a Robust Paradigm for Brain-Computer Interfacing

2012-21 Roberto Cornacchia (TUD)
Querying Sparse Matrices for Information Retrieval

2012-22 Thijs Vis (UvT)
Intelligence, politie en veiligheidsdienst: verenigbare grootheden?

2012-23 Christian Muehl (UT)
Toward Affective Brain-Computer Interfaces: Exploring the
Neurophysiology of Affect during Human Media Interaction

2012-24 Laurens van der Werff (UT)
Evaluation of Noisy Transcripts for Spoken Document Retrieval

2012-25 Silja Eckartz (UT)
Managing the Business Case Development in Inter-Organizational
IT Projects: A Methodology and its Application

2012-26 Emile de Maat (UVA)
Making Sense of Legal Text

2012-27 Hayrettin Gurkok (UT)
Mind the Sheep! User Experience Evaluation & Brain-Computer Interface Games

2012-28 Nancy Pascall (UvT)
Engendering Technology Empowering Women

2012-29 Almer Tigelaar (UT)
Peer-to-Peer Information Retrieval

2012-30 Alina Pommeranz (TUD)
Designing Human-Centered Systems for Reflective Decision Making

2012-31 Emily Bagarukayo (RUN)
A Learning by Construction Approach for Higher Order Cognitive
Skills Improvement, Building Capacity and Infrastructure

2012-32 Wietske Visser (TUD)
Qualitative multi-criteria preference representation and reasoning

2012-33 Rory Sie (OUN)
Coalitions in Cooperation Networks (COCOON)

2012-34 Pavol Jancura (RUN)
Evolutionary analysis in PPI networks and applications

2012-35 Evert Haasdijk (VU)
Never Too Old To Learn – On-line Evolution of Controllers
in Swarm- and Modular Robotics

2012-36 Denis Ssebugwawo (RUN)
Analysis and Evaluation of Collaborative Modeling Processes

2012-37 Agnes Nakakawa (RUN)

A Collaboration Process for Enterprise Architecture Creation

2012-38 Selmar Smit (VU)
Parameter Tuning and Scientific Testing in Evolutionary Algorithms

2012-39 Hassan Fatemi (UT)
Risk-aware design of value and coordination networks

2012-40 Agus Gunawan (UvT)
Information Access for SMEs in Indonesia

2012-41 Sebastian Kelle (OU)
Game Design Patterns for Learning

2012-42 Dominique Verpoorten (OU)
Reflection Amplifiers in self-regulated Learning

2012-43 Withdrawn

2012-44 Anna Tordai (VU)
On Combining Alignment Techniques

2012-45 Benedikt Kratz (UvT)
A Model and Language for Business-aware Transactions

2012-46 Simon Carter (UVA)
Exploration and Exploitation of Multilingual Data for Statistical Machine Translation

2012-47 Manos Tsagkias (UVA)
Mining Social Media: Tracking Content and Predicting Behavior

2012-48 Jorn Bakker (TUE)
Handling Abrupt Changes in Evolving Time-series Data

2012-49 Michael Kaisers (UM)
Learning against Learning - Evolutionary dynamics of reinforcement learning algorithms in strategic interactions

2012-50 Steven van Kervel (TUD)
Ontologogy driven Enterprise Information Systems Engineering

2012-51 Jeroen de Jong (TUD)
Heuristics in Dynamic Sceduling; a practical framework with a case study in elevator dispatching

====
2013
====

2013-01 Viorel Milea (EUR)
News Analytics for Financial Decision Support

2013-02 Erietta Liarou (CWI)
MonetDB/DataCell: Leveraging the Column-store Database Technology for Efficient and Scalable Stream Processing

2013-03 Szymon Klarman (VU)
Reasoning with Contexts in Description Logics

2013-04 Chetan Yadati(TUD)
Coordinating autonomous planning and scheduling

2013-05 Dulce Pumareja (UT)
Groupware Requirements Evolutions Patterns

2013-06 Romulo Goncalves(CWI)

The Data Cyclotron: Juggling Data and Queries for a Data Warehouse Audience

2013-07 Giel van Lankveld (UvT)
Quantifying Individual Player Differences

2013-08 Robbert-Jan Merk(VU)
Making enemies: cognitive modeling for opponent agents in fighter pilot simulators

2013-09 Fabio Gori (RUN)
Metagenomic Data Analysis: Computational Methods and Applications

2013-10 Jeewanie Jayasinghe Arachchige(UvT)
A Unified Modeling Framework for Service Design.

