Cyber-physical solution for an engagement enhancing rehabilitation system

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Cyber-physical solution for an engagement enhancing rehabilitation system

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CHAPTER ONE

INTRODUCTION

1.1. Background of research

1.1.1 Stroke rehabilitation and brain plasticity

According to World Health Organization, stroke is the clinical syndrome of rapid onset of focal (or global, as in subarachnoid haemorrhage) cerebral deficit, lasting more than 24 hours (unless interrupted by surgery or death), with no apparent cause other than a vascular one. There are two main types of stroke: ischemic, which is due to lack of blood flow, and hemorrhagic, which is due to bleeding. According to the estimations, some 16 million people per year experience stroke, from which about two-thirds survive worldwide (Strong et al., 2007). Stroke remains the most common cause of disability for adults. Stroke survivors suffer various deficits that generate disability in motor, perceptual, and cognitive functioning (Carr & Shepherd, 1996). Among these disabilities, motor deficits have a large impact on managing everyday activities (Feys et al., 1998). Hemiplegia caused by stroke brings terrible burden on patients and their families, especially with the impaired upper extremity, because lack of arm-movement control affects independent daily living.

This thesis studies the field of stroke rehabilitation mainly regarding upper limb. It has been proved that activity-based rehabilitation can improve the regaining of upper-limb motor functions (Richards et al., 2008), which enable patients to perform daily living activities and maintain independence (Whitall et al., 2000). Activity-based rehabilitation utilizes the phenomenon of brain plasticity (Hallett, 2001), which means that human brain is able to reorganize neural pathways by motor relearning. The changes caused by plasticity in the lesioned hemisphere coincide with motor function improvement after activity-based rehabilitation (Richards et al., 2008). In addition to neural plasticity changes in the lesioned side, motor recovery may occur because of a shift of balance in the motor cortical recruitment toward the undamaged hemisphere via the neural pathways in the same side of the brain (Jang, 2009) (Timmermans et al., 2009).

1.1.2 Post-stroke pathophysiological status of patients

During rehabilitation, (i) acute, (ii) sub-acute, and (iii) chronic phases are distinguished in the literature as after-event pathophysiological states of stroke survivors. Stroke survivors should receive different therapies and treatments in each phase according to their pathophysiological states. The acute phase starts right after the occurrence of the stroke and typically last not more than a week. The sub-acute phase is the beginning of healing. It normally begins in the second week after the event and lasts until the 12th week (Zhu, 2001). It is followed by the chronic phase in which intense therapy is applied. The duration of this phase is vague. It depends on many factors such as heaviness of the stroke, the physical condition of the patient, and the applied rehabilitation therapy.

Based on observing a large amount of hemiplegic patients, Brunnström (1970) proposed to consider six stages of sequential motor recovery after a stroke, which is mainly used in current clinical rehabilitation practice. The principles implied by this model are to adapt the therapy to the pathophysiological states, to avoid abnormal movements of the patients, and to encourage the correct mode of movement training according to the successive stages. An overview of the stages and the description of the related therapies are shown in Table 1.1.

Rehabilitation training can start from sub-acute phase, and brain plasticity mainly happens in the first three months post-stroke (Zhu, 2001). However, research has shown that even in rehabilitation of patients with chronic stroke, the motor function of the upper-limb can also be improved (Van der Lee et al., 1999), (Page et al., 2004). However, due to the limited resources in the hospital, such as access to physical therapy, availability of the hospital beds and rehabilitation equipment, most stroke patients are discharged from the hospital six month after stroke when motor recovery can be still enhanced.

Table 1.1 Description of the stages of recovery identified by Brunnstrom

Phase	Stages of recovery	Duration	Goal of treatment	Therapy
acute		post-stroke first week	pain reduction and stabilization of the injured tissue	ensure proper position in bed, turn over every second hour to pat back
sub-acute	stage I: flaccid	post-stroke second week	prevent spasticity	maintain proper position and training in bed
	stages II - IV	post-stroke third week to third month	prevent spasticity and induce correct modes of movement	passive movement, body weight training, trunk control training, and correct abnormal movement
chronic	stages V or higher	post-stroke fourth month -	improve ADL, functional ability, and movement coordination	active movement, coordination training, and fine movement training

1.1.3 Specific rehabilitation treatments

In upper limb stroke rehabilitation, besides traditional treatment delivered by physical therapists, other treatments that are mainly used in clinical rehabilitation include (i) bilateral arm training, robotic therapy, (ii) constraint-induced movement therapy (CIMT), (iii) electromyographic feedback, (iv) electrostimulation, (v) high-intensity therapy, (vi) mental practice with motor imagery, (vii) repetitive task training, (viii) robotics, and (ix) strength training. Explanations of these treatments are listed in Table 1.2.

Langhorne et al. summarized that among these treatments only CIMT or modified CIMT and robot-assisted training are beneficial or likely to be beneficial for the patients; while only uncertain benefit or unknown effect can be identified in other treatments (Langhorne et al., 2011). Since CIMT restrains the less-affected arm, it is only applicable to patients with relatively mild impairment (Green et al., 2011), whereas robot-assisted training is able to cover the range from assistive training to resistive training, so it is applicable to patients in all stages.

Robot assisted rehabilitation systems were introduced some 30 years ago with the goal to assist physical therapists in providing consistent, repeatable training to stroke patients. Robot

Table 1.2 Description of specific rehabilitation treatments for upper limb (Langhorne et al., 2011)

Bilateral arm training	Training involving use of both arms for identical activities in a simultaneous but independent manner
CIMT	Involves many repetitions of task-specific training of the affected limb with restraint of the unaffected limb
Electromyographic feedback	The use of external electrodes that are applied to muscles to capture electrical potentials of motor units. Instrumentation converts the recorded potentials into visual or auditory information.
Electrostimulation	Electrostimulation is delivered to the peripheral neuromuscular system by internal or external electrodes
High-intensity therapy	An increased amount of focused therapy compared to another reference group
Mental practice with motor imagery	Mental practice of a physical action that aims at improving movement
Repetitive task training	Repeated practice within a single training session of an active motor sequence that is aimed at a clear functional objective
Robotics	Robotic devices can allow repetitive, interactive, high-intensity, task-specific treatment of a limb.
Strength training	Progressive resistance exercises aiming at improving muscle strength

assisted rehabilitation enables patients to train independently of a therapist and to improve upon their own functional level. The use of robotic devices in rehabilitation can provide high-intensity, repetitive, and interactive treatment of the impaired upper limb. With robotic devices, patients can achieve increased gains from rehabilitation treatment (Prange et al., 2006). In the next section, we will review the current trends in robot-assisted stroke rehabilitation with the aim of casting light on the attainments and some limitations.

1.2. Current state and limitations of robotic assisted rehabilitation

1.2.1 Review of the instruments

There are two major branches of assistive robotics, namely socially assistive robotics and therapy assistive robotics. Many therapy assistive robotic devices have been developed in the last decade, for example, Amadeo Robot (Sale et al., 2012), Assisted Rehabilitation and Measurement (ARM) Guide (Reinkensmeyer et al., 2000), ARMin (Nef & Riener, 2005), Bi-Manu-Track (Hesse et al., 2003), Mirror Image Motion Enabler (MIME) (Burgar et al., 2000), Massachusetts Institute of Technology (MIT)-Manus (Krebs et al., 1999), Neurorehabilitation Robot (NeReBot) (Rosati et al., 2007), and Wrist Gimbal (Martinez et al., 2013). These robotic instruments have been used in clinical rehabilitation. The results of the first large randomized study, in which training with MIT-Manus have been compared with intensive therapist-provided therapy and usual care, have revealed that there is no significant difference in the outcomes of the two intensive forms of the therapy (Lo et al., 2010). Recently, the issues of user-robot personality matching and assistive robot behavior adaptation have come to the limelight (Tăpus et al., 2008). While the first generation therapy assistive instruments were typically controlled by therapist, the second generation instruments support patient-controlled therapeutic exercises (Burgar et al, 2000).

An overview of some typical instruments developed in the last 20 years is presented in Table 1.3. They are compared from some important aspects, such as (i) target, (ii) type of assistance, (iii) feedback, (iv) degree of freedom, (v) type of exercises, and (vi) type of robot.

The overview presented in Table 1.3 is compiled based on the information available at the website: http://www.strokengine.ca/intervention/robotics-introduction/ (accessed on 17/06/2016). For further information, the links given in Table 1.4 can be used. The explanations on the various aspects are as follows.

1) Target

Robotic devices may focus on the whole of the upper limbs on specific part of it, as target. In the literature, devices focusing on the recovery of shoulder and elbow are referred as “proximal”, while “distal” refers wrist, hand, and fingers.

2) Type of assistance

Various types of assistance are identified in the literature, such as active, assisted, active assisted, and passive. 'Active' means that the patients have to move by themselves 'assisted',

Table 1.3 Versatility of the robotic rehabilitation instruments (part one)

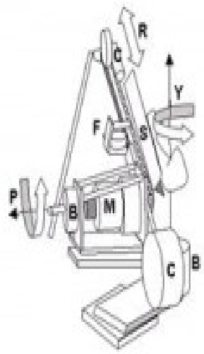
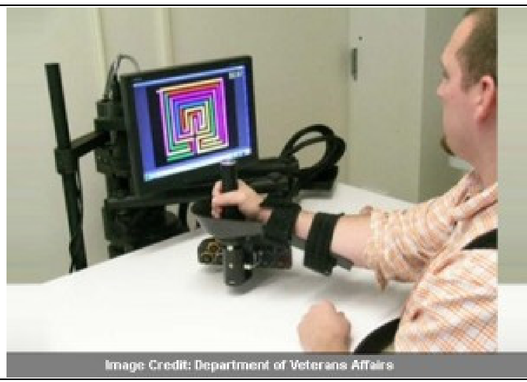
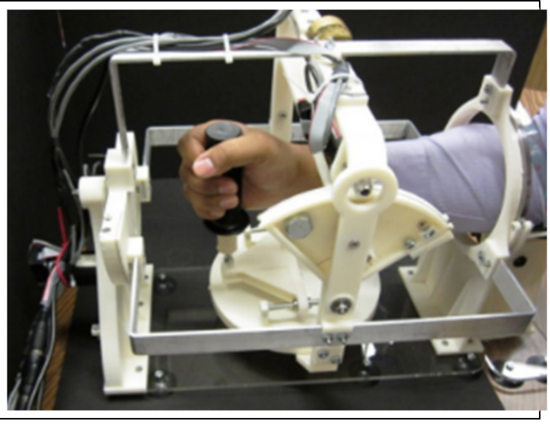
Robot characteristics	Image
Device: Amadeo Robot[1] *Target*: Distal *Type of assistance*: Assisted and active *Feedback*: Visual and auditory *Degree of freedom*: 5 *Type of exercise*: Fingers' movement *Type of robot*: End effector	
Device: ARMGuide[2] *Target*: Proximal *Type of assistance*: Active-assisted *Feedback*: Graphical feedback of the hand position and feedback on the amount of motor assistance *Degree of freedom*: 3 *Type of exercise*: Reaching movements in different directions *Type of robot*: singly-actuated	 
Device: ARMin I and ARMin II[3] *Target*: Proximal and distal *Type of assistance*: Passive and active *Feedback*: Visual and auditory *Degree of freedom*: 6 independently actuated DOF and 1 coupled DOF *Type of exercise*: Functional 3D workspace repetitive exercises *Type of robot*: Exoskeleton	
Device: Bi-Manu-Track[4] *Target*: Distal *Type of assistance*: Passive-passive, passive-active, active-active *Feedback*: Visual *Degree of freedom*: 1 *Type of exercise*: Bilateral elbow pronation and supination, wrist flexion and extension in a mirror or parallel fashion. *Type of robot*: End-effector	

Table 1.3 Versatility of the robotic rehabilitation instruments (part two)

Robot characteristics	Image
Device: MIME[5] *Target*: Proximal *Type of assistance*: Passive, active –assisted, active-constrained, bilateral modes *Feedback*: Feedback of the fraction of the movement completed or the time to complete was used to track and motivate performance *Degree of freedom*: 6 *Type of exercise*: Unilateral or bilateral shoulder and elbow movement in target reaching activities *Type of robot*: End effector	
Device: MIT-Manus[6] *Target*: Proximal *Type of assistance*: Assisted *Feedback*: Visual, auditory, and tactile *Degree of freedom*: 2 *Type of exercise*: Shoulder and elbow movement in horizontal plane, repetitive reaching exercises *Type of robot*: End effector	
Device: NeReBot[7] *Target*: Proximal *Type of assistance*: Assisted *Feedback*: Visual and auditory *Degree of freedom*: 3 *Type of exercise*: Flexion and extension, pronation and supination, adduction and abduction, circular movements of shoulder and elbow *Type of robot*: Direct drive wire actuation	
Device: Wrist Gimbal[8] *Target*: Distal *Type of assistance*: passive, assistive, and resistive *Feedback*: Visual and auditory *Degree of freedom*: 3 *Type of exercise*: Forearm Pronation and supination, wrist flexion and extension, and wrist adduction and abduction *Type of robot*: Exoskeleton	

and ‘active-assisted’ means the robot will assist the patients when they cannot complete the task. ‘active-constrained’ means the robot can exert resistance for the advance patients. ‘Passive’ means the patients are unable to move voluntarily, but the robot drives the patients’ arm to move. These modes enable different difficulty levels of motor task training during rehabilitation. Different modes can be tailored to the patients according to their motor capability. ‘Active’ and ‘active-assisted’ modes can help the patients who are unable to complete the task to move along the trajectory toward the goal.

3) Feedback

Current robotic systems are able to provide visual, tactile, and auditory feedback to the patients. Sensory modalities, such as visual, tactile, olfactory and auditory, play an important role in functional recovery of stroke patients, as they can significantly increase the sense of presence during training (Dinh et al., 1999). Conscious, active involvement during rehabilitation shortens the recovery time, and contributes to mental well-being of patients. Therefore, integration of multi-sensory feedback mechanisms into robot assisted training is of importance for robot assisted rehabilitation systems.

4) Degree of freedom

Robot assisted rehabilitation devices are capable to fully support all 7 degrees of freedom of movement of the shoulder, elbow and wrist. However, an increase in degree of freedom also increases the complexity of the development of the instrument.

5) Type of exercises

The type of exercises supported by current robotic devices are focused on delivering therapy for a single joint movement type of movement, but complex motion or direct support of daily activities is still a challenge. Nevertheless, some recent findings of research in rehabilitation

Table 1.4 Links to websites

	Links
1	http://tyromotion.com/en/products/amadeo
2	http://www.rehab.research.va.gov/jour/00/37/6/reink376.htm
3	http://cabrr.cua.edu/devicegallery.cfm
4	http://www.reha-stim.de/cms/index.php?id=60
5	http://www.strokengine.ca/intervention/robotics-introduction/
6	http://www.rehab.research.va.gov/jour/06/43/5/lum.html
7	http://www.techshout.com/science/2010/17/mit-manus-robot-assisted-therapy-may-help-stroke-patients-regain-function
8	http://www.mechatronics.it/index.php?lingua=ENG&pag=res&sub=att&id=16 http://inside.mines.edu/~ocelik/research.html

therapy showed that ADL focused exercises not only increases patient motivation but also yields an improved therapeutic outcome compared to single joint movements (Langhammer & Stanghelle, 2000). So it is a limitation for the current robotic devices that they cannot enable natural movements of the patients.

6) Type of robot

The term 'end effector robot' refers to robots interacting with the patient using a single distal attachment point on the forearm by means of orthosis. It simplifies the structure of the device. However, it may complicate the control of the limb position in the case of multiple possible degrees of freedom. The term 'exoskeleton robot' refers to robots having a mechanical structure, which mirrors the skeletal structure of the limb. This design allows independent control of movements in a few limb joints. Maciejasz et al., (2014) found that the mechanical and control algorithm complexity of these devices are significantly higher than of the end-effector devices, and the complexity escalates as the number of DOF increases. Major limitation of the current robotic devices from the instrument point of view is the high cost of the system; therefore, there is still a significant need to reduce cost of home-based devices for therapy and ADL assistance (Maciejasz et al., 2014).

1.2.2 Review of clinical experiments

A review of clinical experiments conducted with robotic assisted rehabilitation devices suggested that physical rehabilitation performed with robotic devices can enhance arm-movement recovery following stroke. However, there are still some questions to be further studied. Prange et al. (2006) found that robot-aided therapy of the proximal upper limb improves short- and long-term motor control of the paretic shoulder and elbow in sub-acute and chronic patients; however, they did not find any significant improvement on functional abilities after robot-assisted motor trainings. This entails that only limited improvement was achieved in the ADL of patients.

For example, the results obtained by applying the Fugl-Meyer Assessment method, which mainly measures motor ability of a single joint, show that robot assisted therapy is more effective in recovering motor control abilities, such as motor power, than conventional therapy. On the other hand, studies that used Function Independence Measurement method and the Wolf functional ability test, which measures functional independence, such as coordination of joints, communication, and social cognition, found no significant improvement on motor function abilities of patients (Finley et al., 2005), (MacClellan et al., 2005). In some cases, conventional therapy had achieved even greater gains in reclaiming motor function abilities than robot assisted therapy (Masiero et al., 2011). So, from the clinical efficiency point of view, the major limitation of the current robot-assisted rehabilitation is to transfer the gains of motor control abilities to functional independence of

Table 1.5 Assessment means for evaluating patient's capability

Mean	Measurement	Purpose	Outcome after robot-assisted training
Fugl-Meyer Assessment (Fugl-Meyer et al., 1974)	Motor functioning, balance, sensation, and joint functioning	To measure motor control ability	Significant improvement
Function Independence Measurement (McDowell & Newell, 1996)	Motor and cognitive: self-care, sphincter control, mobility, locomotion, communication, and social cognition	To measure functional independence	No significant improvement
Wolf functional ability test (Wolf et al., 2001)	Upper extremity motor ability through timed and functional tasks	To measure motor function ability	No significant improvement

the patients (Loureiro et al., 2011). Table 1.5 introduces the assessment means for evaluating patient's capability and concludes the outcome using each mean after robot-assisted training.

1.2.3 Limitations in robot-assisted rehabilitation

Evidence suggests that (i) repetitive training (Kwakkel et al., 2008), (Krouchev and Kalaska, 2008), (ii) intensive use of the impaired limb (Wu et al., 1998), (Fisher & Sullivan, 2001), (Bach-y-Rita, 2003), (iii) task-specific motion practice (Bayona et al., 2005), and (iv) high patient motivation and engagement (Bach-y-Rita et al., 2002), (Wood et al., 2003), (Johnson et al., 2005), and (Langhorne et al., 2011), are the factors influencing and the major opportunities for a brain plasticity-based motor recovery. As we discussed above, robotic devices can allow repetitive, interactive, high-intensity, task-specific treatment of a limb. However, robot-assisted training cannot guarantee high patient motivation and engagement during the training.

Maintaining and enhancing patient's engagement in stroke rehabilitation exercises are in the focus of current research. In general, engagement, as the act of engaging, is defined as the motivation of beginning and carrying on an activity with a sense of emotional involvement or commitment and deliberate application of effort (Lequerica and Kortte, 2010). They found engagement in rehabilitation appears to be much more than just a patient attending a therapy; although stroke patients are supposed to proactively and intensively participate in the rehabilitation program and therapy exercises, it does not mean that they are actually always engaged. It has been shown that there are many inhibitors of building up engagement, therefore, the most up-to-date conceptualization of the engagement challenge extends the construct of participation well beyond therapy attendance and motivation. It needs to be noted here that stimulation is seen as extrinsic motivation, which can lead to intrinsic motivation, and directly addresses the role and quality of engagement of the patients in short and long term rehabilitation processes (Kortte et al., 2007). Kortte et al., proposed that rehabilitation engagement is “a construct that captures multiple elements, including the patient’s attitude toward the therapy, level of understanding or acknowledgement of a need for treatment, need for verbal or physical prompts to participate, level of active participation in the therapy activities, and level of attendance across the rehabilitation program” (Kortte et al., 2007). In 2010, Lequerica and Kortte defined engagement as a construct that is driven by motivation and executed through active and effortful participation in the context of rehabilitation exercises (Lequerica and Kortte, 2010). The difference between participation and engagement in this context is that engagement involves high levels of invested interest (Lequerica and Kortte, 2010).

Motivation is often conceptualized as a prerequisite to engagement in rehabilitation. Recent research regards motivation as a complex construct with both internal (e.g., effects of injury, psychological adjustment reactions related to injury, and personality traits) and external (e.g., rehabilitation environment, social support system, and cultural variables valued in society) determinants (Huyser et al., 1997). Although motivation influences the promotion of engagement, engagement and motivation should be considered as two distinct constructs (Lequerica and Kortte, 2010). Motivation is conceptualized as energy directed in a particular way, while engagement is that energy put into action (Frydenberg et al., 2005). Motivation to engage in an activity is influenced by one’s attitudes about the behavior and its consequences, one’s perceived ability to perform the task in question, and the desire to comply with perceived behavioral norms (Azjen, 1991). “External determinants”, or external stimulation, could facilitate internal motivation, thereby providing the “energy” needed to engage the participants.

Research has shown that passive movement, which refers to the movement driven by the robot while the patients do not have the attempts to move, is insufficient to achieve motor recovery (Lynch et al., 2005), and that active engagement and movement attempts, which means the patients want to move, even though they may not have the ability to complete the movement by themselves, are essential to acquire the beneficial effects of robotic rehabilitation (Hogan et al., 2006), (Krebs et al., 2009) and (Cauraugh et al., 2010). Maintaining attention and engagement during the learning of new motor skills or the re-learning of forgotten skills are important for inducing brain plasticity after neurological impairments (Fiedler et al., 2000), (Bach-y-Rita, 2001), (Fisher & Sullivan, 2001), and (Lynskey et al., 2008). Moreover, active engagement can remarkably improve the functional outcome of technology-assisted stroke rehabilitation (e.g., Prange et al., 2006), (Henderson et al., 2007) and (Kwakkel et al., 2007). Therefore, increasing engagement has been considered to be crucial in terms of the outcomes of rehabilitation (Langhorne et al., 2011).

The conclusion is that the factor for recovery that the robot-assisted training cannot sufficiently address is the possible highest level of patient motivation and engagement. Current robot-assisted training cannot provide highly motivating and engaging training. This may in turn lead to a low efficiency in regaining motor function ability of the patients in the clinical experiments conducted with robotic devices. Recent research has focused on increasing patients' engagement during robot-assisted rehabilitation exercises; patient-specific training protocols, depending on each patient's type of injury, level of impairment, and phase of recovery, should be designed for enhancing engagement during rehabilitation training. (Blank et al., 2014).

Even if, some robots can be adaptive in the difficulty level of the motor tasks for the patient, the current robotic devices have not been designed to provide personalized training for each patient in a comprehensive point of view, which also considers patient's interest, perceptive, and cognitive functioning of the patients. This means there is no reliable solution to avoid mundane exercising that is prone to become a routine or even boring for the patients in current robotic rehabilitation. Current robot-assisted rehabilitation devices cannot provide neither automated personalized training, nor adapt to the patients' state in run time according to individual's needs and motivate the patients' initiative, respectively. In other words, their potentials to recover can be developed to their fullest. Therefore, the motivation of this thesis is to develop a system that is capable to maintain the engagement of patients during robot assisted rehabilitation training of stroke patients.

1.3. Opportunities for cyber-physical system-based rehabilitation

The current trend of developing complex networked and smart systems has created novel opportunities for assistive rehabilitation development. Having their roots in many various kinds of engineered technical system manifestations and enabled by cyber-physical computing, the concept of cyber-physical systems (CPSs) have penetrated into our daily reality just a bit more than a decade ago (Rajkumar et al., 2010), (Horváth and Gerritsen 2012). The current standard definition of CPSs combines three different views. First, they are results of the exploitation of the fourth wave of digital computing (following centralized mainframe, networked personal and ubiquitous/pervasive computing). Second, they represent a new paradigm of system realization, which concentrates on providing novel services, rather than only on production and marketing artifacts. Third, they are enablers of satisfying human and social needs in various contexts and adjusted to different conditions. This comprehensive definition is a historical development, and was not in the mind of the experts who stimulated the formation of the discipline of CPSs, based on the knowledge and objects of disciplines such as advanced mechatronics, embedded systems, real-time systems, networked computing systems, distributed agent systems. In the recent period of the formation of the paradigm of CPSs, they have been seen and studied as complex technical systems (Horváth 2015).

Cyber-physical computing (CPC) creates a high level interaction and synergy among all physical (hardware and software) and cyber (algorithms and knowledge) constituents of a CPS (Poovendran 2010). Computing becomes deeply embedded in these systems, but it will be just a part of them, without its own teleology. Being equipped with computing potentials, systems are becoming parts of the fabric of the natural, social, technical and/or cognitive world (Shi et al., 2011). From a technical perspective, CPSs achieve a higher level of integration and synergy of hardware, software and cyberware functionalities, technologies and components than any other comparable type of engineered systems (Conti et al., 2012). Many CPSs are distributed and tightly interacting with the natural and engineered environments, but also penetrating into the cognitive domains of humans, and strongly influencing the social life. All these changes transform the originally technical and technology-driven systems into socially deeply embedded, cognitively interacting, environment-aware, and partially autonomous smart systems. This orientation of the development of cyber-physical systems makes it possible to consider them in various medical and care taking applications. Current research is engaged with working out the principles that can facilitate their proper intellectualization, design, implementation and application, for instance, in the field of medical rehabilitation.

Adaptability of CPSs and self-adaptability of smart CPSs are the capabilities to rapidly adjust behavior according to changes of the operational objectives and conditions, and to the dynamics of the environment based on control or reasoning, respectively (Horváth and Gerritsen 2013). Two major forms of adaptation of systems are stakeholder-made adaptation and self-adaptation. Self-adaptation is the strategy to change a system without human interaction, which may be necessary for several reasons, such as change in the objectives, dynamics of the operating environment, distributed and decentralized system architecture, large number of operational parameters and interdependencies, and the availability of intelligent behavior. Literature advises us that self-adaptation may be a useful capability of complex systems to achieve objective and operational or behavioral requirements (Sokolsky 2011).

If, like living systems, CPSs are to adapt to their environments, they need to use: (i) sensory perception (detecting and anticipating changes in the environment), (ii) cognition (reasoning about perceived changes and deciding on the best action), and (iii) execution (controlling the implementation of cognitive decisions). Systems equipped with this capability are variously called self-adaptive systems (SAS), self-managing systems (SMS), or self-organizing systems (SOS). Often self-healing systems (SHS) and self-optimizing systems (SoS) are also sorted in this category. As Weyns et al. (2012) recognized, there are different communities behind these notional descriptions, as well as different vocabularies There is no clear standpoint in the current literature concerning how self-adaptation actually contributes to tackling the challenges of engineering and managing complex software systems.

CPSs are typically closed-loop systems, where sensors make measurements of physical processes, the measurements are processed in the cyber subsystems, which then drive actuators that affect the physical processes. Cyber components in a CPS application often include algorithms that react to sensor data by issuing control signals via actuators to the physical components of the CPS. Such closed-loop systems are the domain of the classic field of control theory, which studies stability and dynamics of such interactions. CPS, however, requires extending control theory to embrace the dynamics of the physical subsystems. The control strategies implemented in the cyber subsystems need to be adaptive (responding to changing conditions) and predictive (anticipating changes in the physical processes) (Canedo et al., 2013). Literature claims that self-adaptive CPSs should be capable to adjust or change their structure, functionality and behavior at run-time as a response to emerging requirements, changing objectives, environments, and contexts that may be unknown at design-time. Not only need the physical subsystem to be adaptive (responding to changing conditions), but also the software and the cyber subsystems, which should in addition be predictive (anticipating changes in the physical processes) (Lee et al., 2012).

1.4. Scientific objective of the work

1.4.1 Research problem and research domain

According to the above analysis, the research problem of this PhD project was formulated as aggregation of specific knowledge and the development of a cyber-physical computing enabled system, which goes beyond the current rehabilitation systems by penetrating into the physical processes of stroke patient in the case of robot assisted stroke rehabilitation with the aim of maintaining and enhancing the patients' engagement. In an ideal situation, a cyber-physical rehabilitation system consists of a sophisticated physical part and a smart cyber part, which have balanced role and provide complementing functionalities for monitoring and enhancing engagement of stroke patients. However, conceptualization and implementation of such an ideal cyber-physical system is a huge challenge and goes beyond the possible scope and extent of a PhD study. It would involve both foundational and operative research, and hardware, software and cyberware development and integration.

These altogether were deemed to be too complex and ambitious to address in this PhD project. Consequently, a decision was made that the research would focus on the cyber-part of the system, which has anyway not been sufficiently addressed in the studied literature (Figure 1.1). With the intention of arriving at a manageable complexity and

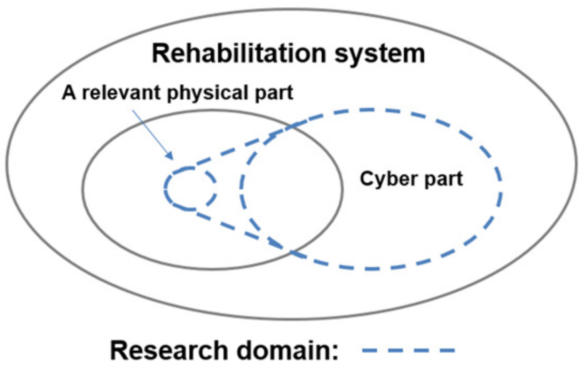


Figure 1.1 Specification of the addressed research domain

utility, the scope of research was defined so as to conduct extensive experimental studies and research means development concerning the cyber part, and to provide a proper but only minimal physical part that allows operationalization of the cyber part and testing and validating its usability and utility in practical cases. The functionality of the cyber part of the target system facilitates: (i) interaction with the patient, (ii) monitoring the patient's status, and (iii) reasoning about a personalized approach to enhancing the engagement of different patients.

1.4.2 Research objective

The main research objective addressed in this PhD research was to deal with cyber-physical augmentation of assistive robotics-based rehabilitation and to study the effectiveness of a cyber-physical solution in enhancing the engagement in stroke rehabilitation. The overall objective was decomposed into three sub-objectives based on the following research questions:

- What are the influencing factors of and their causalities with regards to patient engagement in the context of robot assisted rehabilitation?
- What are the limitations of the current engagement enhancing methods, which result in inefficiency in terms of providing engaging training during robot-assisted rehabilitation?
- How the characteristics and the reasoning affordances of CPSs can enhance patient engagement during robot assisted rehabilitation?

Thus, the first sub-objective was to identify the factors that influence engagement as well as the engagement enhancing methods and their effects on engagement. In order to evaluate the different engagement enhancing methods, there was a need to identify the indicators for evaluating engagement

The second sub-objective aimed at identifying some of the major limitations of the current engagement enhancement approaches. Based on this knowledge, opportunities for cyber physical solutions can be identified to integrate robot-assisted rehabilitation engagement enhancement techniques.

The third sub-objective was to explore which characteristics and reasoning potentials of CPSs can be used for enhancing patient engagement during rehabilitation. Based on the identified opportunities, a first manifestation of a CP-SRS has been conceptualized, implemented in a testable form, and validated. The target cyber-physical stroke rehabilitation system will profit from cyber-physical computing and will demonstrate the benefits of a CPS solution in enhancing engagement.

1.4.3 Research hypotheses

Based on the objectives and the research questions, the research hypothesis is that the CP-SRS is able to enhance the patient engagement in robot assisted rehabilitation. This hypothesis is decomposed to three sub-hypotheses:

- There are reliable indicators to represent the engagement from the motor, perceptive, cognitive and emotional aspects;
- There are technologies that can reliably measure the level of engagement in these four aspects;
- There are cyber-physical based engagement enhancing methods that can be applied to maintain and enhance the patient engagement;

1.5. Research methodology

Due to the variety of objectives and contexts, a multi-methodological framing was applied to set up the research design. The whole of the PhD research project was divided into five

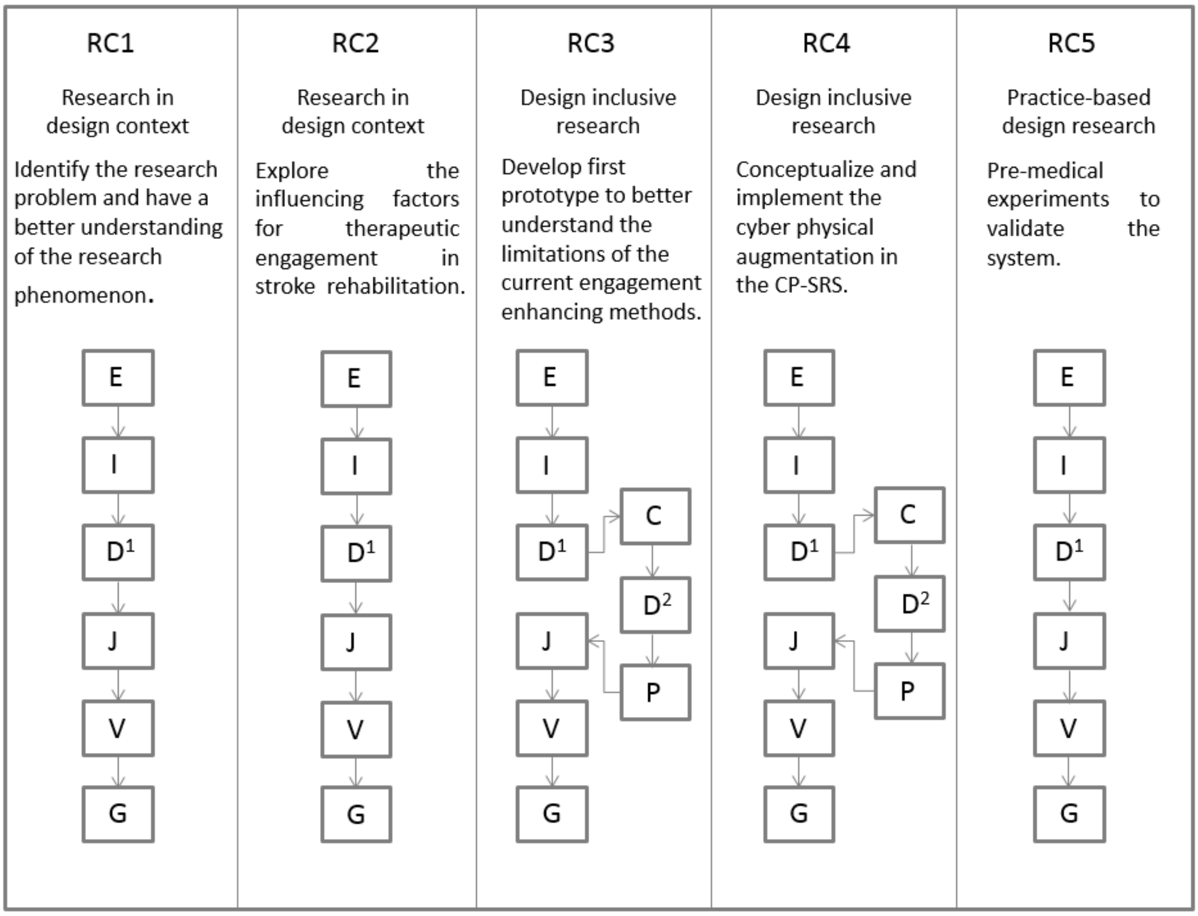


Figure 1.2 Methodological framing of the research project

(Meaning of the letters are: E: exploration, I: induction, D^1: deduction, J: justification, V: validation, G: generalization, C: conceptualization, D^2: detailing, P: prototyping) interrelated research cycles (RCx) as it is shown in Figure 1.2. Each cycle had its own objective, context, and framing methodology. For this purpose, the methodological framing theory, proposed by Horváth (2013) has been applied.

In research cycle 1, the objective was to collect information about the current state of knowledge and art concerning engagement in rehabilitation. To achieve this, we aggregated knowledge about existing models of engagement, the various manifestations of engagement, the current state of engagement enhancement methods and tools, and the opportunities of influencing enhancement of stroke patients.

In research cycle 2, a prototype was developed in order to understand the limitations of the current engagement enhancing methods from a practical perspective. The prototype is an upper limb rehabilitation robot integrated with video games and used in the conducted experiment. The experiment concentrated on exploring the influence of complementing this robotic upper limb rehabilitation system with video games on the engagement of the participants. The findings were combined with the findings of the theoretical investigations in research cycle 1, and were used to create a robust knowledge platform for conceptualization of the whole and the smart reasoning mechanism of our cyber-physical stimulating rehabilitation system (CP-SRS) proposal.

In research cycle 3, the concept of the smart reasoning components of the CP-SRS was developed and concept feasibility testing has been carried out. CP-SRS includes multiple functional components, which have been defined and integrated. The learning and reasoning mechanisms were created. A computer simulation was conducted to study the feasibility of the smart learning mechanism (SLM) as part of the cyber physical augmentation.

In research cycle 4, a tangible prototype of the concept was implemented. Experiments were conducted to test if the identified indicators for engagement can represent the actual level of engagement. In this pre-medical experiments, the goal was to characterize the range and accuracy of the engagement indicators by influencing the subjects into different engaged states. Different setups were created to mimic the situations in which the subject was in engaged, unengaged, or neutral engagement state. Our assumption was the measurement of the indicator could reflect subject’s engaged state.

In research cycle 5, More pre-medical experiments were conducted to test the system from the perspective of two assumptions: (i) if the stimulation strategies can maintain and enhance the level of engagement, and (ii) if the effects of the stimulation strategies on the level of engagement can be captured by smart learning mechanism.

1.6. Structure of the thesis

The next chapter summarizes the findings of the conducted literature study and explores the influencing factors for the therapeutic engagement. The third chapter provides information concerning the experiment conducted with the developed upper limb rehabilitation robot integrated with video games, aiming at investigating the limitations of this currently widely used approach and methods of engagement enhancement. Then, the concept of an engagement enhancing cyber-physical stroke rehabilitation system is proposed in Chapter 4. Chapter 5 introduces the reasoning components and the implementation of the proposed system. Chapter 6 validates the concept of the prototype in a pre-clinical experiment. Finally, Chapter 7 reflects on the research project and the findings, concludes about the contributions and the impacts of the thesis as a whole, and sketches up possible immediate and long term future research work.

1.7. Own publications related to the topic of the thesis

1) Li, C., Rusák, Z., Horváth, I., Ji, L., & Hou, Y. (2014). Current status of robotic stroke rehabilitation and opportunities for a cyber-physically assisted upper limb stroke rehabilitation. Proceedings of TMCE 2014, May 19-23, Budapest, Hungary, 899-914.
2) Li, C., Rusák, Z., Horváth, I., & Ji, L. (2014). Influence of complementing a robotic upper limb rehabilitation system with video games on the engagement of the participants: a study focusing on muscle activities. International Journal of Rehabilitation Research, 37(4), 334-342.
3) Li, C., Rusák, Z., Horváth, I., Hou, Y., & Ji, L. (2014). Optimizing patients' engagement by a cyber-physical rehabilitation system. In INFORMATIK 2014, Stuttgart, Germany, 1971-1976.
4) Li, C., Rusák, Z., Horváth, I., &Ji, L. (2016). Development of engagement evaluation method and learning mechanism in an engagement enhancing rehabilitation system. Engineering Applications of Artificial Intelligence, 51, 182-190.
5) Li, C., Rusák, Z., Horváth, I., Kooijman, A., & Ji, L. (2016). Implementation and validation of engagement monitoring subsystem in an engagement enhancing rehabilitation system IEEE Transactions on Neural Systems & Rehabilitation Engineering. DOI: 10.1109/TNSRE.2016.2591183
6) Li, C., Rusák, Z., Horváth, I., & Ji, L. (2016). Validation of the reasoning of an entry-level cyber-physical stroke rehabilitation system equipped with engagement enhancing capabilities. Engineering Applications of Artificial Intelligence, 56, 185–199.

1.8. References

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CHAPTER TWO

RESEARCH CYCLE 1:

Understanding the essence and causalities of the phenomenon of engagement in rehabilitation

2.1 Objectives and reasoning model of the survey

2.1.1 Objectives

In common language, engagement has many meanings. Interestingly, most of the common definitions associate it with presence at a specific time or at a specific place. In our context, however, engagement is also considered in many more dimensions. Therefore, using the preliminaries in the literature, we will synthesize a definition in the end of this chapter that reflects our interpretation and objective. The survey presented in this chapter was completed in the first research cycle, considering scientific articles and papers, as well as web pages and repository documents that could be found on the Internet. The main objective of the survey was to collect information about the current state of knowledge and art concerning engagement in rehabilitation. In addition to focusing on definitional and conceptual issues, we intended to aggregate knowledge about existing models of engagement, the various manifestations of engagement, the current state of engagement enhancement methods and tools, and the opportunities of influencing enhancement of stroke patients. Together with the investigation of the current day practical limitations, which will be presented and discussed in Chapter 3, this knowledge will be used to create a theoretical platform and conceptual framework for our support system development objectives.

2.1.2 The reasoning model

The literature of medical rehabilitation is very broad, and the phenomenon of engagement in rehabilitation has been addressed from many perspectives. Driven by our objectives explained in chapter one, we were not striving after analyzing the reported investigations and their results from all of the perspectives. We came to the decision that the starting body of knowledge necessary for the intended research and development work can be synthesized by considering three perspectives. Shown graphically in Figure 2.1, these perspectives were used to frame and provide a reasoning model over the knowledge domains of importance for our explorative survey. These knowledge domains are mutually connected and the interconnections have been considered at drawing our conclusions.

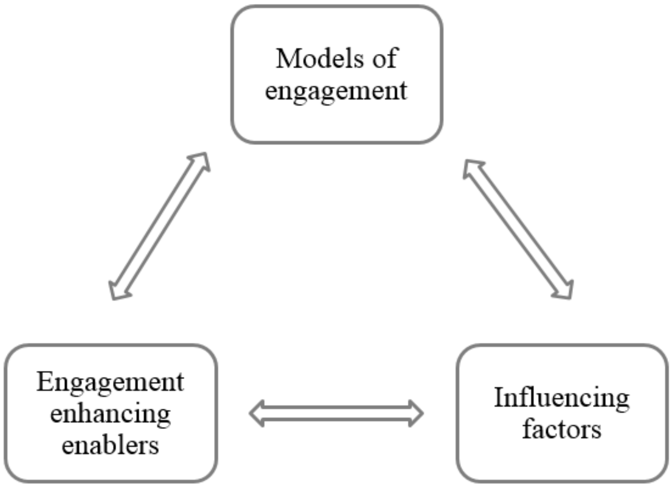

Figure 2.1 Reasoning model used in the survey

The first domain of interest is *engagement models* that have been discussed in the literature in various contexts, such as engagement increased by gamification, enhancement of engagement in education, social and cognitive engagement, and engagement in therapeutic context. The variety of the models is large, ranging from theoretical through conceptual and procedural models to operation models.

The second domain of interest is *influencing factors*, which play a role in therapeutic engagement in stroke rehabilitation and within which the human-related ones play an important role. Actually, we concentrated mainly on these human-related factors in our review. We observed that the overwhelming majority of engagement models were probably defined by considering a set of fundamental influencing factors. We imposed a classification on the influencing factors. This created an interrelationship between the engagement models and the influencing factors.

The third domain of interest is *enablers of engagement enhancing*. Enablers are various resources that are operationalized in and by various methodologies. Surprisingly, we found that formal methodologies, which rest on some underpinning theories, and includes procedural specifications, pools of methods, dedicated instruments, and quality indicators and measures, have not received explicit attention in the literature yet. There have been approaches, rather than systematic methodologies, related to models of engagement, which are based on less rigorous theoretical fundamentals and conceptual frameworks. On the other hand, various engagement enhancing systems have been developed considering the influential factors, which create a basis for making causalities and dependences explicit. While the enablers are addressed dominantly from a therapy-centered view in the current literature, in our survey the technical perspectives of instrumentation and system aspects also received attention. There have been many different proposals for systems and principles for enhancing the efficiency of rehabilitation. These include technical systems, social systems, and even socio-technical systems. It will be shown that many of them just tangentially touch upon the specific topic on monitoring, maintaining, and enhancing therapeutic engagement.

2.2 Models of engagement

Various models have been proposed to capture the essence of engagement from various fields, such as psychology, technology, education, social interaction, medicine and so on. Based on our study, we identified: (i) flow theory-based model, (ii), model of technology application raised engagement, (iii) models of social engagement, (iv) models of education engagement, and (v) model of therapeutic engagement. They will be analyzed and compared below.

2.2.1 Flow theory-based models of engagement

The first model that can be used to explain engagement is the theory of flow (Csikszentmihalyi & Csikszentmihalyi, 1988). Csikszentmihalyi defined flow as a discrete state of human experience in which one's potential is realized through a specific activity that demands an optimal amount of individual resources. The notion of flow is well-known from cognitive psychology. There is a clear definition and explanation of these tem on Wikipedia. It is understood as the mental state of operation in which a person performing an activity is fully immersed in a (i) feeling of energized focus, (ii) full involvement, and (iii) enjoyment in the process of the activity. In essence, flow is characterized by complete absorption in what one does. Flow is set to the position of a completely focused motivation and immersion, which represents a kind of ultimate experience in harnessing the emotions in learning and performing. The flow theory-based models of engagement intend to achieve emotions that are positive, channeled, energizing, and aligned with the task at hand.

The flow theory identified several components that made an experience enjoyable, namely: (i) a challenging but tractable task to be completed, (ii) full immersion in the task, while no other concerns intrude, (iii) feeling of being fully in control, (iv) sensing a complete freedom to concentrate on the task, (v) the task has clear unambiguous goals, (vi) provisioning and receiving immediate feedback on actions, (vii) becoming less conscious of the passage of time, and (viii)

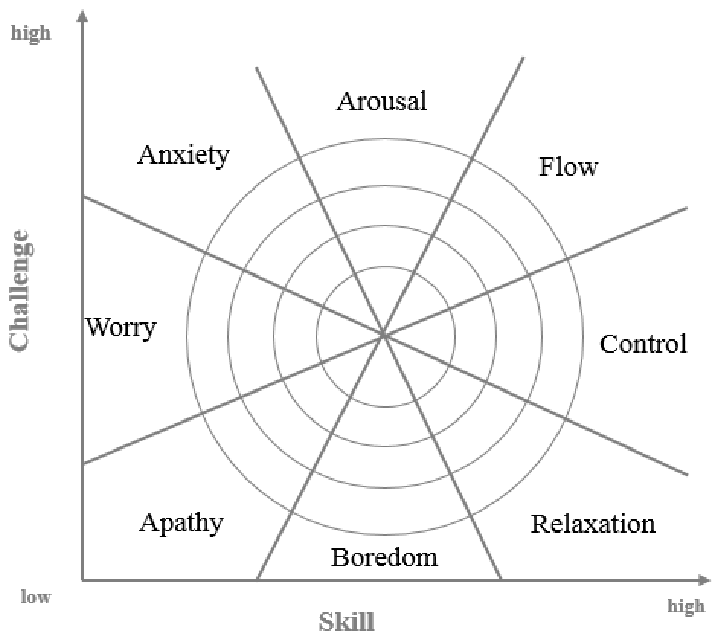

Figure 2.2 Implication of the flow theory (Nakamura and Csikszentmihalyi, 2014)

sense of identity lessens, but is afterward reinforced (Csikszentmihalyi, 1990).

Figure 2.2 is adapted to show a current model interpreting the flow state (Nakamura and Csikszentmihalyi, 2014), in which the challenge/skill terrain are divided into eight experiential channels. Flow is experienced when perceived challenges and skills are above the actor's average levels. When they are below, apathy is experienced. The intensity of experience increases with distance from the actor's average levels of challenge and skill, as shown by the concentric rings. The model showed in Figure 2.2 also informs us about the fact that, towards a highest level of flow, the skill has to be practiced at a high level and it has to happen in a context of high challenge. Nakamura and Csikszentmihalyi concluded the conditions of flow include:

- perceived challenges, or opportunities for action, that stretch existing skills; a sense that one is engaging challenges at a level appropriate to one's capacities;
- clear proximal goals and immediate feedback about the progress that is being made;

Under these conditions, experience unfolds from moment to moment, and one enters the flow state with the following characteristics:

- intense and focused concentration on what one is doing in the present moment
- merging of action and awareness
- loss of reflective self-consciousness
- a sense that one can control one's actions
- distortion of temporal experience
- experience of the activity as intrinsically rewarding, such that often the end goal is just an excuse for the process

This theory has widely been used to understand engagement in association with media and video game entertainment (Weber et al., 2009), (Brockmyer et al., 2009). Theorizing flow and media enjoyment as cognitive synchronization of attentional and reward networks gave the motivation for practical developments. This model indicates the influencing factors for engagement during the process of video game playing. Obviously, this process models engagement for a short term, which is quite similar to each session of rehabilitation training exercise, especially for those integrated with video games. However, it differs from therapeutic engagement as this engagement model does not take therapeutic aspects of the patients into consideration.