2013-11 Evangelos Pournaras(TUD)
Multi-level Reconfigurable Self-organization in Overlay Services

2013-12 Marian Razavian(VU)
Knowledge-driven Migration to Services

2013-13 Mohammad Safiri(UT)
Service Tailoring: User-centric creation of integrated IT-based
homecare services to support independent living of elderly

2013-14 Jafar Tanha (UVA)
Ensemble Approaches to Semi-Supervised Learning Learning

2013-15 Daniel Hennes (UM)
Multiagent Learning - Dynamic Games and Applications

2013-16 Eric Kok (UU)
Exploring the practical benefits of argumentation in multi-agent deliberation

2013-17 Koen Kok (VU)
The PowerMatcher: Smart Coordination for the Smart Electricity Grid

2013-18 Jeroen Janssens (UvT)
Outlier Selection and One-Class Classification

2013-19 Renze Steenhuizen (TUD)
Coordinated Multi-Agent Planning and Scheduling

2013-20 Katja Hofmann (UvA)
Fast and Reliable Online Learning to Rank for Information Retrieval

2013-21 Sander Wubben (UvT)
Text-to-text generation by monolingual machine translation

2013-22 Tom Claassen (RUN)
Causal Discovery and Logic

2013-23 Patricio de Alencar Silva(UvT)
Value Activity Monitoring

2013-24 Haitham Bou Ammar (UM)
Automated Transfer in Reinforcement Learning

2013-25 Agnieszka Anna Latoszek-Berendsen (UM)
Intention-based Decision Support. A new way of representing and
implementing clinical guidelines in a Decision Support System

2013-26 Alireza Zarghami (UT)
Architectural Support for Dynamic Homecare Service Provisioning

2013-27 Mohammad Huq (UT)
Inference-based Framework Managing Data Provenance

2013-28 Frans van der Sluis (UT)

When Complexity becomes Interesting: An Inquiry into the Information eXperience

2013-29 Iwan de Kok (UT)
Listening Heads

2013-30 Joyce Nakatumba (TUE)
Resource-Aware Business Process Management: Analysis and Support

2013-31 Dinh Khoa Nguyen (UvT)
Blueprint Model and Language for Engineering Cloud Applications

2013-32 Kamakshi Rajagopal (OUN)
Networking For Learning; The role of Networking in a Lifelong
Learner's Professional Development

2013-33 Qi Gao (TUD)
User Modeling and Personalization in the Microblogging Sphere

2013-34 Kien Tjin-Kam-Jet (UT)
Distributed Deep Web Search

2013-35 Abdallah El Ali (UvA)
Minimal Mobile Human Computer Interaction

2013-36 Than Lam Hoang (TUe)
Pattern Mining in Data Streams

2013-37 Dirk Borner (OUN)
Ambient Learning Displays

2013-38 Eelco den Heijer (VU)
Autonomous Evolutionary Art

2013-39 Joop de Jong (TUD)
A Method for Enterprise Ontology based Design of Enterprise Information Systems

2013-40 Pim Nijssen (UM)
Monte-Carlo Tree Search for Multi-Player Games

2013-41 Jochem Liem (UVA)
Supporting the Conceptual Modelling of Dynamic Systems: A Knowledge
Engineering Perspective on Qualitative Reasoning

2013-42 Leon Planken (TUD)
Algorithms for Simple Temporal Reasoning

2013-43 Marc Bron (UVA)
Exploration and Contextualization through Interaction and Concepts

====
2014
====

2014-01 Nicola Barile (UU)
Studies in Learning Monotone Models from Data

2014-02 Fiona Tuliyano (RUN)
Combining System Dynamics with a Domain Modeling Method

2014-03 Sergio Raul Duarte Torres (UT)
Information Retrieval for Children: Search Behavior and Solutions

2014-04 Hanna Jochmann-Mannak (UT)
Websites for children: search strategies and interface design -
Three studies on children's search performance and evaluation