2.2.2 Model of technology application raised engagement

Engagement has also been studied in the field of technology applications. For instance, in video games, factors of engagement, such as feedback, intrinsic motivation, fun, user control, and interactivity, have been studied (Carroll and Thomas, 1988), (Vorderer, et al., 2003), (Choi and Kim, 2004). Said (2004) varied the amount of control participants had over a video game, e.g., some children took on the role of characters, some manipulated the characters' world, and the others watched the game unfold without being able to intervene; results indicated that immediate feedback from the system, well-defined goals, prior experience, and increasing challenge in proportion to game playing skills were essential factors of engagement.

In online shopping and web searching applications, qualities of web sites, such as novelty (Toms, 1998) and aesthetics (Lavie and Tractinsky, 2004), as well as feedback, navigability, control, and interactivity (Huang, 2003), can be associated with user intentions. Actually, it was demonstrated that users' needs for information and entertainment are to be satisfied when it comes to engaging searching and shopping experiences. Based on the analysis of the engagement attributes in the above technology applications, O'Brien and Toms (2008) proposed an engagement model. This is applicable to people's experiences with technology, such as web searching, online shopping, webcasting, and gaming applications.

This model of engagement identifies four stages, which are: (i) point of engagement, (ii) engagement, (iii) disengagement, and (iv) reengagement. Point of engagement can be initiated by the aesthetic appeal or novel presentation of the interface, the users' motivations and

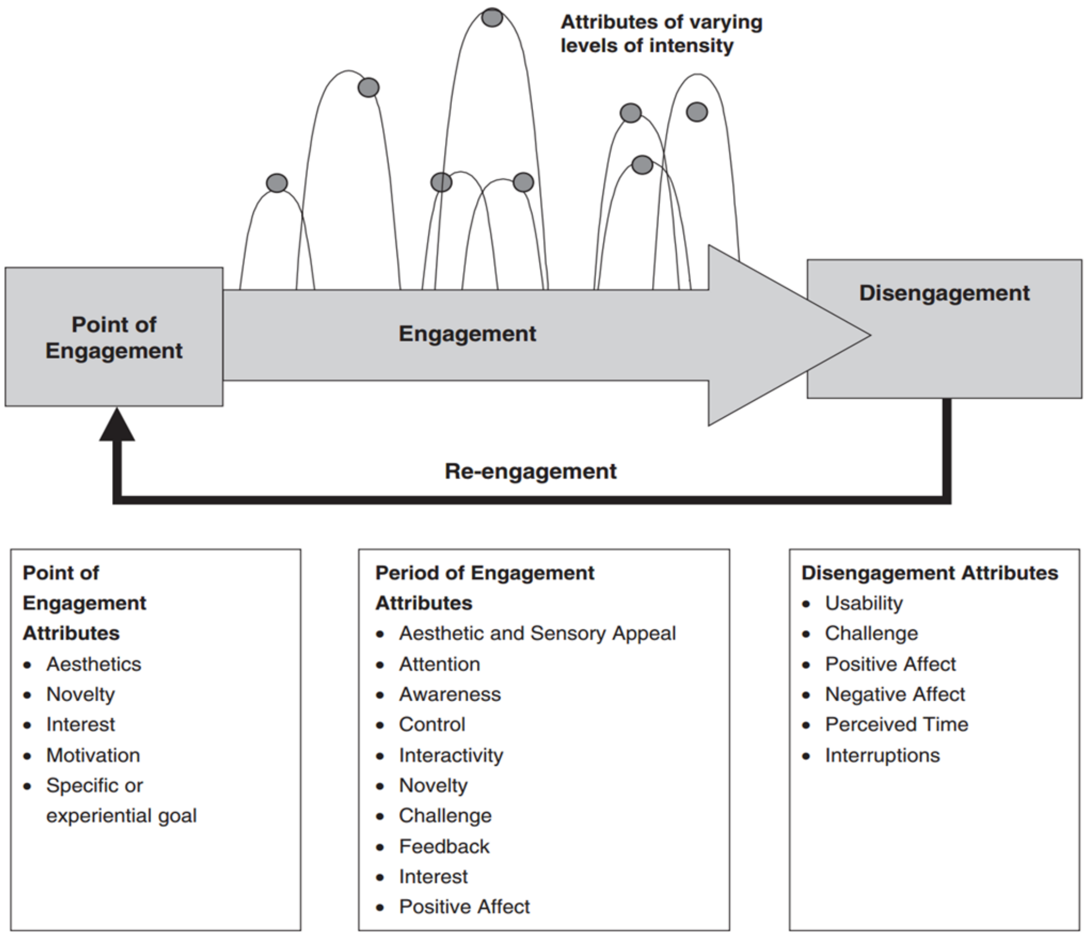

Figure 2.3 Model and influential factors of technology application raised engagement (O'Brien and Toms, 2008)

interests, and the users' ability and desire to be situated in the interaction and to perceive that there is sufficient time to use the application. Engagement can be maintained when the users are able to keep their attention and interest in the application and is characterized by positive emotions. During this stage, users want to customize the interface and receive appropriate feedback from the application. Disengagement can be caused by many reasons, such as challenge and interactivity of the technology, or distractions in the environment. As far as reengagement is concerned, users may return to the application because they have past success with it, or it can offer them something new; positive experiences increase the likelihood of returning to an application.

This model can also be used to explain the engagement during playing video games, and it considers more factors or attributes than the flow theory-based model, such as aesthetic and sensory appeal, novelty of the application, attention, awareness, and emotional aspect. Moreover, it extents the above model with the process of engaging. Therefore, it can explain the engagement both for a short term and a long term, since it explains why the user would reengage with the application. However, therapeutic aspects are missing from this model.

2.2.3 Social models of engagement

Models of social engagement intend to capture (i) engagement of individual with the objectives and activities of a team, (ii) engagement of a team with the activities of an organization, (iii) engagement in networked sociality, and (iv) models of specific social engagement. Engagement of individual with the objectives and activities of a team is of a strong social nature. The engagement model of social interaction proposed by Tyler and Blader (2003) captures the influencing factors of group engagement. They have identified attitude, value, and cooperative behavior towards groups as essential components of motivation for participating in group activities.

Engagement of a team with the activities of an organization is another form of social engagement. Networked systems and web-based communities increase the virtual proximity of participants in near social interactions (Mejias, 2007). Engagement in networked sociality has been described and explained by several different models. Singletary and Starner, (2001) studied social engagement based on visual models. Mahmud, J., et al. (2014) analyzed how word use can predict social engagement behaviors such as replies and retweets in Twitter, and computed psycholinguistic category scores from word usage. Online social engagement is operationalized through concepts such as connectivity, social presence and social space (Kim, Y., et al. 2015). The issue of online social engagement is important since it can promote quality social interactions that increase belonging and directed participation. Engagement defines the phenomena of being captivated and motivated. Engagement can be measured in terms of a single interactive session or of a more long-term relationship with the social platform across multiple interactions. Thus, social media engagement is not just about how a single interaction unfolds, but about how and why people develop a relationship with a platform or service and integrate it into their lives (Jaimes, et al, 2011).

One typical specific social engagement is employment. The engagement model of employment by Zigarmi and Nimon (2011) suggests that employee engagement is highly correlated with work intention, which is defined as a composition of different work-related intents including, intent to perform, intent to endorse, intent to stay, intent to use discretionary effort, and intent to use organizational citizenship behaviors. Though this model presents valuable insight into the influencing factors of intent forming, it is rather incomplete in terms of factors that are relevant for engagement for short term. Social entrepreneurship has also been interpreted as a specific form of social engagement (Martin, R., & Osberg, S., 2007). They identified pure forms of social engagement and demarcated social entrepreneurship from social service provisioning and social activism based on this (Figure 2.4).

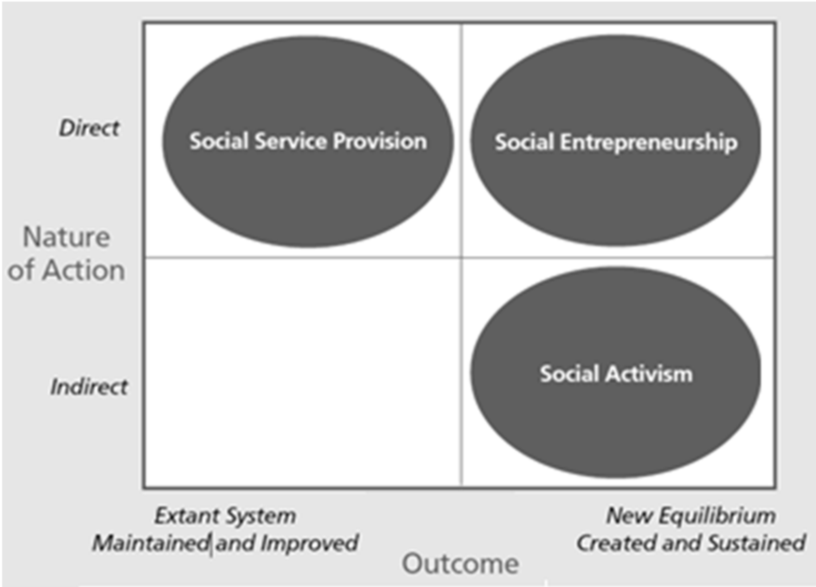

Figure 2.4 Pure forms of social engagement (Martin R., & Osberg S., 2007)

2.2.4 Models of engagement in education

Under this topic, we investigated only those publications that reported on subject engagement in education, and neglected those addressing various aspects of policy engagement in education, though some policy initiatives considered concrete actions in order to reduce the ‘diminished self, to develop emotional well-being, and to encourage emotional engagement in educational conducts (Yonezawa, S., et al., 2009). The emotional needs and the triggered commitment of individuals have been put into the center of a huge number of studies in education and training. As a typical empirical approach of examining whether learners routinely experienced challenge, stimulation and enjoyment, experience sampling forms are used as questionnaires (Johnson, L.S. 2008). Though many efforts were made to formally and rigorously study engagement in education, comprehensive models are rather scarce (Harris, L. 2010). The one, which relies on the assessment model of the National Survey of Student Engagement (NSSE) benchmarks, is seen as the most relevant. As reported by Kuh, G.D., (2003), it takes into account five aspects: (i) academic challenge (AC), (ii) active and collaborative learning (ACL), (iii) student-faculty interaction (SFI), (iv) supportive campus environments (SCE), and (v) enriching educational experiences (EEE). Based on this, LaNasa, S.M. et al., (2009) developed the so-called five factor model of student engagement that actually decomposes the above five aspects into 37 items and accounts for the inter-correlations underlying aspects. This is shown in Figure 2.5. An exploratory factor analysis of the data obtained was completed by the abovementioned authors in order to benchmark the 37 NSSE items, using principal components with *varimax* rotation. Based on the outcome of this, an eight-factor model was derived as a solution. It considers factors such as (v) learning strategies, (ii) academic integration, (iii) institutional emphasis, (iv) co-curricular activity, (v) diverse interactions, (vi) exerted efforts, (vii) overall relationships, and (viii) workload. The authors validated the results and explain the engagement situation with a single first-time freshman cohort at an urban 4-year institution. They did not explicitly address the issue of long term monitoring or possible enhancements.

Corrigan et al. (2013) regarded engagement as a mix of components, related to: (i) behavioral: persistence and participation, (ii) emotional: interest, value and valence, (iii) cognitive: motivation, effort and strategy, and (iv) achievement and development. Engagement model of education shows

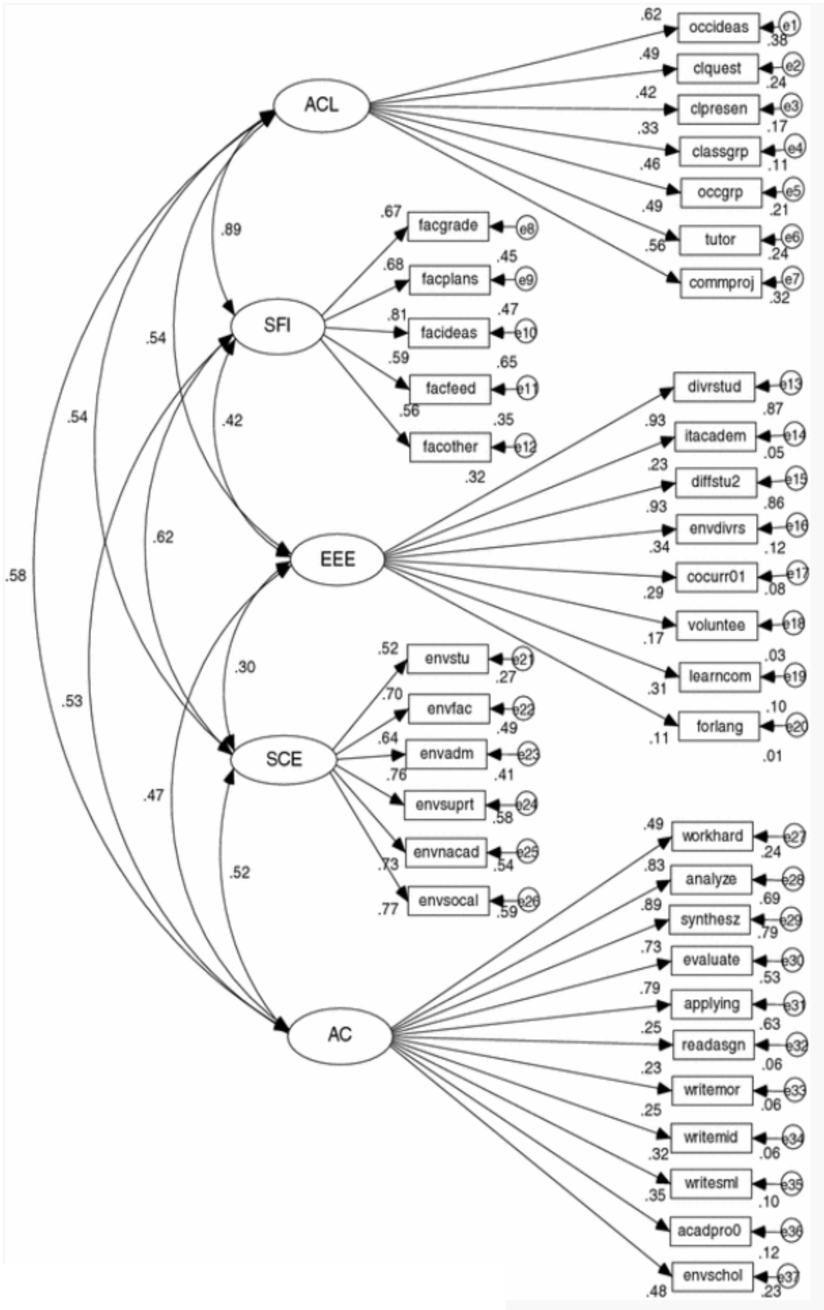

Figure 2.5 The five-factor model of student engagement (Kuh, G.D., 2003)

many similarities to therapeutic engagement as both fields are dealing with cognitive training of people. Therefore, the influencing factors of engagement in education are relevant for cognitive training of stroke patients. Digital disruptions such as multimedia, social portals, augmented reality, and connected peer learning are all based on vaguely formulated models of educational engagement (Lester and Perini, 2010). The promises of the emerging educational groupware are that it permits new forms of engagements (Kelly 2007).

2.2.5 Therapeutic model of engagement

Shown in Figure 2.6, a dedicated model of engagement for therapeutic treatments was proposed by Lequerica & Kortte (2010). This model can be interpreted as having a motivation driven by attitudes and beliefs that lead up to the intention to engage in the treatment. More specifically it captures, (i) the perceived need of treatment, (ii) the perceived likelihood of a successful outcome, and (iii) the perceived self-efficacy to complete the tasks are the necessary drivers of the willingness of a person to get engaged in treatment. Besides this intention, preparation is also a necessary component for therapeutic engagement. It consists of: (i) the setting up rehabilitation goals and development of a treatment plan to achieve these goals, (ii) the energy that is depicted as one takes on more active involvement. In the active phase of engagement, a feedback loop assessing the costs and benefits is used to form a decision whether to remain engaged in the exercise or not. In conclusion, the components influencing therapeutic engagement in this model includes (1) perceived need of treatment, (2) perceived likelihood of a successful outcome, (3) perceived self-efficacy to complete the tasks, and (4) reassessment of beliefs, attitudes, & expectations (Lequerica & Kortte, 2010). In the process of rehabilitation program, these influencing factors are necessary to maintain the engagement of the patients. However, it lacks the specific details about engaging the patient during the rehabilitation training exercise. Instead, the influencing factors for engagement in this model have to be addressed outside the process of the training exercise.

2.2.6 Time related differentiation of engagement

In the above-discussed model of technology application raised engagement (Figure 2.3), ‘reengagement’ is a crucial element since it implies consideration of order and timing in modeling of the process. This resonates with the issue of maintenance of engagement in the therapeutic model of engagement (Figure 2.6), which points at the necessity of considering the duration of engagement and the influential factors. What these elements of the two engagement models imply is the inevitability of differentiation of engagement from a time (temporal) perspective, from which engagement can be differentiated as: (i). long term engagement (LTE) and short term engagement (STE). These notions can be projected onto the above engagement models. For instance, STE is achieved according to the model of technology applications raised engagement while the user is interacting with a video game, an online shopping application, or web searching. On the other side, LTE is achieved when the user comes back to the application with a high frequency and over a relatively long period of time, and when this becomes a kind of routine.

Likewise, the model of therapeutic engagement also reflects temporal factors, by allowing for over the whole of a rehabilitation program (which can last for years) and engagement during single rehabilitation session or exercise (which may happen in a predefined time window). The differentiation of LTE and STE can be applied to the model of education engagement as well. In this context, they may concern engagement during the whole educational program and engagement during one specific lesson, respectively. In the realm of video games, long term engagement has been identified and defined as the degree of voluntary use of a system

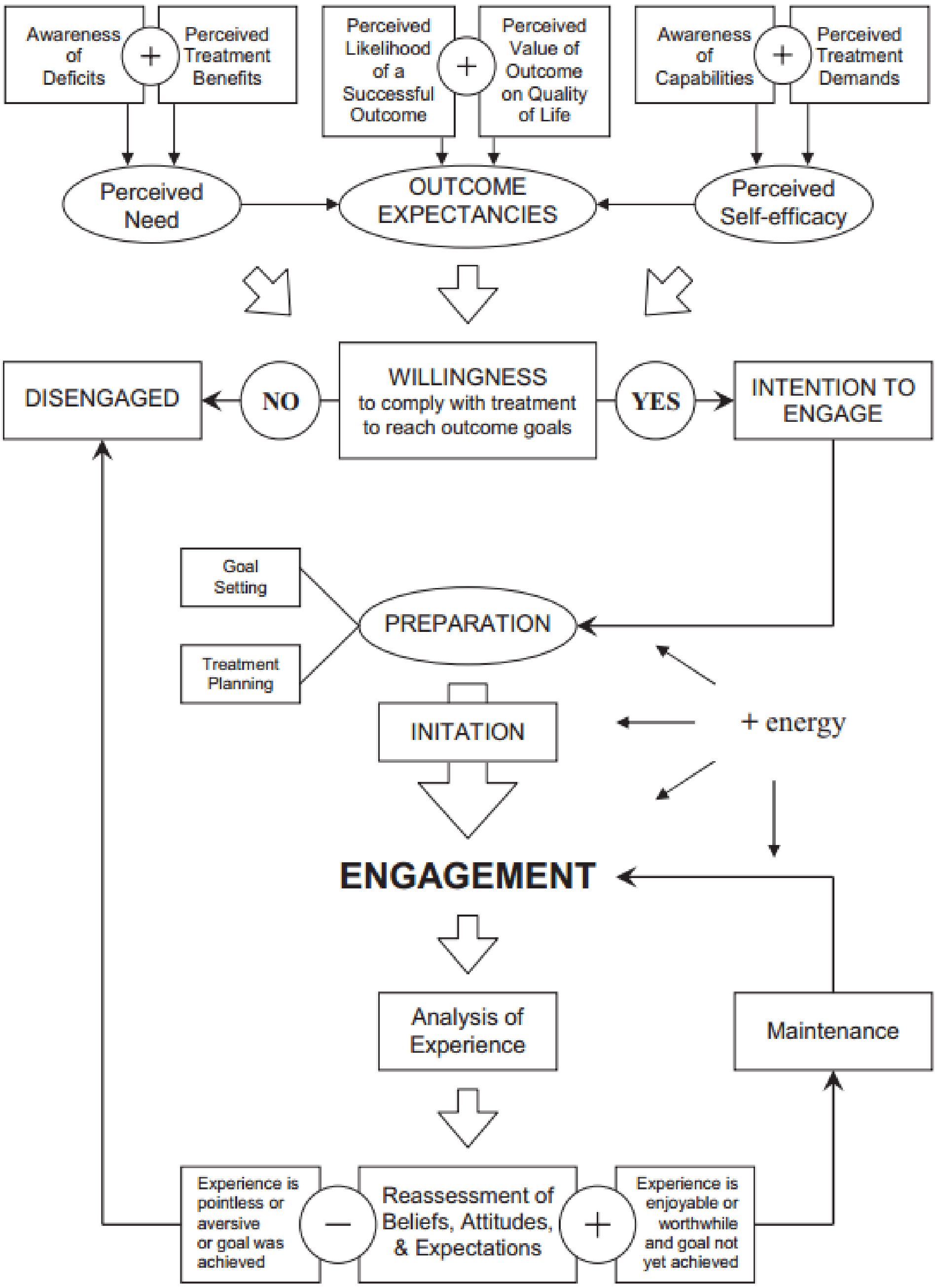

Figure 2.6 Model of therapeutic engagement (Lequerica & Kortte, 2010)

along a long period of time (i.e., weeks, months, or years), involving dozens, if not thousands, of interactions, each one spanning for significantly longer than few seconds or minutes (Febretti and Garzotto, 2009). Since the influencing factors for these two kinds of engagement are different, as well as the strategies to achieve them, differentiation between long term engagement and short term engagement has a legacy.

Since a complete stroke rehabilitation program usually takes months, investigation of LTE is of importance at defining complete rehabilitation programs conducted in a hospital or a rehabilitation center, and typically finished with home care servicing. According to the model of therapeutic engagement (Lequerica & Kortte, 2010), possible strategies of enhancing LTE are identified. One possible of strategy is ensuring the awareness of patients about their deficits and the potential outcome of the therapy, considering their actual medical status, existing functional capabilities, and regained skills. This improves their willingness to comply with the treatment and dedication to achieve the goals. Another strategy is based on the communication of the potential benefits of the treatment on their daily life. This strategy focusses on the management of expectations so that anticipation, recovery, and the treatment of the patients are continuously harmonized with the goal of maintaining the motivation and engagement in the rehabilitation program. A third strategy can involve setting a clear and properly adjusted goal for the patient, for instance, in terms of completing a series of tasks or reaching gradually increasing Fugl-Meyer score. This is a keen issue because if the previous goal has been achieved, then the patients may opt to disengage themselves according to the forecast of the therapeutic engagement model. Therefore, a recurrent update of the goals is an important element of long term engagement of the patients in enduring rehabilitation programs. A fourth strategy to increase LTE can be based on encouragement and convincing the patients. The related literature advises that self-confidence and self-efficacy of the patients are also important factors with regards to the success of a rehabilitation program.

In the present-day practice of stroke rehabilitation, these strategies are often applied by physical therapists in various combinations in order to motivate, encourage and convince the patients effectively in a personalized manner. Many researchers have endeavored to enhance engagement of the patients during robot-assisted rehabilitation exercises (Krebs et al., 2003) and (Loureiro et al., 2006). Wolbrecht et al., (2008) reported on three desirable features that they found important to maintain STE in robot-aided movement training following stroke: (i) high mechanical compliance of the device, (ii) the ability to assist patients in completing desired movements, and (iii) the ability to provide only the minimum assistance necessary. Burke, et al., (2009) proposed the use of serious games in order to optimize STE for stroke rehabilitation. Hu, et al., (2013) investigated the opportunities of influencing motor engagement in the case of an electromyography-driven hand rehabilitation robot. Sarac, et al., (2013) experimented with the application of brain-computer interface in robotic rehabilitation in order to maintain engagement through online modification of task speed. Among many others, the work of Zimmerli, et al., (2013) concentrated on patient engagement during virtual reality-based motor rehabilitation exercises. Hinted at by the current practice of rehabilitation, combination of strategies should receive attention whenever a cyber-physical system based support of rehabilitation is planned.

In the context of rehabilitation, STE is defined as measure of the motivated involvement during a single session of a rehabilitation training exercise. Obviously, short term engagement also influences LTE since positive experiences in engaging therapeutic exercises and treatments maintains the willingness of the patients to keep participating the rehabilitation program. On the other hand, a higher level of LTE typically implies that patients even more engage themselves in (short term) rehabilitation training exercises, assumed that they are aware of the need for the concerned exercise. Based on the interpretation of the models, we came to the conclusion that different factors influence STE than LTE. The difference in influencing factors entails that different strategies are needed for the enhancement of STE and LTE. In this PhD research, we will focus on enhancing the engagement during the rehabilitation exercises, that is, we will deal with STE since there are still many challenges and unresolved issues in this field. Consequently, in the rest of the thesis, the term 'engagement' will always be used to refer to engagement during rehabilitation exercises, unless indicated otherwise.

2.3. Factors influencing therapeutic engagement

The analysis of the models in sections from 2.2.1 to 2.2.6 revealed that the concerned authors considered many influential factors at constructing these engagement models. Some of the influencing factors reflect human aspects, which can be associated with therapeutic engagement. After sketching up the interrelationships between the found influential factors in the next subsection, we concentrate on these human-related factors.

2.3.1 Discussion of the interrelationships of influential factors

Our literature review has been made with two interconnected objectives. On the one hand, we intended to gain insight in the state of the art of assisting stroke rehabilitation, and to explore and aggregate knowledge about engagement in general and in therapeutic rehabilitation. We also concentrated on the influential factors of engagement of patients in rehabilitation, the proposed engagement models, and the causalities of the engagement phenomenon in rehabilitation. The point of embankment of our review was the analysis of the existing engagement models, which provided insight into the influencing factors of engagement from the perspective of different knowledge domains (i.e. cognitive psychology, education, technology raised engagement, social science, rehabilitation therapy). Our study also offered an overview of the methods, techniques and systems that aim to enhance engagement. The main findings of our study are summarized in Figure 2.7.

The engagement models proposed by researchers of the different knowledge domains identified a wide range of influencing factors. Although these models aimed at understanding and representing engagement from different perspectives, they identified several common factors that we considered as substantial influencing factors of the phenomenon of engagement. For instance, each of engagement models emphasizes as important factor the understanding the goal of the patients/users as the most essential contributor to engage humans in any activity. There are however some differences. While flow theory stresses the need for clearly setting the proximal goals (short term), the therapeutic engagement also puts emphasis on the individual's perception of the long term goals and expected outcome of engagement. However, awareness of the activity and goal of the task has to go beyond the pure cognitive understanding. It must be valued and shared by the individual, which in the end influences his/her attitude towards the tasks at hand.

Besides the goal of activities/tasks, challenge is another key factor. Challenge in the context of enhancing engagement means not only creating and managing tasks that meet the skills and capabilities of the users, but it also means that an individual has self-desire to seek out new things and new tasks (i.e. the individual has an intrinsic motivation to engage in an activity). Besides skills and capabilities of the individual, physical, mental, and emotional readiness to

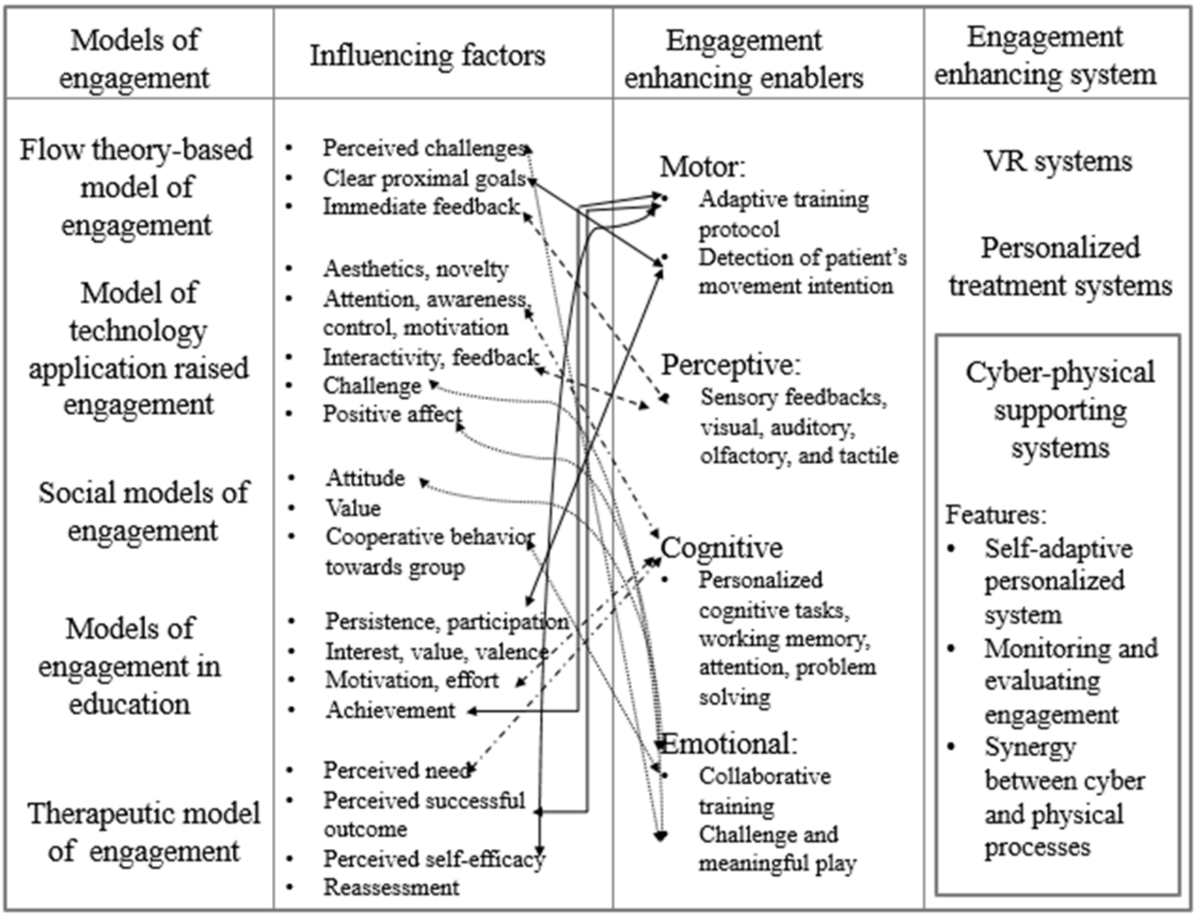

Figure 2.7 Conclusions based on the reasoning model

engage in a new challenge is of importance. Challenge is a dynamically changing aspect of engagement, as learning influences the actual skills and capabilities of humans. It may be negatively influenced by the individual's task familiarity, predictability, event and temporal uncertainty. First time experience with a task or activity on the other hand can be considered as the most effective way of therapy therapeutic engagement or relearning of functions as it first time experience leaves a strong impression in the mind that is difficult to erase.

The third group of influencing factors is the circumstantial elements, including the settings of an activity, aesthetics of the environment, feedback, and control. It was found that sharp, clear, vivid, dramatic, or exciting realistic activities are more likely to engage and retain individuals. It was also shown that activities should engage the several modalities of senses (hearing, sight, touch, taste, smell, balance, rhythm, depth perception, and others). Well-designed engaging exercises should simultaneously incorporate the aspects discussed above. They should engage individuals so that they perform at their competency, they are guided by clear goals and they receive proper feedback. Methods and systems aiming to enhance engagement should address specific aspect of motor, perceptive, cognitive and emotional aspects. Based on a logical analysis of the influencing factors for therapeutic engagement and the current engagement enhancing methods and systems, the opportunities of a cyber-physical solution are identified as following. CPS enabled specific stimulations that could be able to enhance the engagement during rehabilitation exercises are also identified. The current technology trends are pointing towards adaptable or self-adaptive systems. This indicates that the future will see the realization of self-adaptive systems, in which the system features and functions can be adjusted by the system itself.

2.3.2 Initial categorization of human-related factors

We started out of the fact that the studied flow theory establishes interrelationships between various emotional factors (Figure 2.2). By doing so, it also creates a bridge between flow and therapeutic engagement through four sets of human-related factors in our interpretation. These sets include: (i) motor, (ii) perceptive, (iii) cognitive, and (iv) emotional factors, respectively (Figure 2.8).

With some simplification, the ultimate goal of stroke rehabilitation is recovering the motor ability of patients. Therefore, a strand of recent research concentrates on the understanding and manipulation of the motor engagement of patients. Active involvement in rehabilitation of motor functions was found indispensable. Adaptive robotic training protocols were proposed, as well as detecting the effect profile and responding to the movement intent of patients (Blank, et al., 2014). Actually, most of the known approaches provide assistance by exploiting the motor potential and capability of the patients in during the training exercises. Research has shown that some of these approaches are able to improve not only the motor ability of the patients, but also their functional ability (Squeri, et al., 2014). As mentioned in Chapter 1, functional ability enhancement was seldom reported as the outcome of robotic rehabilitation.

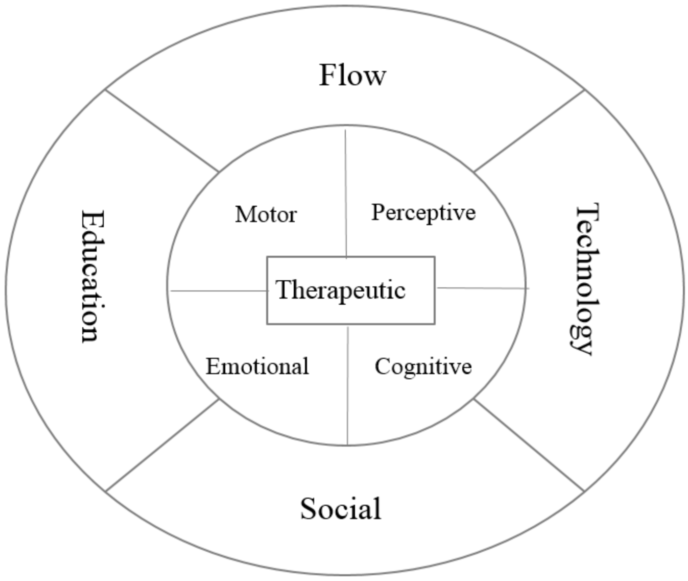

Figure 2.8 Extraction of influencing factors based on the studied engagement models

The sense of presence and timely feedback were also incorporated in the above models as important factors of engagement. These perceptive factors can contribute to engagement in technology-assisted rehabilitation and training. By executing robot-assisted rehabilitation training exercises in a virtual reality (VR) environment, the patient can have strong and immediate perceptive feedback. Efforts have been made to extend it also with haptic feedback in the case of motion therapies. This indicates the trend that advanced robot-assisted rehabilitation environments are supposed to react on the activities of the patient, but also the patient should know how to properly interact with the rehabilitation system (Zimmerli, et al., 2013). Visual feedback, auditory feedback, and tactile feedback should be perceived real time an on a perpetual basis by the patients in order to be able to properly interact with the rehabilitation system.

Many of the above models also identified cognitive factors crucial to achieve and maintain engagement, such as attention, awareness, control, and motivation. According to the therapeutic model of engagement, the patients have to perceive the need of treatment, the potential benefits of the treatment, self-efficacy to complete the task, and the need of further treatment in order to stay engaged. These cannot be realized without a certain level of cognitive functioning from the patients. Moreover, understanding and reacting to the feedbacks of the systems in the rehabilitation exercises also presumes the cognitive functions of the patients (Cicerone et al., 2005). Contrary to the awareness of these issues, many stroke survivors leave the hospitals with cognitive impairments, such as attention, orientation, and task execution deficits (Tatemichi, et al., 1994), (Stephens, et al., 2004). Cognitive impairments can hinder the patients from understanding the rehabilitation tasks, perceiving the need and benefits of the treatment, and more importantly, lowering the attention level of the patients during rehabilitation training. Research has shown that impaired cognitive status negatively affects the rehabilitation outcome of stroke patients (Heruti, et al., 2002). Therefore, engagement in the cognitive aspect should not be neglected at considering therapeutic engagement in rehabilitation.

The investigated engagement models also identified influencing emotional factors, such as enjoyment, interest, positive affect, and willingness. Researchers has come to the conclusion that the relationship between the emotional factors and the therapeutic engagement are somewhat vaguer and has a huge variance compared to the other influencing factors. Nevertheless, Kortte et al., (2007) developed the so-called Hopkins Rehabilitation Engagement Rating Scale (HRERS) for evaluating patients' engagement during rehabilitation program in hospitals. The HRERS scale takes many measurements into account, including emotional functioning and affective state. Based on these results, therapeutic engagement can be conceptualized as a construct that captures also the patient's emotional state and takes emotional factors into account.

2.3.3 Factors influencing motor engagement

Providing adaptive robotic training protocols and detecting movement intent were considered as the best practice of engaging patients in therapeutic activities (Blank et al., 2014). In addition, providing motor challenge according to the patient's capability has also been proposed. Krebs et al. (2003) used a performance-based impedance control algorithm to determine the robot assisted therapy, which is optimally tailored to various stroke patients. The aim of using this algorithm was to motivate the patients to try and move their arms, and not just passively let the robot to move it. The algorithm relied on signals such as speed, time, and EMG. However, physical therapists found a significant reduction in arm tone after the therapy. The reason is that there is a tendency among the patients to rely heavily on the provided assistive force (Reinkensmeyer, et al., 2007). Of course, it means that proper motivation cannot be achieved.

With the aim of ensuring that patients attempt to actively move during robot assisted therapy, Dipietro, et al. (2005) developed an EMG-based control mechanism. This mechanism used the muscle signals to detect patient's intent and assisted the patient in performing point-to-point movements in a horizontal plane. Though the preliminary experiments validated the functionality of the system, information about further clinical experiments was not found in the literature. Hu, et al. (2013) reported on a similar study. In order to encourage the patients to make voluntary movements, they developed an EMG-driven control algorithm for a hand robot. Their algorithm was based on real-time detection of the levels of the EMG signals in the respective muscles. After conducting the therapy with ten chronic patients, significant motor improvements were found in the Fugl-Meyer hand/wrist and shoulder/elbow scores, and significant reduction in spasticity of the fingers. Tough detection of intent to initiate movement is an important element of the engagement in physical exercises, other factors (e.g. motor function abilities of the patient) should also be considered at determining the right level of assistive forces during robotic rehabilitation.

Wolbrecht, et al. (2008) proposed an assistance-as-needed controller to provide only the minimum necessary assistance in order to increase the involvement of the patient's motor system. The controller used a standard, model-based adaptive control approach to adjust the assisting force when small errors in task execution were observed. A problem with the model-based control of assistive forces was that it was not able to adapt neither to the individual needs of patients, nor to the motor function development, or fatigue. With the aim of maximizing the recovery of the active range of motion, Squeri, et al., (2014) developed an adaptive control scheme, which trained wrist movements with slow oscillatory, small amplitude patterns and progressively increasing bias. They observed improvements in the active range of motion and in the motor function, measuring it by the Fugl-Meyer assessment. They also observed the increase in functional capability, measuring it by the Wolf motor function test. Their approach demonstrated that increased motor challenge not only helps improving the range of motion, but it also maintains and enhances motor engagement.

2.3.4 Factors influencing perceptive engagement

Sensory feedbacks, including visual, auditory, olfactory, and tactile, have been applied to enhance multi-channel perceptive engagement of patients. For example, Dinh, et al. (1999) conducted an experimental study with 322 subjects in order to investigate the effects of tactile, olfactory, audio, and visual sensory cues on the participants' sense of presence in a virtual environment. The results indicated that increasing the modalities of sensory input could increase the sense of presence in a virtual environment and memory for objects in this environment. As suggested by the flow theory-based engagement model, presence is one of the most important components of engagement. Therefore, meaningful stimulation of the perceptive channels of patients in sensory-motor interaction during rehabilitation trainings is an essential factor of influencing their engagement.

In order to assess the effectiveness of rehabilitation training with computer games integrated with haptic force feedback and three-dimensional visualization, Broeren, et al. (2007) conducted a clinical experiment with the involvement of five chronic patients. They found significant improvements in terms of the speed of movement, the time needed to reach, and the hand path ratio (reflecting superfluous movements) after the therapy. Feintuch, U., et al. (2006) integrated haptic-tactile feedback into a video-capture-based virtual environment. Fan, R.E., et al. (2009) developed and tested a haptic feedback rehabilitation system on a lower-limb amputee. The results of these and many other works indicate that haptic feedback during rehabilitation training helps recover motion control functions, which is essential to improve other aspects of motion recovery.

In general, as a feedback modality, auditory feedback is underexploited in current robotic rehabilitation systems. Among the pioneers, Batavia, M., et al (1997) developed an augmented auditory feedback device. In order to investigate the effect of auditory feedback in robot-assisted rehabilitation, Rosati, et al. (2011) conducted a study in which auditory feedback was provided in the form of sequences of tonal beeps. Each beep was of 800 Hz, lasted for 0.1s, and was delivered through headphones either to the left or to the right ear (audio channel) according to the sign of the error. The result of this study was that generating a proper sound cue during the training can help patients in improving their engagement, performance, and learning in the exercises. Furthermore, it was found in the above study that single channel of perceptive feedback can contribute to increasing engagement. Thielman, G. (2010) conducted an investigation concerning tactile versus auditory feedback for trunk control. Contrary to these studies, the knowledge about using multi modalities of sensory feedback in the field of rehabilitation in order to engage the patients is not sufficient.

2.3.5 Factors influencing cognitive engagement

To examine the effects of working memory training in adult patients with stroke, Westerberg et al. (2007) completed a randomized pilot study with 18 participants. The study consisted of computerized training on various working memory tasks for five weeks. At the end of this interventional study, there was a significant improvement in patients' working memory and attention. It demonstrated that training exercises, which involve cognitive tasks such as working memory, attention, and problem solving, can be applied in order to retrain cognitive abilities of patients. However, few randomized control trial has been conducted to compare computerized training and conventional therapy. Therefore, no information about the efficiency of the trainings has been reported. Monitoring of EEG signals was used to evaluate participant's attention levels. For instance, Szafir and Mutlu (2012) used adaptive agents that monitor students' attention using EEG and recapture diminishing attention levels by applying verbal and nonverbal cues to maintain their attention. They found that adaptive agents can improve students' recall abilities and significantly improve female motivation and rapport. However, the cues were only dependent on the event, but were not personalized.

Lao, J., & Kuhn, D. (2002) investigated the relationship between cognitive engagement and attitude development. As they wrote, the results were consistent with the view that more active forms of engaging a topic are conducive to cognitive growth, but that there is a limit to the degree of exposure to opposing views that is beneficial. Sarac, et al. (2013) developed an approach that enabled online adaptation of robot assisted rehabilitation exercises by monitoring cognitive intention levels of patients utilizing an EEG based brain-computer interface. They used passive velocity field control to change the speed of contour following tasks with respect to intention levels of motor imagery; the aim was to motivate active involvement of patients throughout exercise, but clinical experiment results were not reported yet. This study did not monitor the patient's involvement in the motor aspect, which may lead to inaccurate analysis of the patient's involvement.

2.3.6 Factors influencing emotional engagement

Evidence suggests that when a client "focuses" on a game, rather than on their impairment, the prescribed exercises become more enjoyable and motivating (Lange, et al., 2009). Furthermore, it is more likely that their focus is maintained over the many trials needed to induce plastic changes in the neural system. Competitive features such as identified by (Wood et al., 2004) and (Burke, et al., 2009), and collaborative features (Loureiro, et al., 2006) have been found not only more interesting, but also more motivating in games. Specifically, Loureiro et al. (2006) developed a collaborative rehabilitation environment that encouraged a long-distance collaborative play using two robot-mediated therapies. The subjects found the collaborative environment more valuable, interesting, and enjoyable. Aiming at minimizing the loss of independence, isolation, and depression of the patients, Johnson, et al. (2008) used this approach to socially engage patients. They found that engagement of patients in the training could be maintained longer with this approach.

Matarić et al. (2007) developed a socially assistive robot, which can provide encouragement and reminders by helping the patient to remember to follow a rehabilitation program. The results showed that this method had a positive impact on patients' willingness to perform prescribed rehabilitation. It was concluded that collaborative training with other users can engage the patients by increasing their positive emotion due to social interaction with the other users during the training. In order to optimize the engagement of the patients in stroke rehabilitation training, Burke, et al., (2009) designed video games with meaningful play and challenge for the participants. They argued that majority of the participants found the games enjoyable. This study pointed at the fact that challenges and meaningful play can also increase the patient's positive emotions.

2.3.7 On some limitations of current approaches

The majority of the above discussed studies integrate game features into rehabilitation training exercises. In general, gamification is a proliferating approach of rehabilitation training in robot assisted stroke rehabilitation. It is underpinned by evidences that assistive devices integrated with gamification provide more engaging motor, perceptive and cognitive training. However, the existing solutions have typically addressed only one specific aspect of engagement, rather than the whole of the phenomenon and the issues. Holistic models for short term engagement of patients in rehabilitation are still representing an unresolved research challenge. On the other side of the coin is that there are no reliable solutions to comprehensively and efficiently enhance therapeutic engagement in rehabilitation.

As shown in Chapter 1, current robotic rehabilitation devices do not provide personalized therapy for patients, which in turn may easily result in a decline of motivation and engagement in therapeutic exercises. On the other hand, recent results studying engagement enhancing methods indicate that need for personalized treatment according to the patient's capabilities and needs. Because of the nature of engagement, there is no quantitative method to evaluate the level of engagement. This can be seen as another limitation. The current methods developed to evaluate and measure engagement are subjective and qualitative (Kortte et al., 2007). The same patient's engagement could be different according to different therapists, which may lead to an inaccurate assessment. Consequently, without precise measurement, the methods of engaging the user cannot be validated. Therefore, quantitative assessment of engagement is required for evaluating the effectiveness of the engagement enhancing methods.

2.4. Engagement enabling systems and technologies

Basically, three kinds of beyond-assistive-robotics systems have been developed with the capability of enhancing engagement: (i) virtual reality-based environments/systems, (ii) personalized treatment systems, and (iii) cyber-physically supporting systems.

2.4.1 Virtual reality-based environments/systems

Proliferation of virtual reality (VR) in stroke rehabilitation is admitted to its capability to deliver customizable biofeedback and personalizable rehabilitation program in a safe and motivating environment (Yin, et al., 2014). These virtual rehabilitation environments are designed to provide audio-visual and haptic-tactile feedback that promotes motor learning and enhances participation in a rehabilitation process (Burdea, G.C., 2003). VR-based rehabilitation enables therapists to adjust target tasks to the abilities of individual patients, offering the potential of greater engagement in treatment sessions and increased sensory feedback to enhance motor learning. As argued by da Silva Cameirão, M., et al. (2011), VR-based rehabilitation speeds up functional recovery of the upper extremities after stroke. Tracking technologies of VR also enables therapists to quantitatively monitor the skill development and recovery process of patients and perform real time diagnosis of movement dysfunction.

VR solutions aim at augmenting the information gained from intrinsic sensory organs with the goal to offer motivation, guidance and encouragement (Holden, M.K., 2005). Interactive environments can be used to encourage sensory-motor integration by providing feedback relevant to a specific function through various modalities, and present this information in a meaningful and intuitive way (Sveistrup, H., 2004). The task and feedback should encourage active physical and cognitive participation by the patient to learn generalizable movement strategies (Schmidt, R.A., 1991). Measuring the activities has an important role, as argued by Adamovich, S.V., et al., (2005). The task and feedback must also be adaptable to the patient's individual ability and progress, allowing for patients to be challenged physically and cognitively without frustrating them (Piron, L., et al., 2005).

VR-based rehabilitation systems offer numerous advantages. On the other hand, they also have weaknesses and limitations such as: (i) challenging user interface and interaction methods, (ii) using instruments, displays and wiring, (iii) immature engineering processes, (iv) platform compatibility and interoperability, (v) front-end flexibility, (vi) back-end data extraction, management, analysis, and (vii) visualization side effects (Kim, G.J. 2005). In order to overcome some of the non-technical limitations, the cognitive integration of gaming features in VR- based rehabilitation systems was also considered (Rizzo, A.A., et al., 2004). Efforts were made to work out methodologies and systems for remote tele-rehabilitation (Rizzo, A.A., et al., 2004). As alternatives of VR-based systems, socially assistive robots/systems have been studied and developed for supporting personalized rehabilitation.

Paiva, A., et al. (2004) presented an agent based system that is capable to offer empathy to patients by adjusting the facial expression, voice and body posture of virtual avatars. They proposed two approaches to adjust the behavior of agents of the system. The first approach has a cognitive nature, in which the character must behave in ways that show empathy by understanding others, mimicking others' (e.g. other characters or people) emotions, and acting as if the others' emotions affected it. The second approach implemented an affective nature, in which the character expressed emotions in facial expressions, voice and body posture, presents it to the external world and learns from the reactions. Both approaches have their merits in developing systems that implement a virtual therapist, capable to stimulate and offer empathy to patients. Tapus and Mataric (2008) introduced a socially assistive robot which is capable of adjusting its social interaction parameters toward customized rehabilitation therapy based on the user's personality traits and performance. Their experiments validated the feasibility of mapping the user's extroversion-introversion personality dimension to a spectrum of robot therapy styles that range from challenging to encouraging. This system can customize the rehabilitation therapy based on the patient's emotional characteristics. Although they have not validated its functionality with real stroke patients, the study demonstrated the promises of a socially assistive system in increase patient's motivation.