2014-05 Jurriaan van Reijsen (UU)
Knowledge Perspectives on Advancing Dynamic Capability

2014-06 Damian Tamburri (VU)
Supporting Networked Software Development

2014-07 Arya Adriansyah (TUE)
Aligning Observed and Modeled Behavior

2014-08 Samur Araujo (TUD)
Data Integration over Distributed and Heterogeneous Data Endpoints

2014-09 Philip Jackson (UvT)
Toward Human-Level Artificial Intelligence: Representation
and Computation of Meaning in Natural Language

2014-10 Ivan Salvador Razo Zapata (VU)
Service Value Networks

2014-11 Janneke van der Zwaan (TUD)
An Empathic Virtual Buddy for Social Support

2014-12 Willem van Willigen (VU)
Look Ma, No Hands: Aspects of Autonomous Vehicle Control

2014-13 Arlette van Wissen (VU)
Agent-Based Support for Behavior Change: Models and
Applications in Health and Safety Domains

2014-14 Yangyang Shi (TUD)
Language Models With Meta-information

2014-15 Natalya Mogles (VU)
Agent-Based Analysis and Support of Human Functioning in Complex
Socio-Technical Systems: Applications in Safety and Healthcare

2014-16 Krystyna Milian (VU)
Supporting trial recruitment and design by automatically interpreting eligibility criteria

2014-17 Kathrin Dentler (VU)
Computing healthcare quality indicators automatically:
Secondary Use of Patient Data and Semantic Interoperability

2014-18 Mattijs Ghijsen (VU)
Methods and Models for the Design and Study of Dynamic Agent Organizations

2014-19 Vinicius Ramos (TUE)
Adaptive Hypermedia Courses: Qualitative and Quantitative Evaluation and Tool Support

2014-20 Mena Habib (UT)
Named Entity Extraction and Disambiguation for Informal Text: The Missing Link

2014-21 Kassidy Clark (TUD)
Negotiation and Monitoring in Open Environments

2014-22 Marieke Peeters (UU)
Personalized Educational Games - Developing agent-supported scenario-based training

2014-23 Eleftherios Sidirourgos (UvA/CWI)
Space Efficient Indexes for the Big Data Era

2014-24 Davide Ceolin (VU)
Trusting Semi-structured Web Data

2014-25 Martijn Lappenschaar (RUN)
New network models for the analysis of disease interaction

2014-26 Tim Baarslag (TUD)

What to Bid and When to Stop

2014-27 Rui Jorge Almeida (EUR)
Conditional Density Models Integrating Fuzzy and Probabilistic Representations of Uncertainty

2014-28 Anna Chmielowiec (VU)
Decentralized k-Clique Matching

2014-29 Jaap Kabbedijk (UU)
Variability in Multi-Tenant Enterprise Software

2014-30 Peter de Cock (UvT)
Anticipating Criminal Behaviour

2014-31 Leo van Moergestel (UU)
Agent Technology in Agile Multiparallel Manufacturing and Product Support

2014-32 Naser Ayat (UvA)
On Entity Resolution in Probabilistic Data

2014-33 Tesfa Tegegne (RUN)
Service Discovery in eHealth

2014-34 Christina Manteli(VU)
The Effect of Governance in Global Software Development:
Analyzing Transactive Memory Systems.

2014-35 Joost van Ooijen (UU)
Cognitive Agents in Virtual Worlds: A Middleware Design Approach

2014-36 Joos Buijs (TUE)
Flexible Evolutionary Algorithms for Mining Structured Process Models

2014-37 Maral Dadvar (UT)
Experts and Machines United Against Cyberbullying

2014-38 Danny Plass-Oude Bos (UT)
Making brain-computer interfaces better: improving usability through post-processing.

2014-39 Jasmina Maric (UvT)
Web Communities, Immigration, and Social Capital

2014-40 Walter Omona (RUN)
A Framework for Knowledge Management Using ICT in Higher Education

2014-41 Frederic Hogenboom (EUR)
Automated Detection of Financial Events in News Text

2014-42 Carsten Eijckhof (CWI/TUD)
Contextual Multidimensional Relevance Models

2014-43 Kevin Vlaanderen (UU)
Supporting Process Improvement using Method Increments

2014-44 Paulien Meesters (UvT)
Intelligent Blauw. Met als ondertitel: Intelligence-gestuurde
politiezorg in gebiedsgebonden eenheden.