There are very few research projects (e.g., Bickmore, 2003), in human-computer interaction (HCI) that attempt to emulate empathy in virtual agents. We are not aware of any studies that have examined the role of empathy in assistive embodied human-robot interaction. While machines cannot feel empathy, they can express it. The strand of the related research leads to the concepts and development of personalized treatment systems, which well be analyzed below.

2.4.2 Personalized treatment systems

Personalization is an elementary need in recommendation oriented rehabilitation systems. Various methods have been developed to make recommendations to users. Most of the methods are based on: (i) collaborative filtering, (ii) content based filtering, (iii) ant colony optimization, (iv) particle swarm optimization, and (v) different combinations of these techniques (Nilashi, et al. 2013). Currently, there have been various computer supported tools developed for personalized rehabilitation. Most of these tools can only calibrate the difficulty of the training exercise according to the capability of the patients, or customize the difficulty level of the training exercise or the game according to the performance of the patients (Borghese, et al., 2013), (Ding, et al., 2013), (Pastor, et al., 2012), (Chen, et al., 2010), (Duff, et al., 2010), (Szturm, et al., 2008), (Johnson, et al., 2007), (Nef, et al., 2005).

Collaborative filtering methods operate with a large amount of information concerning users' behaviors, activities or preferences and, based on their similarity to other users, make predictions on what users will like. A benefit of the collaborative filtering method is that it is capable to accurately recommend content and items without requiring a model of the content itself. Algorithms such a k-nearest neighbor or Pearson Correlation has been used to measure user similarity or item similarity in recommender systems. The use of collaborative filtering methods in the domain of stroke rehabilitation, however, raises many issues (Li, et al., 2013). It is rather difficult, if not impossible, to collect reliable information about the preferences of patients concerning particular rehabilitation programs. The reason is that patients may have little or no experience with rehabilitation exercises until they undergo the treatment. Choosing of therapy based on the earlier experiences cannot be based on the preferences or activities of patients.

Content-based filtering methods use data collected or modelled based on (i) content (e.g. learning material, therapeutic training) or items (e.g. products) and (ii) a profile of the user's preference (Aher, et al., 2013). In a content-based recommender system, keywords are used to describe the items and a user profile is built to indicate the type of item this user likes. In other words, these algorithms try to recommend items that are similar to those that a user liked in the past (or is examining in the present). Content-based filtering has been used to maintain long term user engagement in stroke therapeutic programs and to offer personalized therapies. However, recommendations and system adaptations during rehabilitation and for enhancing short term engagement is still an unresolved research challenge.

Ant colony optimization (ACO) is a metaheuristic technique that operates with a set of software agents, called artificial ants, to search for sufficient solutions to a given optimization problem (Yang and Wu., 2009). The optimization problem is transformed into a path search problem on a weighted graph. The ants (i.e. agents) explore possible paths by moving on the graph and gradually construct a stochastic solution influenced by the pheromones (i.e. weights of the nodes or edges of the graph). Krynicki, et al., (2016) have developed an evolutionary algorithm, which extends ACO with three important features to be utilized in recommending personalized long term rehabilitation programs for people with brain injury. Their algorithm (i) takes into account the state of the individuals to drive the optimization search, (ii) dynamically adapt the recommendation according to the recent behavior of individual user or a group of users with similar characteristics, and (iii) models the cognitive state of the user as the set of deficits (deductive reasoning, sustained attention, short-term memory, etc.). Their solution offers a hybrid model for personalizing possible routes through the rehabilitation program, which found to be effective in composition of personalized programs, but enhancement of engagement on exercise levels is not addressed. Until the publication of this thesis there were no attempts reported in the literature that have managed to transform the problem of engagement enhancement to a search problem of a weighted graphs.

Particle swarm optimization (PSO) is a population-based metaheuristics technique used for stimulating social behavior. PSO is a subset of swarm intelligence developed in the late 1980s in the context of cooperating cellular robotic systems. It applies a number of agents in an environment interact based on local rules. Liu, et al., (2015) has developed a new student engagement measurement algorithm based on PSO technique to find the optimized parameters for the engagement measurement algorithm. In their study, the proposed algorithm measures the engagement of two groups of students in two different writing activities (long-term and short term writing activities) carried out in our cloud-based writing platform. The system uses parameters of writing time to monitor social, behavior and emotional engagement and uses PSO to predict how people will be engaged in writing in the future with writing. Similar to ant colony optimization, this method also requires transforming the engagement enhancement problem to an optimization problem, which is rather difficult to formulate on an individual basis. Although some users' behavior can be modelled, other users do not exhibit typical behavior. These users can skew the results of a recommender system and decrease its efficiency. Furthermore, users can exploit a recommender system to favor one product over another, based on positive feedback on a product and negative feedback on competitive products, for example. A good recommender system for engagement must manage these issues.

Few studies have been conducted to address personalized treatment in other relevant aspects, such as cognitive, perceptive, and emotional. Alankus, et al., (2010) developed customizable games for stroke rehabilitation, in which cognitive and motor challenges can be adjusted by physical therapists. In a case study, they found one stroke patients recovered significant motor abilities training with customizable games for six weeks (Alankus, et al., 2011). This system personalized the cognitive aspects during rehabilitation, which has been shown to be beneficial for the motor recovery, but they did not evaluate the patient’s engagement in the study. Tam et al. developed tele-cognitive rehabilitation program which can be customized to patient’s functional levels and living environment. Specifically, the software can customize immediate visual, auditory and personalized feedback to motivate the client. Three persons with brain injury showed improving trends and levels of specific cognitive performance during the treatment phase (Tam, et al., 2003). This system customized the perceptive feedback in the study, but they failed to demonstrate if this customization actually enhanced the patient's engagement.

2.4.3 Cyber-physically supporting systems for enhancing engagement

Our literature study informed as that the rapidly emerging and proliferating field of cyber-physically supporting rehabilitation systems provides opportunities for: (i) self-adaptive personalized treatment, (ii) monitoring and evaluation of engagement, (iii) creating synergy between real life cyber and physical processes. From the above studies, we concluded that most of the current personalized treatments only consider the patient's motor capability or performance. But perceptive, cognitive, and emotional factors also influence engagement – a fact implies that comprehensive personalization methods are needed in rehabilitation.

Cyber-physical rehabilitation systems (CPRS) has the potential to address personalization in rehabilitation training (Bideaux et al., 2014) using autonomous problem solving strategies and situational learning. CPRS is able to activate parts of the rehabilitation system to provide adaptive solutions. In the context of rehabilitation, based on the patient's capability monitored by the system, CPRS can provide adaptive training protocol to each patient. For instance, CPRS can provide assistance as needed for the patient not only in completing motor tasks but also in perceptive and cognitive training. It can adjust the level of assistance or even resistance for more advanced patients. Additionally, learning mechanism in CPRS can monitor the skill development and the performance of the patients in different situations and context, and enable the system to solve the problem automatically based on situational reasoning. This affordance of CPRSs can help to achieve personalized training by applying suitable treatment that has been proven to be more effective.

Monitoring and medical status evaluation by CPRSs raised the research interests of both rehabilitation experts and CPS developers (Yang, 2008) (Wang, 2012). For instance, their use is widely proliferating in monitoring the patients' status in applications as well as in homecare environments (Annese & Venuto, 2015) (Prittopaul, 2015) (Zhang, 2015). More specifically, Bidaux, et al. have developed a CPS system to monitor brain seizure of epileptic patients. Their system is reconfigurable to accommodate the needs of monitoring according to the type of epilepsy, different brain and body parameters, and length of assessment. The different monitoring parameters used for multi-parametric analysis included ECG, GSR, multichannel EEG and physical activity sensor (acceleration sensors), and sensors providing context information about the measurement conditions and the patient's environment.

HealthMote is a remote elderly monitoring CPS system developed by Dagale, et al., (2015). It can be remotely configured for periodic data acquisition and time period for which the data are to be sensed. The HealthMote communicates data retrieved from several biosensors, e.g. IMEC ECG module, over Bluetooth and BPL SPO2 sensor using on-board analog front-end. The system is capable of doing real time remote analysis of biometric data and is embedded into a Hospital Management System. Cloud-supported cyber-physical localization system proposed by Hossain, M.S, (2015) facilitates the seamless integration of devices in the physical world (e.g., sensors, cameras, microphones, speakers, and GPS devices) with cyberspace. This CPS supports patient monitoring using smartphones and acquiring voice and electroencephalogram signals in a scalable, real-time, and efficient manner. As demonstrated by the examples above, CPSs offers mechanisms for data fusion, which enables real time processing of several bio signals and reasoning with processed information about the patient's status, well-being and engagement. CPRSs can be used in rehabilitation to monitor the patient's engagement state during rehabilitation training, if reliable indicators of all aspects of engagement can be identified.

It is not only known, but also has been proven by researchers that CPSs create synergy between cyber and physical processes (Horváth and Gerritsen, 2012). In this context synergy means, on the one hand, architectural and functional holism, on the other hand, demolishing the demarcation between the physical hardware (both analogue and digital), the digital software (control, middleware, application programs), and the cyberware contents (media, data/info, codified knowledge, concept ontologies, learnt agency). Model-based design has been identified in as a driver for enhanced synergy of CPS (Jensen, J.C., et al., 2011). Model-based design and model-based development (application implementation) automates the mapping from one representation into the next, and as such reduces interpretation errors (Karsai, G., & Sztipanovits, J., 2008). Furthermore, modelling can generally be shifted to the higher level primitives. Incidental designer errors can be trapped by comparing the two levels through forward and backward chaining based on the model. However, model-based design is not sufficient for developing personalized cyber physical rehabilitation systems, as the individual needs of the users are not predictable at design time (Derler, P., et al., 2012). Extending model-based design with data driven reasoning methods is a promising approach, which aims to utilize information collected about the user and the context of use at run time. The synergy of formal modelling and data driven modelling, nevertheless, needs to be addressed at both design and development time in order to assure reliable model adaptations and responses to contextual information (Lee, I., & Sokolsky, O., 2010).

Collecting information about the user and context requires approaches capable to handle issues of data fusion, such as signal and data synchronization, reasoning with real time data, and handling of data consistency (Lee, I., et al., 2012). Monitoring of engagement typically requires synergetic integration of biometric devices measuring indicators of engagement. These devices may operate at different sample rates and with different computational latencies, and may use different signal processing methods (Lim, et al., 2011). On the other hand, data produced from different sources representing the same indicators of engagement can show inconsistencies for the reasoning mechanisms (Ma, et al., 2011). These issues can be overcome by relying on service oriented development principles of CPSs, as reported in

(La, H.J., & Kim, S.D., 2010). Cyber-physical systems offer many opportunities for run time learning and development of various stimulation strategies. Below, we provide an overview of the related concerns.

2.4.4 Stimulation strategies for motor engagement

Stimulation of patients during rehabilitation should be harmonized with the process of human activities and personal profiles (such as personality and interest, but also with the physiological and mental well-being of patients). This requires the implementation of smart CPSs capable to classify user activities and create profiles of patients. On the other hand, stimulation approaches improving specific aspects of engagement needs to be combined into synergetic stimulation strategies in order to overcome possibility of the cancelling effect of their combinations. This requires the development of learning mechanisms capable to explore how the combination of stimulation strategies in order to have more intense effect on the engagement of individuals. There are two issues to expose here: (i) training natural movements that cover full motion envelop, and (ii) adaptive training protocol that remains challenging for the patients.

Concerning the first issue, it is known that one of the major limitations of current robot assisted rehabilitation training methods that engagement of motor functions is not able to offer adaptive assistance for training of fine motoric movements and natural motion patterns. The range of motion envelop, the capability of performing natural movement, as well as the level of motor assistance are influenced by factors of learning and skill development of patients. There are no devices that would be able to offer assistance for full range of motion of the hand, which would enable the training of grasping functions that are the most important motor functions of independent daily living. Instead of focusing on training the strength of the muscles as current devices do, cyber-physically assisted motor training should focus on the training of hand function and coordination of all the muscles of the affected limb.

Concerning the second issue, active participation in robot assisted motor training has been shown to lead to faster recovery of motor functions. One of the limitations of current rehabilitation systems is that they are not able to exploit the patients' full potentials in motor training. Cyber-physical solutions could offer remedy for this problem by monitoring active participation and the effort of patients during therapy, measuring the capabilities and skill development of patients, and automatically adapting their rehabilitation programs to maintain or enhance engagement and the level of assistance offered during exercises. Consequently, model driven control of robot assistance should be extended with data driven control. This makes the systems capable to learn from the history of exercises and performances of patients with similar profile and offer adaptive control strategies to robot assisted training. The future systems of cyber physical rehabilitation will be intervening inactive participation and stimulate patients to make bigger effort.

2.4.5 Stimulation strategies for perceptive engagement

One expectation toward cyber-physical rehabilitation systems is to provide functional feedback that makes the patients aware of the training exercise. Stroke patients have typically deficits in their sensory-motor and cognitive functions, and as a result their ability to control voluntary and involuntary movement is limited. Our literature study has shown that feedback on the functional capabilities of the patients and their performance of exercises has a positive influence in the execution of rehabilitation training program. This implies that methods and systems should be developed that are able to inform the patients about their motor function abilities (i.e. position, motion of and forces exerted by their affected limb), cognitive abilities, and perceptive abilities, as well as the stage of recovery. However, the currently used methods and measures for assessing patient capabilities (Fugl-Meyer, Brunstrom, etc.) were developed for medical assessment by therapists and require assistance of medical personnel. They are limited to measure long term developments. In conclusions, functional feedback on the capabilities of patients requires methods that are able to measure both short and long term development and provide feedback that is meaningful for patients.

Another opportunity of using CPSs in rehabilitation is generating an immersive environment with multisensory feedback. The current robotics-based rehabilitation systems are still limited in providing the patients with a fully immersive training environment. As discussed above, cyber-physical augmentation can go beyond the capabilities of existing augmented reality and VR technologies by deeply penetrating the physical processes of daily activities and connecting it to mental world and capabilities of the patients. For example, sensory deficiencies of patients may be compensated by extra stimulation of other senses using technologies developed for VR (visual, auditory, tactile, olfactory, and even gustatory sensors). CPSs may provide strategies for adaptive stimulation of various senses of patients based on information collected from sensors of smart environments, patient performance measures and monitoring of and learning from reactions of patients to various stimulations. The realization of this scenario, however, needs to rely on the real time information processing capability of cyber physical systems. Training of patients for daily activities with cyber physical augmentation has potential impact on engaging and motivating the patients in a deeper level, and stimulating larger part in the central nervous system leading to a faster recovery.

2.4.6 Stimulation strategies for cognitive engagement

While gamification has become the de facto standard of cognitive interaction with patients in therapeutic treatments, serious games are not the only and exclusive cognitive tasks that cyber-physical systems can get them involved in. The latest trends of gamification of training exercises have demonstrated the potential of combining cognitive and motor exercises. The wider integration of various modalities offered by CPSs can also result in strong stimulating experiences. This opportunity is strongly needed because in the current rehabilitation practice, cognitive and motor exercises are handled separately. Cognitive games extended with kinetic interfaces and kinetic games extended with cognitive elements have been developed to create multimodal engagement for patients. Despite the initial successes in medical experiments, proliferation of these solutions is not happening due to high development costs and the need for smart systems. CPS-based generic kinetic interfaces combined with learning mechanisms are capable to reconfigure the interaction with the games according to the need of patients and may overcome the abovementioned problems. Likewise, self-reconfigurable generic interfaces can adapt themselves to the profile of patients, content and settings of the games and actual engagement level.

2.4.7 Stimulation strategies for emotional engagement

Though the role of emotional and habitual engagement is often discussed in the literature, the methodology of managing and controlling it in exposure therapies seem to be stepchild of researchers (Andersson, S., et al., 1999). For instance, what works in the context of learning, i.e. identification with school and a sense of school belonging (Wang, M.T., & Eccles, J.S., 2012), cannot be transferred directly to the domain of medical rehabilitation. On the other hand, the proposed new definitions for emotional engagement as “the amount of subconscious 'feeling' that is independent of attention or do not require high levels of attention are also not working with impaired (Heath, R., 2009). In the context of robotics assisted rehabilitation it has been argued that the effective outcomes depend on the people's emotional engagement with robots (Choi, J.J., et al., 2004). In the context of neurorehabilitation it was found that key concerns are such as the patient's emotional engagement with his or her problems and potential goals, and harnessing patients' intrinsic motivation to change (van den Broek, M.D., 2005). Cyber-physical systems may apply high level person-adapted control to each patient individually and bring together multiple patients in social set-ups. This way, they are able to replace game-entailed ‘competition’ into cooperation, ‘training program’ into social coaching. Under person-adapted control, even competitive training among the patients, or “rehabilitation match”, is imaginable, which can engage the patients to exploit their fullest potential. Since cyber physical systems may manifest as a distributed and decentralized multi-user system, the patients can do the same exercise at the same time in order to cooperate with each other to complete a task. Cooperation with the other patients and interaction with the system may have the potential to emotionally engage the patients into the status of flow.

2.5. Concluding comments

Our major finding in this chapter is that there are tremendous opportunities for utilizing CPS to enhance engagement during rehabilitation. According to the literature review, there are mainly three limitations in the current engagement enhancing approaches, namely: (i) they typically consider only one form of engagement of the four identified forms (motor, perceptive, cognitive, and emotional), (ii) there is no reliable solution to engage the patients because the current rehabilitation systems fail to deliver a fully personalized training, and (iii) no quantitative measurement of engagement is available in the current rehabilitation practice. Since CPSs offer the affordances of multi-sensor networking, generation of problem solving strategies, conducting situational learning, and synergistic coupling cyber and physical processes, they have the potential to improve the efficacy of rehabilitation based on personalized enhancement of engagement. A CPRS can offer comprehensive personalized rehabilitation therapies by monitoring the patient's engagement status, and applying dedicated stimulation strategies to maintain short engagement during rehabilitation. Utilizing self-adaptation and self-learning principles of CPS, the effect of stimulation strategies can be learned by the systems enabling personalization of stimulation and adaptation of system environment and therapy settings. In order to create a robust knowledge platform for the research work and conceptualization of the kernel elements of a CPRS, the finding of this first research cycle will be blended with the findings of the second research cycle at the end of the next chapter.

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CHAPTER THREE

RESEARCH CYCLE 2:

Experimental investigation of current limitations of enhancing engagement in practice

3.1 Objective and methodological frame of research cycle 2

Based on the survey in Chapter 2, gamification of rehabilitation is a proliferating approach of robot assisted stroke rehabilitation. One of the objectives of this chapter was to understand the limitations of current engagement enhancing methods in practice. To this end, an upper limb rehabilitation robot integrated with video games was designed and developed. Another objective was to understand which gamification method and factors make the video game exercise engaging. Therefore, three exercises were conducted and the measure of engagement of the participants during each exercise was compared. The three exercises were: (i) a video game exercise, (ii) a tracking exercise, and (iii) a traditional exercise. First, this chapter introduces the development of the robot and the user interface used for enabling gamification. Then, the conduct of the experiment and data analyses is demonstrated.

Design inclusive research was applied in this research cycle (Horváth, 2007). In the phase of explorative research actions, the method of gamification was introduced from Chapter 2 as input for this chapter. In order to conduct the video game exercise, a prototype of an upper limb rehabilitation robot integrated with video games was designed and developed. In the phase of creative design actions, an empirical study, which compared the engagement during different exercises, was designed and used as a research means to investigate the causalities of the factors on engagement. In the phase of confirmative research actions, the results from the experiment were generalized as consolidated knowledge.

3.2 Design and implementation of a research means: An upper limb rehabilitation robot integrated with video game

3.2.1 Overview of the upper limb rehabilitation robot

Our starting point at designing the upper limb rehabilitation robot was that training of natural movements, which covers the full motion envelop and mimics the activities of daily living, is effective in stimulation of the motor activities. Therefore, the robot was designed with the intention to focus on training both large movements of shoulder, elbow, and the wrist, and the fine movements of the fingers. According to the current standard, gamification has been considered for enhancement of engagement. In order to integrate video games into training exercises, the rehabilitation robot should be extended with a user interface, which enables interactive human-computer interaction during the exercises.

The robot subsystem is shown in Figure 3.1 (a) It consists of the platform, two parallel robotic arms, one computer, two servo motors (MAXON RE50, with encoder HEDL 5540, 500 CPT), two controllers, and three screens. The parallel robotic arms are fixed on the platform, in which a horizontal screen is also embedded. The embedded screen and the vertical screen installed on the platform give visual feedback to the patients. The third screen is used by the physical therapist to control the system. The two servo motors, fixed under the platform, drive the robotic arm in the passive mode of the robot.

a

b

Figure 3.1 a. Upper limb rehabilitation robot based on parallel robotic arms b. Elbow tray used in passive mode

We have implemented both passive and active mode for the upper limb rehabilitation robot. In passive mode, the movements of patients are generated by the electric motors of the robotic arms. This enables rehabilitation of acute or sub-acute stroke patients, whose motor control ability of the shoulder and elbow in the impaired limb need active robotic assistance. In the active mode, the patient is supposed to generate the motions and the two motors only record the position. A shown in Figure 3.2, there are two slide rails, two sliders, and one rod (fixed with one of the sliders) in each arm. The redundant degrees of freedom provide the structure with flexibility. This mechanical structure helps the patients move the handle grip precisely in the active mode, according to their will. As discussed in Chapter 1, the literature advised us that passive movements are insufficient to achieve motor recovery (Lynch et al., 2005), and that active engagement and movement attempts are essential to acquire the beneficial effects of robotic rehabilitation (Hogan, et al., 2006), (Krebs, et al., 2009) and (Cauraugh, et al., 2010). Therefore, active mode integrated with video game exercise is used in this study.

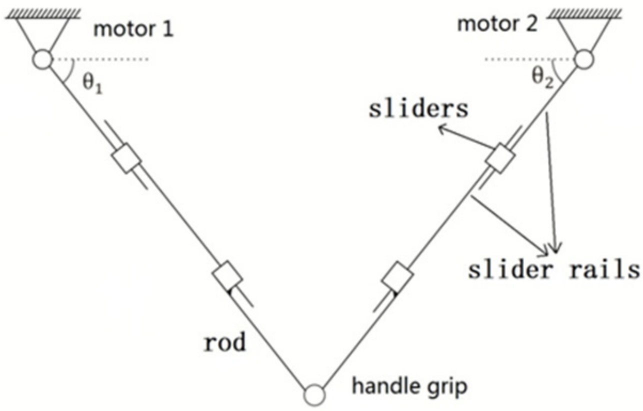


Figure 3.2 Mechanical structure of the parallel robotic arms

To provide static support for the impaired arm, a tray for the elbow is used in the passive mode, as shown in Figure 3.1 (b). In the active mode, the stroke patients, who already have fairly good motor control ability at the shoulder and elbow, move voluntarily. In this case, as mentioned above, the electric motors only record the position of the handle grip of the rehabilitation robot. The active mode makes it possible for the patients to interact with the video game that is displayed in the screens in front of them. The exercise requires the patient to move the handle grip with their impaired limb to certain points and to trigger mouse events by different grasping postures as required by the task of the game. The following part focuses on introducing the active mode integrated with gamification.

3.2.2 Principle of the user interface

To integrate motor training with video games, the upper limb rehabilitation robot subsystem needs an effective, efficient, and easily learnable human-computer interface. In addition to making possible for the patient to play video games, it should also support engagement of the patient. In the development of the user interface for the stroke patient rehabilitation system, three challenges had to be addressed.

1) In the context of the fine movements of the fingers, the first challenge was to develop an interface that enables the users to perform different types of grasping tasks.

2) The second challenge was to implement a human-machine physical interface that enables the system to understand which part of the interaction can improve engagement in a particular exercise.

3) Finally, the third challenge was to develop a protocol for adaptive training of different types of grasping, and applying grasping forces of different magnitudes, which is

personalized to each patient.

The relationships between these challenges are represented graphically in Figure 3.3. The principles of finding solutions to the challenges are as follows:

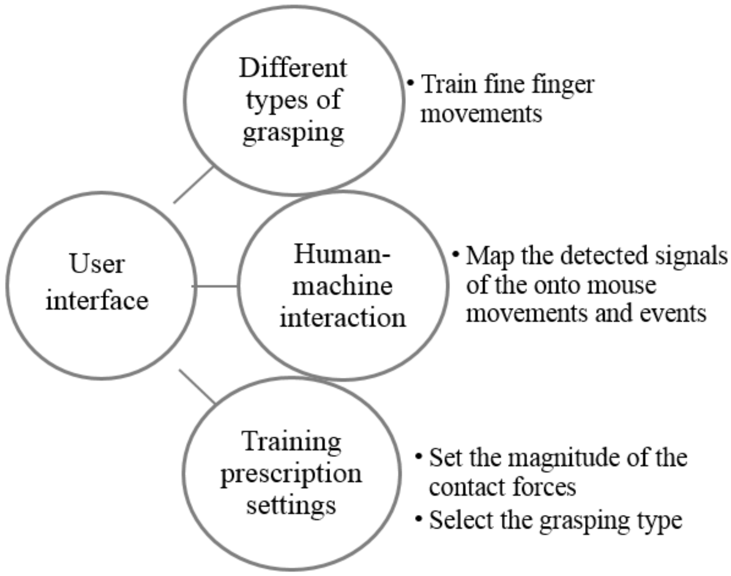


Figure 3.3 Challenges of building the robotic rehabilitation user interface

1) The goal of the interface is to facilitate training fine finger movements. Therefore, what these fine movements exactly are had to be defined first. Cutcosky, et al. (1989), distinguished power grasping and precision grasping as means of manipulating objects in daily activities; Humans typically make a decision on the actual type of grasping based on the combined evaluation of task-oriented and geometric considerations concerning the task at hand; If the object must be clamped, then some basic geometric considerations and the purposes are the most important factors to determine the posture of grasping. Our system concept implements five different types of rehabilitation exercises as presented in Table 3.1. These five grasping postures enable the users to execute meaningful rehabilitation exercises in realistic daily life circumstances. A list of possible video games is given in the second column of Table 3.1 facilitating the practice of specific grasping

Table 3.1 Posture-sensor data mapping table

Posture/ Sensor	Sphere top	Sphere left	Sphere right	Cylinder left	Cylinder right	Flat left	Flat right
Object pick up						Pressed	Pressed
Heavy grasping	Pressed	Pressed	Pressed				
Gripping				Pressed	Pressed		
Finger extension	Pressed	Touche d-Release d	Touche d-Release d				
Lateral pinching small						Pressed	Pressed
Lateral pinching large						Pressed	Pressed

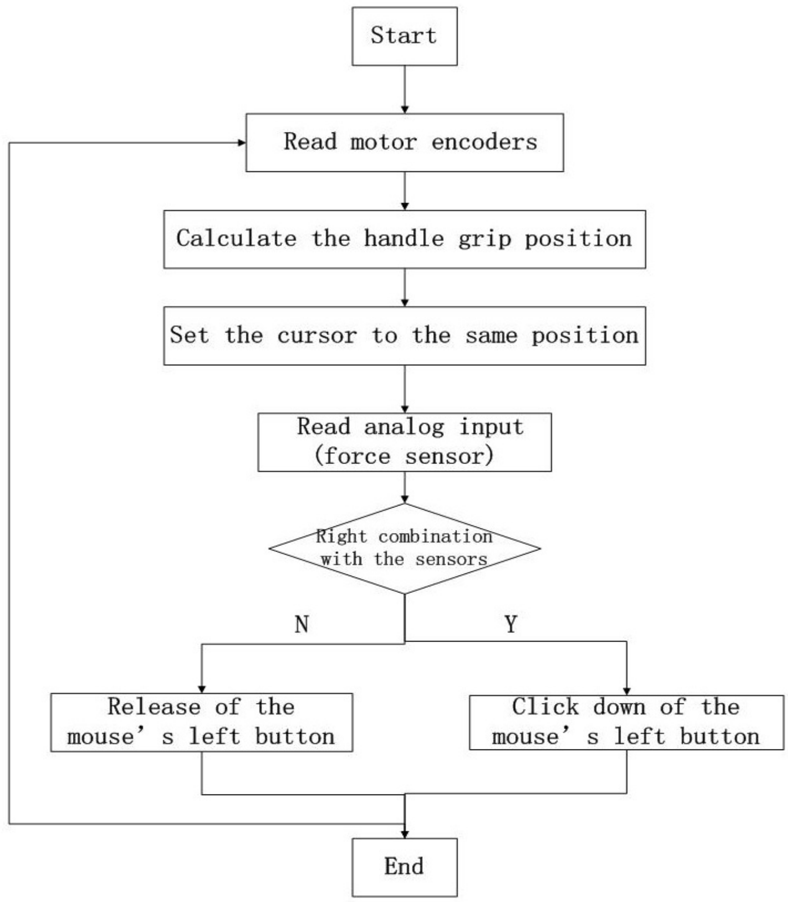
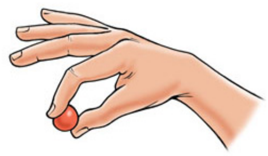
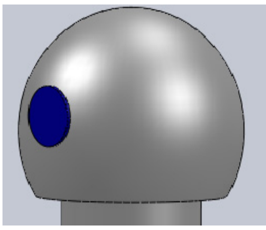
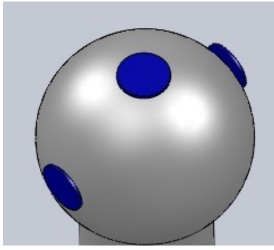
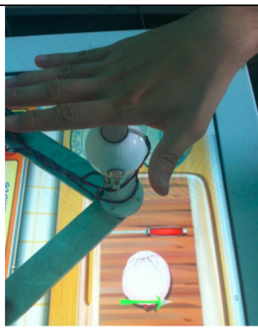
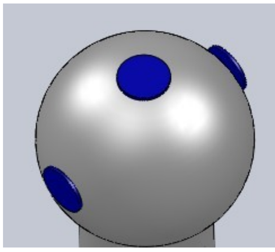
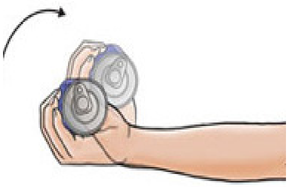
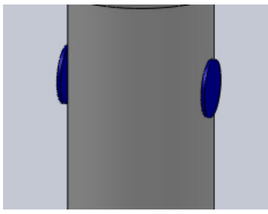
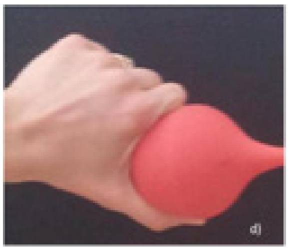
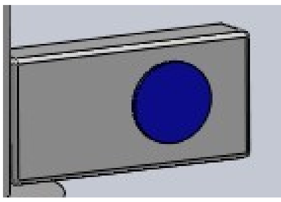


Figure 3.4 Flow chart of the algorithm of the system software

postures in realistic context. The fourth column illustrates how the pressure sensors are placed on the grasping interface in order to be able to detect the posture and strength of grasping. We use Force Sensing Resistors (FlexiForce A401, force range: 0-110N, thickness: 0.208 mm, sensing area: 25.4 mm diameter), which can be attached to different parts of the handle grip flexibly, for the detecting contact and measure the contact forces between the hand of the user and the handle grip.

2) The second challenge was to develop software for enabling natural human–machine interaction for rehabilitation exercises. In order to integrate the hardware interface with video games, we had to map the detected signals of the pressure sensors of the handle grip and angle sensors of the robotic arms onto mouse movements and events. The flow chart of the algorithm of the software is shown in Figure 3.4. In the first step, the cursor of the system is supposed to move as the handle grip moves. This means that the system has to track the position of the handle grip and compute the X and Y coordinate of the cursor based on the actual position of the handle grip. The tracking of the position of handle grip is achieved by using angular position sensors of the electric motor of the robotic arm. In the second step, the system also has to recognize which part of the handle grip is engaged for a particular rehabilitation exercise.

Table 3.2 Different types of training exercises with fingers

Rehabilitation exercise	Video game	Grasping posture	Sensor data
	Picking up small ingredients		
	Grasping an apple, throwing a ball		
	Quiz button, (pushing down a large red button.)		
	Gear shift in a car		
	Using a knife		

To detect that the user is using the appropriate part of the interface and applies to proper grasping posture a mapping algorithm has been developed that recognizes grasping postures based on pressure sensors' signals.

Table 3.2 summarizes the principle of this mapping algorithm. The algorithm reads the analog input of all force sensors, and if signals indicate the right combination with the expected grasping posture, then it proceeds to the next step. To implement this mapping, we have adapted the principle of grasping posture recognition proposed by Rusák, Z. et al. (2010). In their paper, they proposed a new principle to control contact forces and to determine the grasping posture during human-virtual object interaction in virtual reality environments. They used the penetration of a virtual hand into a virtual object as virtual sensor data in order to determine the applied grasping posture based on the distribution of contact patches on the hand.

We have adapted this principle to a real environment by replacing the virtual sensors data by real sensor data. In the last step, the algorithm processes the signals of pressure sensors to compute the magnitude of the grasping forces. The threshold of each force sensor is set in the program in advance. If the force exerted by the patients is higher than this threshold value, which means the finger movement has met the demand, then the system triggers a mouse event expected by the video game.

3) The third challenge was to offer personalized training which is adaptive according to the game tasks and patient's capabilities. The proposed interface enables rehabilitation therapists to select online and offline games for exercising a specific rehabilitation tasks, set the magnitude of the contact forces for the handle grip according to the patient's capability. Ideally, we want to realize a system that could detect the shape and weight of the object used in the games and the recovery level of patients, and automatically set the type of required grasping posture and magnitude of forces. Specifically, the system is supposed to set which part of the interface is engaged and the threshold value of the force sensors according to the shape and weight of the object displayed in the game. For instance, if the object in the game is long and thin, like a pencil, then a small force is required to exert on the lateral pinching part. The system is also supposed to monitor how the patients perform in the training exercise and record their training parameters, such as the magnitude of the force that the patient exerts, the speed and distance that the patient moves, and the time that the patient completes the tasks. Then the system can automatically analyze the gathered data and evaluate the performance of the patient. If the patient finishes the tasks smoothly, the system is expected to make the video game harder in order to develop the patient's potentials. But this self-adaptive capability of the system is not our focus. Therefore, we use adaptable user interface, which means the physical therapist can set the magnitude of the contact forces for the handle grip and select the

grasping type.

3.2.3 Implementation of the user interface

1) Design of handle grip

For different game tasks, patients are required to use different ways of grasping to mimic activities of daily living. For instance, in an online cooking game shown in Figure 3.5, the users are supposed to grasp and move several ingredients and a knife in the screen. Players have to put the correct ingredients in the right order into a bowl

Figure 3.5 Cooking game: Kebab Make

to complete the game task. For grasping the onions, the patients are required to grasp the sphere of the handle grip and exert the proper level of force to pick up and hold the onion and move it to the cutting board. To chop the onion, they have to pick up the knife using the lateral pinching part of the interface of the handle grip. The design of the universal handle is shown in Figure 3.6, which is rotatable to the robotic arm. For the haptic interface, we use the Force Sensing Resistor as the force sensor, and use Arduino (Mega 2560) to read the analog input of the sensors.

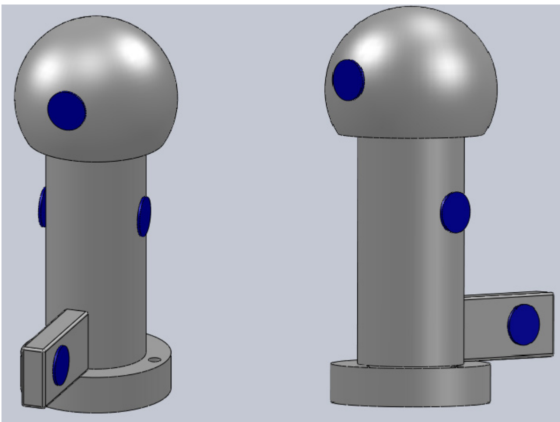


Figure 3.6 Sketch map of the universal handle grip (force sensors are shown as blue parts)

2) Control design

Since the handle grip moves above one of the displays of the rehabilitation device, it offers a platform for almost direct interaction with virtual objects. To track the position of the handle grip on the display, we use the motor encoders to read the angles the motors rotate, θ_1 and θ_2, as shown in the Figure 3.7. We compute the coordinates of the handle grip based on Equation 1.

$$\begin{cases} x = \frac{800}{\sin(\theta_1+\theta_2)} \times \sin\theta_2 \times \cos\theta_1 - 50 \\ y = 400 - (\frac{800}{\sin(\theta_1+\theta_2)} \times \sin\theta_2 \times \sin\theta_1 - 225) \end{cases} \quad (1)$$

The position of the cursor is computed based on the physical dimension of the screen and the applied resolution. Once the cursor's position is determined it can be moved to the same location as the handle grip.

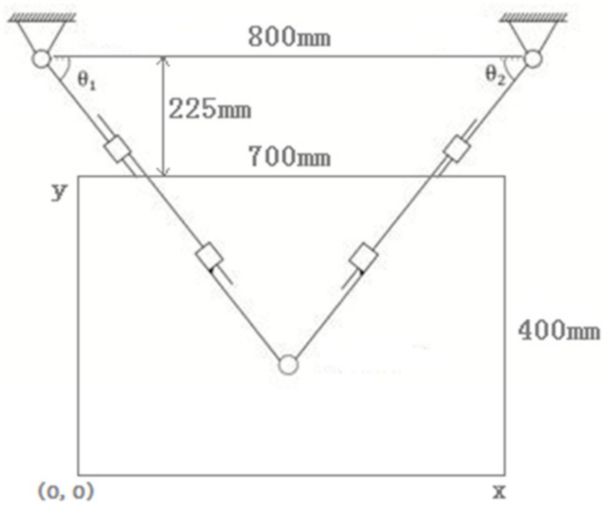


Figure 3.7 Handle grip in the geometry coordinate

The control of the hardware has been implemented in Labview. The control algorithm is shown in Figure 3.4. First the algorithm read analog inputs of those force sensors that are engaged by the user. It detects if the user is applying the expected posture for the rehabilitation exercise. If the force by the hand is higher than the threshold value of all the sensors engaged, it acts a click down of the left button of the mouse. If the force is higher than the value continuously, then it acts a drag of the mouse. It acts a release of the left button of the mouse if the force is lower. In this way the patients can manipulate the computer via this interface.

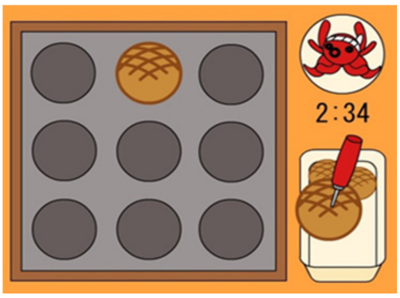
3.2.4 Rehabilitation exercise with video games

This section presents some illustrative examples that enable users to complete their rehabilitation program by playing video games. When this robot is used for delivering therapy integrated with games to the patients, in the first step, physical therapist should set the game settings for the patient. First, a proper game can be selected for the patient. Then the therapist should analyze the type of objects to be grasped in the game and set the expected threshold values for grasping. Next, the physical therapist should help the patient sit in the chair and grasp the handle grip, which is supposed to fix the upper body of the patient because the patient should not move his or her body to complete the task. After these preparatory steps, the physical therapists can run the program and patient can start the motor training exercises. The stroke patients are required to use their fingers to press the right combination of the force sensors according to the task instructed by the physical therapist.

Any online and offline games, that can be controlled by a computer mouse, can be used for rehabilitation exercise. Table 3.3 presents some relevant examples representing daily life activities designed for children to be played on the Internet. As illustrated in Figure 3.5, a cooking game requires the patients to manipulate ingredients and kitchen ware in a virtual environment. As a result, the patients has to apply many kinds of arm-movements, such as humeral adduction, internal rotation, elbow flexion, forearm pronation, and wrist and finger flexion, all of which also needed in the activities of daily life. While playing the games, the patients' functional abilities are trained.

The difficulty of the rehabilitation system integrated with video games can be easily increased to develop the patients' potential. For example, if the pictures of the game on the screen become larger, patients need to move the handle grip to reach further on the screen. Another method is that the threshold value of the force sensor can be increased according to the performance of the patient, so that it will demand larger force from the hand. Thus the potentials of the patients can be developed. Users can use different grasping postures to

Table 3.3 Rehabilitation delivered by different games

Games	Game task	Arm and finger movements
	Grasp the objects and use the knife to slice them. http://spele.nl/kebab-maken-spel/	Shoulder and elbow movement; Grip strengthening; Lateral pinch;
	Keep pressing the force sensor and move the handle grip to track the task path. http://spele.nl/cook-show-buffalo-spel/	Shoulder and elbow movement; Wrist flexion; Grip the handle cylinder to simulate stirring materials.
	Put the raw material on the oven, after the cake is done, move it to the plate. http://spele.nl/poffertjes-spel/	Shoulder and elbow movement; Object picking up;
	Select the proper ball and make it into the bag. http://spele.nl/snooker-2-spel/	Shoulder and elbow movement; Finger extension (press the force sensor to use the proper force to hit the ball.)

manipulate the robot. For instance, they may grasp the cylinder or the ball on the top of the handle grip using two or three fingers. Different grasping posture will exercise different muscles of the hand, wrist and the forearm. Consequently, several ways of grasping in the daily life can be simulated by playing the video games, in which the functional abilities of the patients will be retrained.

3.3 Conduct of the experiment

3.3.1 Experiment protocol

In Chapter 2, the factors for therapeutic engagement have been identified in the four aspects, namely, motor, perceptive, cognitive, and emotional. One objective of this experiment was to investigate which factors in gamification can increase engagement of the participants compared to other exercises, such as tracking exercise and traditional exercise, which were different in addressing the factors. One limitation we found in this field is that there is no quantitative method to evaluate the level of engagement. Another objective of this experiment was to identify the relationship between the engagement level and muscle activities with the aim of identifying indicators to represent engagement in a quantitative way. The considered adjustable parameters were: (i) versatility of motion, (ii) motion envelope, (iii) velocity of motion, (iv) versatility of feedback, (v) cognitive tasks, and (iv) competitiveness. In Table 3.4 the differences of the adjustable parameters of the factors that each exercise addresses are listed. The motion envelope and velocity of motion were analyzed using the motion characteristics. In the next section, the influence of different factors on engagement was analyzed.

1) Video game exercise

The upper limb rehabilitation robot was used for the video game exercise. In the video game exercise, the subject was required to complete the game tasks in the active mode (Figure 3.8). The subjects could choose a game between Air Hockey and Cooking Game. In the Air

Table 3.4 Parameters of the factors in different exercises

Aspects	Adjustable parameters of the potential factors	Video game exercise	Tracking exercise	Traditional exercise
Motor	Versatility of motion	Random	Regular	Regular
	Motion envelope	Analyzed by motion characteristics		
	Velocity of motion	Analyzed by motion characteristics		
Perceptive	Versatility of feedback	Interaction with video game	Continuous feedback	Discontinuous feedback
Cognitive	Cognitive tasks	Attention and problem solving	Attention and judgment	Attention
Emotional	Competiveness/challenge	Play against the computer	Track more precisely	None

Hockey, the subjects played against the computer. While in Cooking Game, the subjects were required to follow the game tasks and complete a dish in a fixed time. Completing the tasks not only required subjects' physical movement but also cognitive reactions, such as attention, understanding the tasks and solving the problems. Therefore, versatility of motion, versatility of feedback and tasks were changing, and it was also combined with the feature of competitiveness in this exercise.

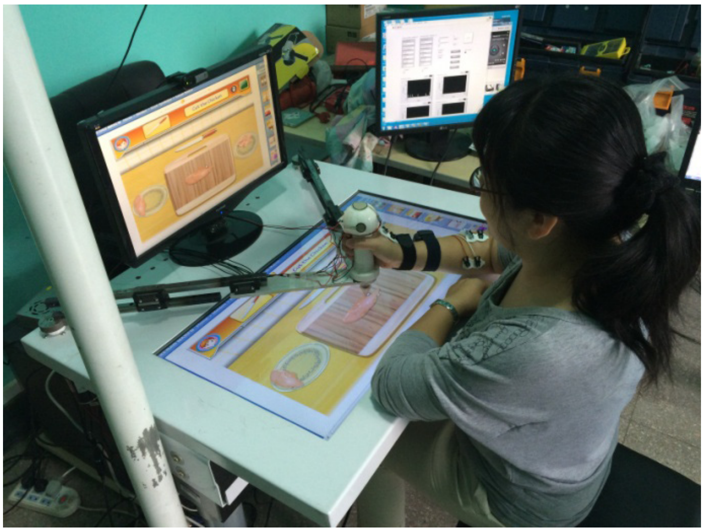


Figure 3.8 Video game exercise

2) Tracking exercise

During the tracking exercise (Figure 3.9), there was a circle shown on the screens. Then the subject was required to grasp and move the handle grip to follow the circle precisely. Since it was the same circle, versatility of motion was relatively regular in the tracking exercise. As for the versatility of feedback, the tracking exercise provided continuous feedback to the subjects with the position of the handle grip. The distance between the handle grip and the circle could make the subjects aware of the error so as to adjust their movement to follow the circle more precisely, which required attention and adjustment as cognitive activities. With regarding to the aspect of challenge, the subjects were required to track the circle precisely.

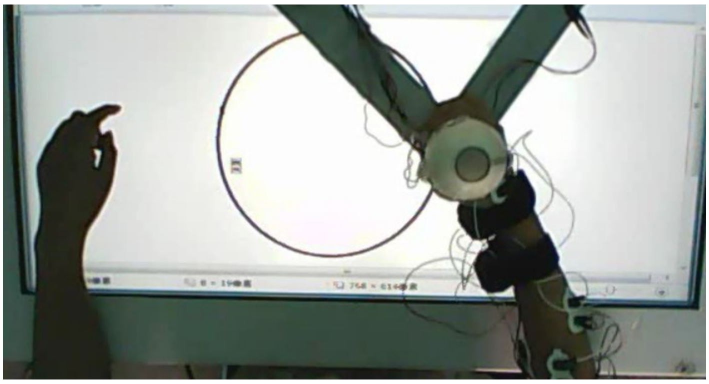


Figure 3.9 Tracking exercise

3) Traditional exercise

In traditional exercise the subject was required to grasp objects with

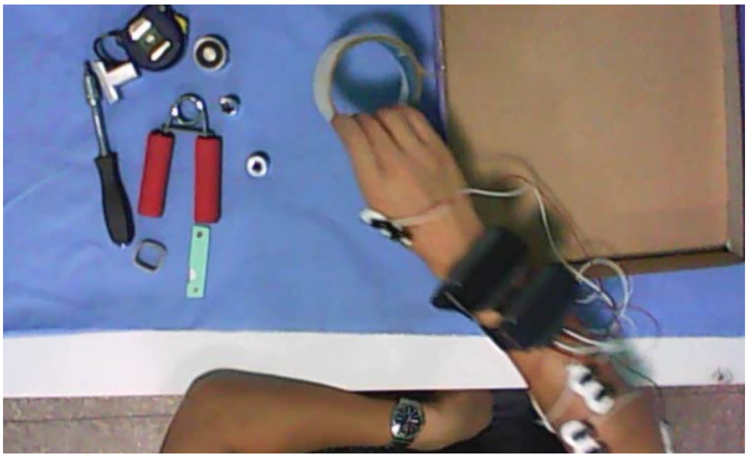


Figure 3.10 Traditional exercise

different shapes and masses and move into and out of the box, and repeat with this regular movement (Figure 3.10). Different from the other two exercises, the traditional exercise did not require the subjects' continuous attention. Because the subjects only needed to notice when grasping the object and putting the object, but the path of movement was not required so that no attention were needed from the subjects between the start position and the end position. That means the traditional exercise could only provide discontinuous feedback to the subjects and attention as cognitive task. There was no competiveness or challenge feature in this exercise.

3.3.2 Subjects and measurements

In this study, 15 healthy subjects, 8 men and 7 women, age between 23 and 55 (mean, 33.4±8.8y), were involved. We assume that the effects of factors on engagement are similar between healthy subjects and stroke survivors. In order to analyze the relationship between engagement level and muscle activities, during the experiment, EMG data on the arm was measured, which represented the muscle activities of the subjects. Several studies have been conducted to investigate the relationship between engagement and EMG. Most of these studies adopted facial EMG as indicator of arousal of engagement (Herbert, et al., 2006), (Schuurink, et al., 2008), (Murray & Goldfarb, 2015). However, in the context of rehabilitation, engagement in the motor aspect should represent how much effort the patient makes in the training tasks. Zimmerli, et al. (2013) used root mean square (RMS) of EMG from the legs to measure engagement during gait exercise in a virtual reality environment.