2014-45 Birgit Schmitz (OUN)
Mobile Games for Learning: A Pattern-Based Approach

2014-46 Ke Tao (TUD)
Social Web Data Analytics: Relevance, Redundancy, Diversity

2014-47 Shangsong Liang (UVA)
Fusion and Diversification in Information Retrieval

====
2015
====

2015-01 Niels Netten (UvA)
Machine Learning for Relevance of Information in Crisis Response

2015-02 Faiza Bukhsh (UvT)
Smart auditing: Innovative Compliance Checking in Customs Controls

2015-03 Twan van Laarhoven (RUN)
Machine learning for network data

2015-04 Howard Spoelstra (OUN)
Collaborations in Open Learning Environments

2015-05 Christoph Bosch(UT)
Cryptographically Enforced Search Pattern Hiding

2015-06 Farideh Heidari (TUD)
Business Process Quality Computation - Computing Non-Functional Requirements to Improve Business Processes

2015-07 Maria-Hendrike Peetz(UvA)
Time-Aware Online Reputation Analysis

2015-08 Jie Jiang (TUD)
Organizational Compliance: An agent-based model for designing and evaluating organizational interactions

2015-09 Randy Klaassen(UT)
HCI Perspectives on Behavior Change Support Systems

2015-10 Henry Hermans (OUN)
OpenU: design of an integrated system to support lifelong learning

2015-11 Yongming Luo(TUE)
Designing algorithms for big graph datasets: A study of computing bisimulation and joins

2015-12 Julie M. Birkholz (VU)
Modi Operandi of Social Network Dynamics: The Effect of Context on Scientific Collaboration Networks

2015-13 Giuseppe Procaccianti(VU)
Energy-Efficient Software

2015-14 Bart van Straalen (UT)
A cognitive approach to modeling bad news conversations

2015-15 Klaas Andries de Graaf (VU)
Ontology-based Software Architecture Documentation

2015-16 Changyun Wei (TUD)
Cognitive Coordination for Cooperative Multi-Robot Teamwork

2015-17 Andre van Cleeff (UT)
Physical and Digital Security Mechanisms: Properties, Combinations and Trade-offs

2015-18 Holger Pirk (CWI)
Waste Not, Want Not! - Managing Relational Data in Asymmetric Memories

2015-19 Bernardo Tabuenca (OUN)
Ubiquitous Technology for Lifelong Learners

2015-20 Lois Vanhee(UU)
Using Culture and Values to Support Flexible Coordination

2015-21 Sibren Fetter (OUN)
Using Peer-Support to Expand and Stabilize Online Learning

2015-22 Zhemin Zhu(UT)
Co-occurrence Rate Networks

2015-23 Luit Gazendam (VU)
Cataloguer Support in Cultural Heritage

2015-24 Richard Berendsen (UVA)
Finding People, Papers, and Posts: Vertical Search Algorithms and Evaluation

2015-25 Steven Woudenberg (UU)
Bayesian Tools for Early Disease Detection

2015-26 Alexander Hogenboom (EUR)
Sentiment Analysis of Text Guided by Semantics and Structure

2015-27 Sandor Heman (CWI)
Updating compressed column-stores

2015-28 Janet Bagorogoza (TiU)
Knowledge Management and High Performance; The Uganda Financial Institutions Model for HPO

2015-29 Hendrik Baier (UM)
Monte-Carlo Tree Search Enhancements for One-Player and Two-Player Domains

2015-30 Kiavash Bahreini (OUN)
Real-time Multimodal Emotion Recognition in E-Learning

2015-31 Yakup Koc (TUD)
On Robustness of Power Grids

2015-32 Jerome Gard (UL)
Corporate Venture Management in SMEs

2015-33 Frederik Schadd (UM)
Ontology Mapping with Auxiliary Resources

2015-34 Victor de Graaff (UT)
Geosocial Recommender Systems

2015-35 Junchao Xu (TUD)
Affective Body Language of Humanoid Robots: Perception and Effects in Human Robot Interaction