RMS is considered to be the most meaningful calculation of the amplitude of the EMG signal, since it gives a measure of the power of the signal. Since the amplitude of EMG is mainly correlated with movement velocity (Mustard and Lee, 1987), we have introduced the normalized EMG signal, which is defined as RMS of the EMG signal divided by the average velocity in window of 0.33 seconds. With this normalization step, the effect of the movement velocity was removed from the signal, which would otherwise alter EMG amplitude (Somasundaram, 1974), (US Department of Health and Human Services, 1992). For this analysis, data from the tracking exercise were used for the reason that the movements in this exercise were fairly the same. EMG signals were recorded from extensor carpi radialis longus, flexor carpi radialis, first dorsal interosseous muscle and extensor digitorum, in order to measure the level of activation of the muscles. EMG signals were sampled at 1000Hz, and filtered by a band pass filter at 20-500Hz and a band stop filter at 50 Hz.

Since there is no objective measurement to quantify engagement for each person, within subject design was used in this experiment. All subjects were required to complete three exercises with their right hands without stop, while the order of these three exercises was random for each subject. This is because engagement in different exercises could also be related with the sequence of the exercises. Each exercise lasted for 5 minutes. It has been

Table 3.5 Indicators for engagement based on facial expressions

Engagement level	Indicators
Engaged	Smile, focus on the exercise
Normal	Normal face, looking at the exercise
Bored	Dull, looking around or looking at the exercise but not concentrating, holding the chin with hand

shown that positive emotions, such as joy and surprise, are the signs of viewers' engagement in watching Internet video advertisements (Teixeira et al., 2012). So web cam was utilized to capture the facial expression of the subjects in order to evaluate the engagement level. The engagement level was identified according to different expressions of the subjects shown on the video. Three levels of engagement can be identified from the video, which were engaged level, normal level and bored level. The characteristics of each level were summarized in Table 3.5. In the normal level, the subjects did the exercise with a normal facial expression. When the subjects were engaged, it could be identified from their facial expression usually with smiles and they were more focused and concentrated their attention on the exercises. The subjects seemed to be more careful with the exercise than they were in the normal level. In the bored level, the subjects lost interests in the exercises, just repeated the tasks and looked around sometimes, usually with a dull expression on their faces. The time durations of the three engaged levels were manually counted based on off-line video analysis. However, there were small periods that were difficult to judge. Therefore, we introduced to transition levels when the subjects' facial expressions were between two levels.

We used another web cam fixed above the platform to record the arm movements of the subjects in order to monitor the motion characteristics. The motion analysis software, Tracker (https://www.cabrillo.edu/~dbrown/tracker/), was used to analyze the motion from the videos. Lastly, post event questionnaires were used to indicate the engagement level (Brockmyer, et al., 2009). This questionnaire was intended to measure the engagement in violent video game playing. As a result, some items in the questionnaires were adopted or deleted. For example, questions like "I feel scared", "I get wound up", "Things seem to happen automatically" and "playing seems automatic" were deleted from the questionnaire. Terms like "play" and "game" were changed to "do the exercise" and "exercise" respectively. Each subject was required to fill in this same questionnaire after each exercise. Some of the questions were categorized into different aspects in order to indicate the engagement in motor, perceptive, cognitive, and emotional aspect. There were three answers for each question, which were yes, maybe or not. Different answer resulted in different scores (Brockmyer, et al., 2009), then the total score was used to indicate the engagement level of the subjects during the exercise. The questions of the adopted questionnaires were listed in Table 3.6.

Table 3.6 Items and scores of the Engagement Questionnaire

Item		No	Maybe	Yes	Aspect
1	I lose track of time	-2.82	-1	0.82	
2	I feel different	-0.82	0.82	2.5	
3	The exercise feels real	-2	-0.32	1.32	Perceptive
4	If some talks to me, I do not hear them	-1.82	0	1.82	Perceptive
5	Time seem to kind of standstill or stop	-1	0.66	2.32	
6	I feel spaced out	-1.16	0.5	2.16	Emotional
7	I do not answer when some talks to me	-1.32	0.32	2	
8	I cannot tell that I am getting tired	-1.5	0.16	1.82	
9	My thoughts go fast	-2.16	-0.5	1.16	Cognitive
10	I lose track of where I am	0	1.66	3.32	
11	I do the exercise without thinking about how to do it	-2	-0.5	1.16	Cognitive
12	The exercise makes me feel calm	-2	-0.5	1.16	Emotional
13	I do the exercise longer than I meant to	-2.32	-0.66	1	Motor
14	I really get into the exercise	-3.5	-1.82	-0.16	
15	I feel like I just cannot stop doing the exercise	-1.82	-0.16	1.5	Motor

3.4 Data analysis and findings

Within subject ANOVA was used to analyze the differences between different groups.

3.4.1 Analysis of engagement level

According to criteria of identifying the engagement level, a typical pattern of facial expression in each exercise was shown in Figure 3.11. 1, 0.5, 0, -0.5 and -1 were referred to engaged, transition between engaged and normal, normal, transition between normal and bored and bored respectively. According to the typical pattern of facial expression in each exercise, the subjects were interested in each exercise at first. As the exercise proceeded and they were getting familiar with the exercise, the level of engagement changed from engaged level to normal level, and then to bored level. In the video game exercise, engagement level may change from engaged level to transition and change back to engaged level from transition, which could be interpreted as new stimulations in the video game. While in the other two exercise, there were no such stimulations.

The mean and standard deviation of time duration of each engagement level in different exercise was calculated as it was shown in Figure 3.12. In the box, the central line was the median, the circle was the mean, and the edges of the box were the 25th and 75th percentiles. Post hoc analysis of the durations in the engaged level showed significant differences between

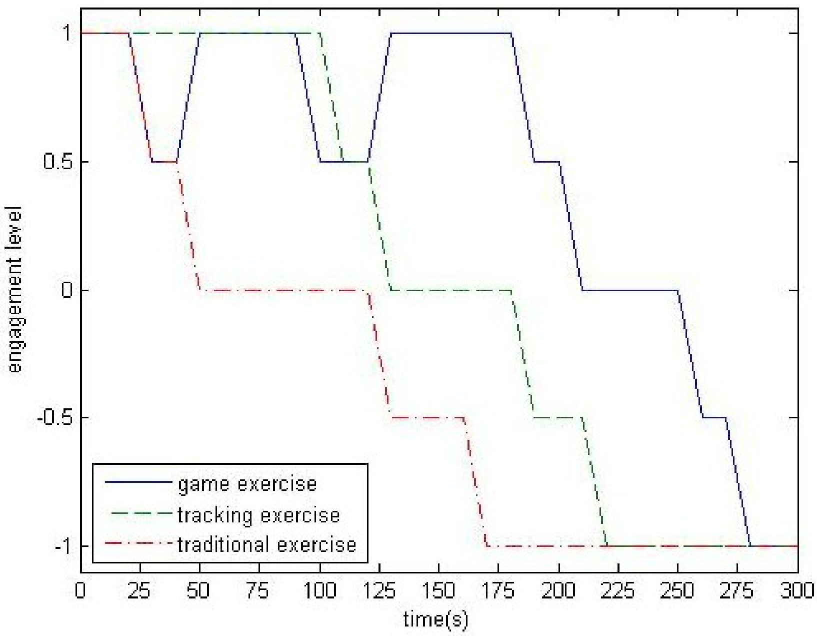


Figure 3.11 Typical pattern of engagement level changes based on facial expression

the video game exercise (175±32/s) and the tracking exercise (85±30/s) (P=2×10(-5)), between the video game exercise and the traditional exercise (46±17/s) (P=3×10(-9)), and between the traditional exercise and the tracking exercise (P=2×10(-4)). Therefore, we could conclude that the video game exercise leads to longer period of engaged level during training exercise than the other two exercises.

Post hoc analysis of the questionnaires also showed significant differences in the scores that indicated engagement, between the video game exercise (3.98±1.2) and the tracking exercise

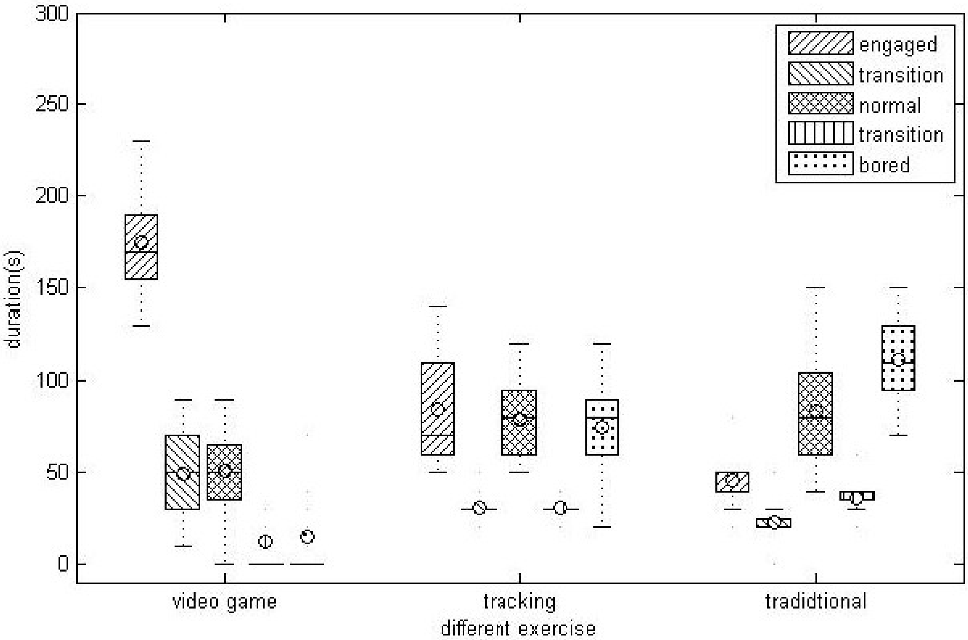


Figure 3.12 Boxplot of the durations of different engagement levels in different exercises.

(-2.64±1.8) (P=0.01), and between the video game exercise and the traditional exercise (-6.28±2.1) (P=0.006). However, no significant differences were found in the scores between the tracking exercise and the traditional exercise (P=0.11). These results could support the reliability of the engagement level based on facial expressions. Therefore, in the followed analyses, engagement level analyzed from facial expressions was used to evaluate the engagement level during each exercise.

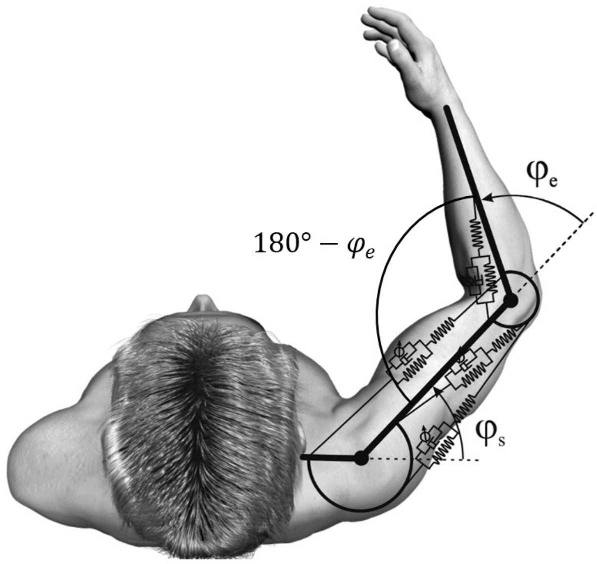


Figure 3.13 Elbow angle

3.4.2 Analysis of motion characteristics and the questionnaire scores in different exercises

In this part, the motion characteristics, such as elbow angle and hand velocity were analyzed and compared between different exercises. As shown in the Figure 3.13, the elbow angel is defined as $180° - \varphi_e$.

As shown in Figure 3.14, in the tracking exercise, the elbow made a regular motion as the subject tracked the same circle. While in the other two exercises, elbow angles changed

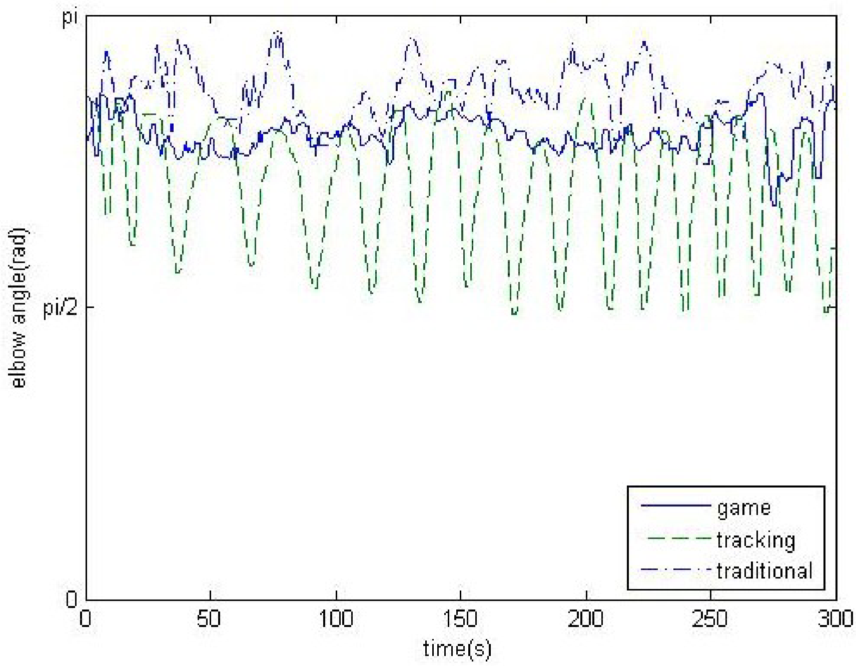


Figure 3.14 Typical pattern of elbow angle changes in different exercises

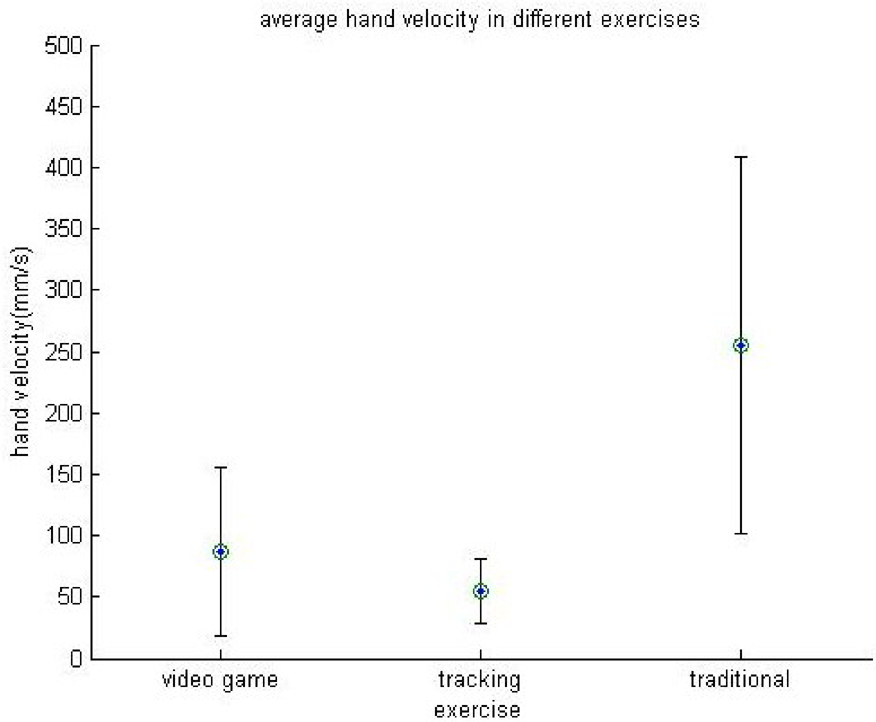


Figure 3.15 Average hand velocity in different exercises for one participant

arbitrarily due to different tasks. This was the same for all subjects. The average motion range of the elbow angle (rad) in each exercise was calculated: the video game exercise (2.12±0.38—2.89±0.46), the tracking exercise (1.51±0.03—2.86±0.06), the traditional exercise (1.90±0.12—3.03±0.07).

As shown in Figure 3.15, average hand velocity (236±12mm/s) in the traditional exercise was bigger than the video game exercise (77±25mm/s) and the tracking exercise (54±14mm/s) for all subjects. Post hoc analysis of the average motion range and average hand velocity both showed significant differences in these three exercises.

Table 3.7 Results from the questionnaires and analyzing facial expressions

Engaging methods	Score of engagement in the motor aspect	Score of engagement in the perceptive aspect	Score of engagement in the cognitive aspect	Score of engagement in the emotional aspect	Total score of the questionnaire	Mean duration in engaged level
Video game exercise	0.51±1.68	1.55±1.37	1.32±1.22	1.88±1.38	3.98±1.2	175±32/s
Tracking exercise	-0.87±1.64	-0.45±1.48	-1.08±1.29	0.11±1.17	-2.64±1.8	85±30/s
Traditional exercise	-1.37±1.62	-1.96±1.21	-1.83±1.47	-1.77±1.32	-6.28±2.1	46±17/s

Table 3.8 Parameters of factors in each exercise

Engaging methods	Versatility of motion	Elbow range (rad)	Hand velocity (mm/s)	Versatility of feedback	Cognitive tasks	Competitiveness/ challenge
Video game exercise	Random	2.12±0.38 — 2.89±0.46	77±25	Interaction with video game	Attention and problem solving	Play against the computer
Tracking exercise	Regular	1.51±0.03 — 2.86±0.06	54±14	Continuous visual feedback	Attention and adjustment	Track more precisely
Traditional exercise	Regular	1.90±0.12 — 3.03±0.07	236±12	Discontinuous visual feedback	Attention	No

Table 3.7 concluded results from the questionnaires and facial expressions, and Table 3.8 concluded the parameters of factors in each exercise.

Post hoc analysis of the score in the motor aspect showed significant differences between the video game exercise (0.51±1.68) and the tracking exercise (-0.87±1.64) (P=0.001), between the video game exercise and the traditional exercise (-1.37±1.62) (P=0.0003), but there is no significant different between the traditional exercise and the tracking exercise. Therefore, we could conclude that versatility of the motion influences the engagement in the motor aspect more than elbow range and hand velocity. Post hoc analysis of the score in perceptive, cognitive, and emotional aspects also showed significant differences between the video game exercise and the other two exercises. Therefore, we could conclude that the factors in the perceptive, cognitive, and emotional aspect influence the engagement in the related aspect of engagement score.

3.4.3 Analysis of EMG and motion characteristics in different engagement levels

In order to identify a quantitative indicator to represent engagement, this section analyzed EMG data in different engagement levels to understand the relationship between engagement and muscle activities. In the tracking exercise, same movement was selected from each engagement level, which was completing one circle. Although the tracking task required large portion of shoulder and elbow movements, we argue that it also required fine wrist and hand movement when the subjects were engaged in the task and dedicated to move as accurate as possible to track the given circle. Then, hand velocity and tracking accuracy in each level were calculated and analyzed.

In Figure 3.16, post hoc analysis of the average distance also showed significant differences between the engaged level (9±2.3mm) and the normal level (18±4.4mm) (P=0.006), between the normal level and the bored level (25±4.9mm) (P=0.01) and between the engaged level and the bored level (P=0.0007). In Figure 3.17, post hoc analysis of the average hand velocity showed significant differences between the engaged level (36±7.9mm/s) and the normal level (54±6.3mm/s) (P=0.01), between the normal level and the bored level (66±11.4mm/s) (P=0.008) and between the engaged level and the bored level (P=0.0004). This may due to when the subjects were concentrating on the exercise, they tracked the circle more carefully with more accurate but slower movements.

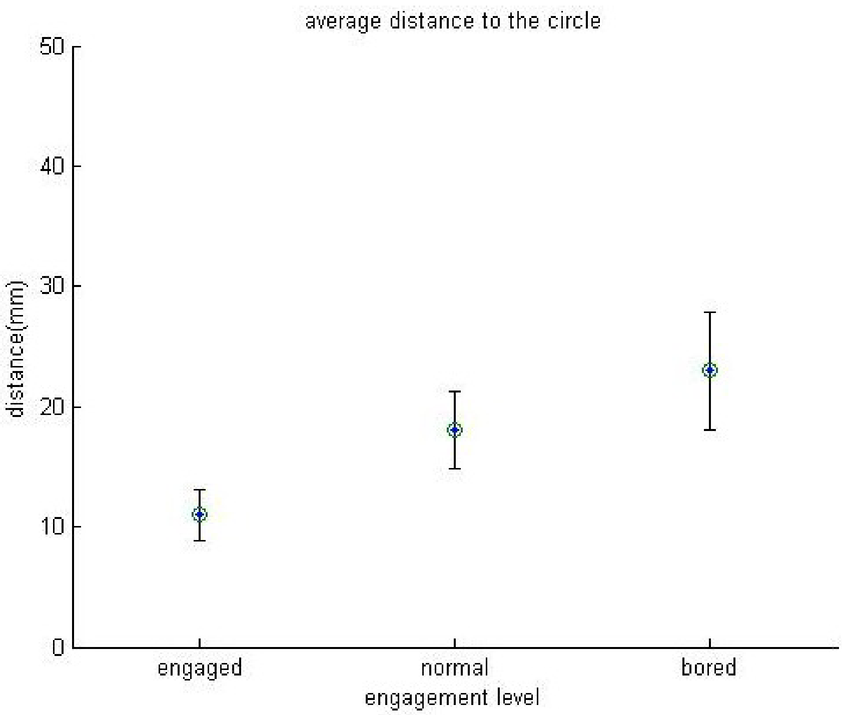


Figure 3.16 Average distance from the handle grip to the circle in different engagement levels for one participant

Then, normalized RMS of EMG were analyzed and compared in different engagement levels. In Figure 3.18, according to the results of this participant, the average of normalized EMG in the engaged level was bigger than the other two levels, which meant that the muscle activity in the engaged level was more intense than the other two. Then the mean normalized RMS in each engagement level of all subjects was calculated.

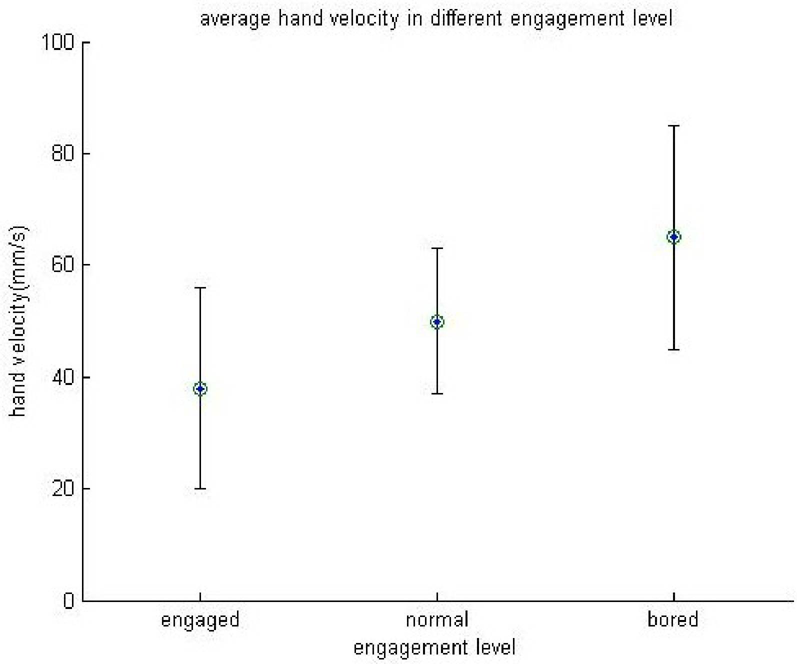


Figure 3.17 Average hand velocity in different engagement levels for one participant

In Figure 3.19, in the box, the central line was the median, the circle

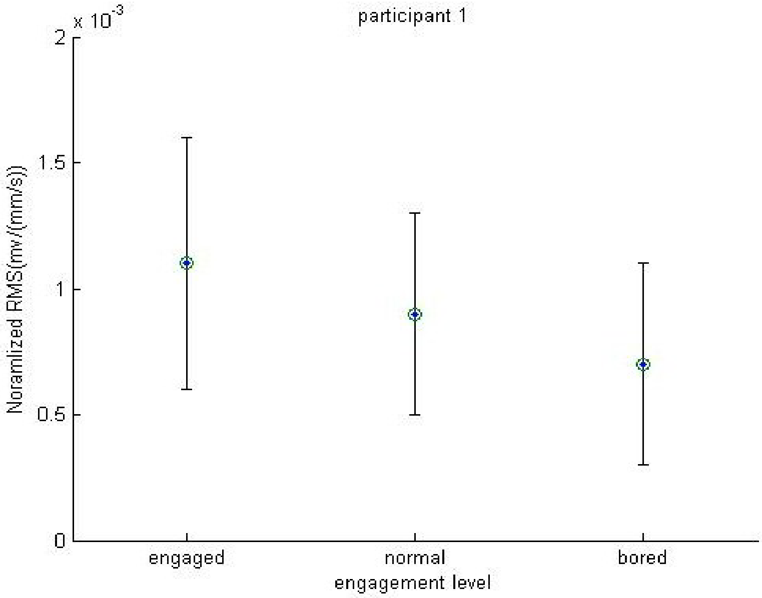


Figure 3.18 RMS of EMG in different engagement levels for one participant

was the mean, and the edges of the box were the 25th and 75th percentiles.

Extensor cr: extensor carpi radialis longus; flexor cr: flexor carpi radialis; first dorsal i: first dorsal interosseous; extensor d: extensor digitorum.

Post hoc analysis of the normalized RMS for the extensor carpi radialis longus showed significant differences between the engaged level and the normal level (P=0.001), between the normal level and the bored level (P=0.04), and between the engaged level and the bored level (P=4$\times 10^{-6}$). Similarly, significant differences were found in the normalized RMS of flexor

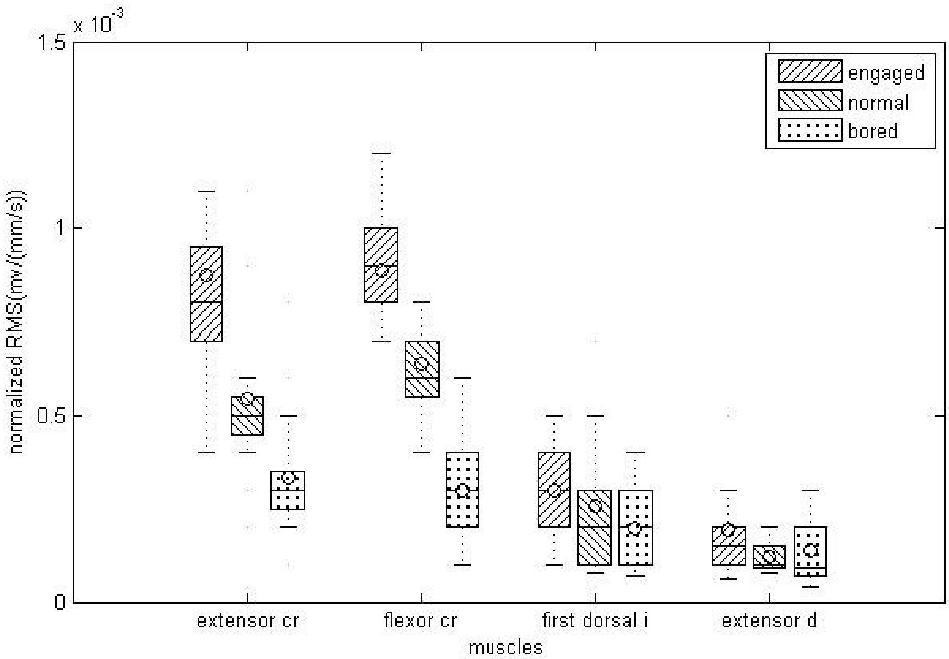


Figure 3.19 Boxplot of the normalized RMS for the four muscles in different engagement levels

carpi radialis between the engaged level and the normal level (P=0.002), between the normal level and the bored level (P=0.0001), and between the engaged level and the bored level (P=2×10^{-6}). No significant differences were found in the normalized RMS of first dorsal interosseous between the engaged level and the normal level, and between the normal level and the bored level, while it revealed significant differences between the engaged level and the bored level (P=0.01). For the extensor digitorum, no significant differences were found between the three levels in the normalized RMS. The results indicated that the muscle activities in extensor carpi radialis longus and flexor carpi radialis were more intense when people were engaged. But the results of first dorsal interosseous and extensor digitorum did not show that. This could be due to the fact that the movement of tracking the circle did not involve the recruitments of these two muscles, which meant that there was little finger motion during the tracking exercise.

3.5 Discussion of findings

3.5.1 Parameters of factors

The results have shown that the three exercises engaged the subjects for different amount of time, which could due to the differences in the parameters of factors each exercise addressed. Specifically, with regards to the versatility of motion, in the video game exercises, the subjects had to move the shoulder and elbow randomly and use different grasping gestures on the user interface according to the game tasks, while in the tracking exercise and traditional exercise, the movements were the same and mundane. The result indicated that adaptive movements according to the game tasks could have a positive effect on engagement.

As for the versatility of the feedback, the video game exercise can provide human computer interaction thereby giving the subjects a feeling of presence. During the tracking exercise, the screen provided continuous feedback, showing the distance between the circle on the screen and the handle grip. The traditional exercise only involved discontinuous feedbacks. Since the traditional exercise engaged the subjects the shortest, we can infer that engagement induced by discontinuous feedback is insufficient.

Regarding cognitive tasks, we found that when the subjects were playing against the computer, they had to understand the feedback and then respond. During the tracking exercise, since they were required to track the circle precisely, the subjects should adjust their movements according to the distance between the target positions and the real positions. These two exercises required continuous attention and synchronizing motor coordination. The traditional exercise, on the other hand, did not require a deeper understanding of the tasks, and the task itself can quickly become routine, which could also lead to the shortest time in the engaged level.

As for the competitiveness in the emotional aspect, both the video game and tracking exercises involved more competitive or challenge elements compared to the traditional exercise. Another interesting result was that the level of engagement always decreased as the exercise proceeded, which meant that the subjects were interested in exercise that was new to them. As they became more familiar with the exercise, they seemed to lose interest, even in the video game exercise. But the video game exercise and the tracking exercise can provide the subjects with certain level of challenge, which meant something new to them. That was also the reason that these two exercises could engage the subjects for a longer time than the traditional exercise which cannot provide challenge. Therefore, in order to maintain a high level of engagement during rehabilitation exercises, interventions should be provided when the exercise becomes too familiar to the subjects.

3.5.2 Personalized stimulations, and relationship between engagement and muscle activities

It can be noticed that there was relative big standard deviation in each average measurement, which indicated that different factors have different effects on different subjects. Therefore, interventions are supposed to be personalized according to the subjects' capabilities, because either too easy or too hard tasks cannot engage the subjects. This implicates that system adaptability is required to deliver suitable exercise to different stroke survivors, or to the same stroke patients but at different stages of recovery.

Normalized EMG showed that muscle activities were more intense when the subjects were engaged than the other two levels. The relationship between engagement and muscle activities could make it possible to evaluate the engagement level during training exercise. As discussed above, the subjects tend to be less engaged when they take the exercise as routine. Therefore, the system could measure muscle activities of the subjects in order to monitor the engagement level.

3.6 Conclusion

Based on the results from the experimental investigation and together with findings from Chapter 2, it can be concluded that:

- Gamification is not enough for maintaining engagement. When the subjects are two familiar with the exercise, the engagement decreases. Therefore, the identified stimulation strategies in Chapter 2 can be applied as interventions to maintain and enhance engagement during rehabilitation exercises.
- As found in Chapter 2, personalized treatment is needed to engage the patients. Results of this experiment have also shown that different factors, such as increasing versatility of movements, providing continuous feedback, involving cognitive tasks, introducing competiveness or challenge in the training tasks, and introducing challenges in both motor

and cognitive aspects, have different effects on different subjects. For stroke patients, parameters of the factors have to be tailored according to their interests and capabilities. Therefore, personalized stimulation strategies are needed to enhance engagement of the stroke patients during rehabilitation training exercises.

- A major limitation in this field is that there is no quantitative method to evaluate engagement. In this experiment, based on the relationship between engagement level and muscle activity, normalized EMG can be used as the indicator to represent engagement level of the muscle activities during rehabilitation exercise. This enables the rehabilitation system can monitor the status of the subjects and apply the interventions when the engagement level decreases.

3.7 References

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CHAPTER FOUR

RESEARCH CYCLE 3:

Conceptualization of a cyber-physical engagement enhancing system

4.1 Overview of current cyber-physical engagement enhancing solutions

4.1.1 Objective of this chapter

The objective of this chapter is to propose a concept for a cyber-physical stroke rehabilitation system (CP-SRS) with the aim of enhancing engagement. According to the findings of the experiment discussed in Chapter 3, even the most engaging methods, such as gamification, need to cope with the decrease of engagement as the users get familiar or bored with the game. We argued that the engagement of patients can be maintained by a continuous monitoring of the engagement level and introducing personalized stimulation strategies during rehabilitation exercises. Based on the affordances of CPSs identified in Chapter 2, a multi-sensor network can be integrated into the enabling system and the integrated sensors can monitor the indicators that represent the engagement of the patients. The learning capability of a CPS makes it possible for the system to accomplish this problem automatically based on the obtained knowledge. This affordance can help the rehabilitation system to implement personalized training by applying treatment that has been proven suitable and effective for the patient.

One of the current limitations is that most of the tools developed to evaluate and measure engagement are subjective and qualitative in rehabilitation. Kortte et al. (2007) developed an engagement rating scale, which took rehabilitation engagement, therapy absences, functional status, emotional functioning, affective state, level of functioning and denial into consideration. The engagement of the same patients could be different according to different therapists, which leads to inaccurate qualitative assessment. Without an accurate assessment, the effectiveness of the engagement enhancing methods cannot be objectively validated. In other therapeutic fields, such as education, researchers have been making effort to evaluate engagement quantitatively. Several studies evaluated student's engagement using postures (D'Mello et al., 2007) and (Sanghvi et al., 2011), body motion (Sanghvi et al., 2011), or log files in e-learning system (Cocea and Weibelzahl, 2007). Szafir and Mutlu (2012). developed an adaptive agent that monitors the cognitive engagement of students and improves their engagement during learning. They used EEG to quantitatively represent the engagement level of students. Although this method is very promising in education, engagement evaluation depends on context, so evaluation of rehabilitation engagement should consider indicators in the rehabilitation context.

In this chapter we will present the concept of our engagement model, which consist of a set of indicators for measuring the engagement level of users during rehabilitation. In Chapter 3, we found a relationship between the engagement level and normalized EMG, i.e. the root mean square of EMG divided by the velocity of movement. In our engagement model, the normalized EMG will be used as the indicator to represent engagement in the motor aspect. Since the influencing factors for therapeutic engagement can be categorized into the four aspects, namely motor, perceptive, cognitive, and emotional, we need a more comprehensive characterization of the engagement that monitors not only the engagement in the motor aspect, but also in the cognitive, perceptive and emotional aspects. In this chapter, we will introduce and explain the specific indicators that have been hypothesized to be able to reliably represent the engagement of the participant, and discuss the concept of a cyber-physical smart rehabilitation system (CP-SRS) that is able to monitor the identified indicators for evaluating engagement, apply personalized stimulation strategies and learn the effect of stimulation strategies on the individuals.

4.1.2 Methodological framing of this research cycle

Design inclusive research was applied in this research cycle to frame the methodological approach and the concept development procedure. This includes an explorative phase, a constructive phase, and a confirmative phase as specified in (Horváth, 2013). In the phase of explorative research actions, the current limitations and the explored opportunities identified in the previous chapters were converted into technical requirements for the cyber-physical augmentation. In the phase of creative (design) actions, the concept of cyber-physical augmentation was developed in order to enhance the engagement during rehabilitation training exercise. In the phase of confirmative research actions, a computer simulation was used to validate the feasibility of the concept. The next section introduces the concept of the CP-SRS. The proposed CP-SRS builds on the concept of an existing upper limb rehabilitation robot system integrated with video games. The cyber physical augmentation is added to the system with the aim of eliminating the identified limitation above in order to enhance the engagement during the training exercises.

4.2 Concept of the cyber-physical engagement enhancing rehabilitation system

The CP-SRS is a modularly architected system. It is composed of five subsystems, namely, (i) an assistive robotic subsystem, (ii) a gamification subsystem, (iii) an engagement monitoring subsystem, (iv) a smart learning mechanism (SLM), and (v) an engagement enhancement subsystem (EES) (Figure 4.1). Specifically, the assistive robotic subsystem supports the stroke survivors during exercises of rehabilitation program in order to compensate for deficits in their motor function disability. Gamification subsystem integrates video games with the training exercises and enables human computer interaction. However, as we found in the previous chapter, even the most engaging exercises integrated with video games should count on the decrease of engagement as the users get too familiar with the game or lost their interest in it. We again argue that the engagement of patients can be maintained by a continuous monitoring of the engagement level and introducing interventions during rehabilitation exercises. Therefore, the main function of the cyber-physical augmentation of the physical system is to enhance the patient's engagement by introducing personalized interventions according to the observations in engagement monitoring. To determine when to introduce the interventions, we used the EMS to monitor the patient's engagement level.

Basically, when the patient's engagement level decreases, the system is supposed to introduce interventions. Based on the interventions the system is able to re-engage the patients and to maintain a high level of engagement of the patient. The interventions are identified as stimulation strategies in motor, perceptive, cognitive, and emotional aspects, which are able to re-engage the patient. The EES applies the stimulation strategies, which are a combination of stimulations, by adjusting a bundle of parameters of the training exercises. There are several stimulations in each

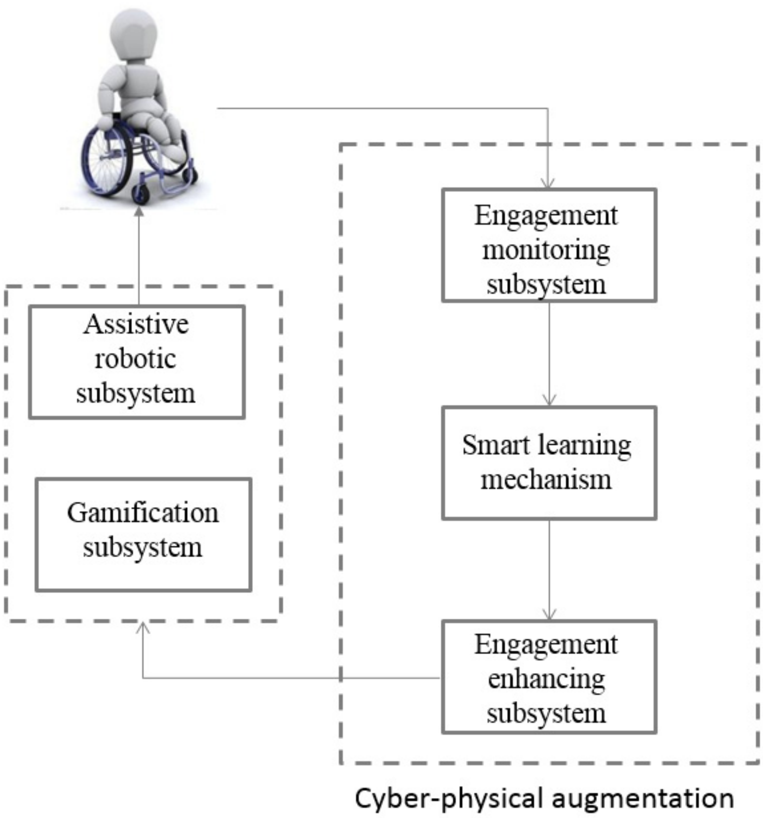

Figure 4.1 Overall concept of cyber-physical stroke rehabilitation system

aspect. Since personalized stimulation is needed, the most suitable stimulation strategy is personalized depending on the patient and the situation. In order to determine which stimulation strategy is the most suitable to be applied in the case of a specific patient, the SLM should be capable to make personalized suggestions on the stimulations to be applied, based on effects of different stimulation strategies on different patients the SLM has learned in previous cases.

This chapter will focus on identifying the indicators for engagement and conceptualizing the SLM to make suggestions on the most suitable stimulation strategies to engage the patient. In order to provide personalized stimulations, one of the main constituents of this system is the SLM, which is able to suggest the most suitable stimulation strategies for different patients to increase the efficiency of rehabilitation exercises. The underpinning strategy considers motor, perceptive, cognitive and emotional aspects of engagement. As a reasoning engine of the CP-SRS, the proposed SLM is able to learn the effects of the stimulation strategies on the actual engagement level. The operation flow of how this subsystem works is shown in Figure 4.2. First, the system monitors the patient's engagement level and represents his/her engagement level in four aspects, which will be discussed in detail later. If there is a decrease in the engagement level, the system applies stimulation strategies in order to enhance the engagement of the patient. Then the SLM will learn the relationship between the stimulations and changes of the engagement level. In the next stage, when the system detects the engagement level decrease, the SLM can act as an artificial expert to suggest the most suitable stimulation strategies. The stimulation strategies are reflected and realized by adjusting the setup and parameters of the therapeutic exercise. After each exercise, the system evaluates the efficacy of the stimulation strategies and refines the model of the SLM in order to update the patterns of the relationship between the stimulation strategy parameters and their effect on the engagement aspect.

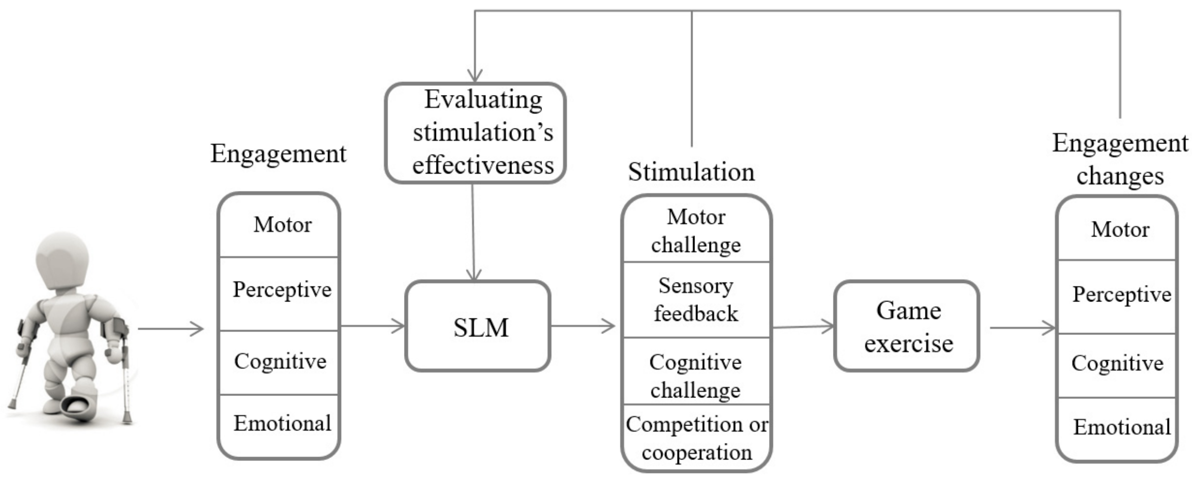

Figure 4.2 Engagement evaluation and SLM

4.3 Specific indicators for engagement monitored in the EMS

4.3.1 Motor engagement

Motor engagement (E_m) is defined as a state in which the patient moves with active and effortful motion. EMG signal represents electrical potential produced by skeletal muscles when they are neurologically activated, which indicates the motor control of the person. In Chapter 3, we found that the normalized EMG was bigger in an engaged state, which means more intense muscle activity was identified, compared to a normal or unengaged state. The normalized EMG can be used as the indicator to represent the motor engagement according to the following definition.

$$E_m = \frac{EMG_{RMS}}{velocity} \tag{1}$$

4.3.2 Perceptive engagement

Perceptive engagement (PE) is defined as task oriented attentive use of the sensory system of the human body, such as visual, auditory and tactile. For monitoring the visual system, eye tracking has been widely used as a method to evaluate user's attention and concentration. Researchers have used several measures to evaluate the engagement, including the number of eye fixations (Kallinen et al., 2007, Renshaw et al., 2009) and gaze time outside the screen (Kallinen et al., 2007). These measures, however, do not provide accurate information about the decay of attention, when the person is staring at the screen, but do not process information. Li et al. (2014) Proposed to use eye movement speed, eye movement total displacement, and validity of eye data as the indicator to represent concentration. They demonstrated that it is possible to reliable quantify the involvement of rehabilitation patients in therapeutic exercises. However, we argue that their method is limited to measure engagement only after the therapeutic exercise is completed, and these parameters are not suitable for measuring engagement during therapy. When the user is interacting with therapeutic game, the gaze will follow the content changes on the screen.

Although the user may sometimes look at the display unit for an overall overview, the most of the time, the focus of the his/her gaze should be on either the system cursor or the changing content elements of the game. This happens because the content change usually demonstrates the tasks to the patient, and the system cursor indicates what the patient controls to complete the tasks. For some games, there may be secondary content changes. For instance, as illustrated in this ice hockey game (Figure 4.3), the goal and the opponent's bat are the secondary changes, which splits visual attention of the user only for a short time. To complete the tasks, the gaze should be mainly concentrated on either of these two locations on the screen. When the patient's attention is decaying, the patient will lose track of the cursor and the content changes on the screen. Therefore, the perceptive engagement is evaluated by analyzing the position of user's gaze (PG), the position of the system cursor (PSC), and the

Figure 4.3 Positions of the elements in an ice-hockey game

position of the content change (PCC)in the video game. The advantage of this method is that this indicator can represent the reaction time of the user responding to the game tasks. In addition, this method can show the perceptive engagement of the user in real time and it is independent of the game content. Therefore, the distance between PG and PCC, and the distance between PG and PSC are calculated for the evaluation of the level of perceptive engagement. Let d_{v1} be the distance between PG and PCC, and d_{v2} the distance between the PG and PSC. The visual engagement is defined as the sum of d_{v1} and d_{v2}. Figure 4.3 shows an example of ice hockey game to illustrate the method of the evaluation of visual engagement. On the right, the main content changes can be detected using ScreenCapture tool[1] in MATALB.

$$\mathrm{E_p} = d_{v1} + d_{v2} \tag{2}$$

4.3.3 Cognitive engagement

Cognitive engagement (CE) is considered to be proportioned with the level of concentration during the execution of cognitive tasks. The electroencephalography a method to monitor the electrical activity of the brain. It is a noninvasive method that measures electrical potential on the surface of the scalp, arising from large areas of coordinated neural activity. The neural activity varies as a function of development, mental state, and cognitive activity, and the EEG signal can detect such variation.

Several studies have been conducted to investigate user's engagement and cognitive workload using EEG signals. These studies aimed to use EEG as measures of engagement, mental workload and attention (Kramer et al. 1996; Parasuraman, 2003). The EEG variables used to monitor engagement includes decreased alpha signal, increased beta signal, increased theta and their ratios such as beta/alpha plus theta and alpha plus theta/beta. In addition, the event

[1] http://nl.mathworks.com/matlabcentral/fileexchange/24323-screencapture-get-a-screen-capture-of-a-figure-frame-or-component

related potential of EEG such as the N100 and P300 components have been employed to assess cognitive tasks and engagement (Kramer, 1996). ERPs, however, have several short comings in assessing cognitive tasks and engagement in naturalistic setups, as they require the introduction of stimuli with precise time tracking, which is expected to generate specific brain response from the user. In a naturalistic setup, such as a rehabilitation exercise, it is not possible to control the stimuli nor it is doable to precisely interpret stimuli of game elements with state of the art technologies. Building on the conventional methods of engagement evaluation, Stevens et al. (2007) have applied a commercial wireless EEG sensor headset and B-Alert system to analyze the EEG data from six channels to represent cognitive workload and engagement in acquiring problem solving skills. Berka et al. applied a four-class quadratic discriminant function analysis using absolute and relative power spectra variables from two EEG channels to analyze engagement in vigilance, learning, and memory tasks (Berka et al., 2007). Galán and Beal used Theta, Alpha, Beta and Sigma wave signals (ranging from 3 Hz to 40 Hz) to indicate engagement (Galán & Beal, 2012) during solving mathematical problems. They have used SVM to make predictions of the expected performance students based on the engagement and workload indicators of EEG signals, difficulty level of the exercise and student profile. They have presented promising results towards implementing and intelligent teaching environment capable to adapt to the personalized needs of students. Mostow et al. used the average value of each standard frequency band to indicate the engagement level of each participant (Mostow et al, 2011). They also identified which EEG components appear sensitive to which lexical features. They found a strong relationship in children between a word's age-of-acquisition and activity in the Gamma frequency band (30-100 Hz). The most widely used method was proposed by Pope et al. (1995), which offered the following formula for calculating a signal, E_c, based on the α, β and θ waves that are highly correlated with participant's cognitive engagement. This formula has been widely used by researchers in analyzing task engagement [Brookhuis & De Waard, 1993, Mikulka et al., 2002, Freeman et al., 2004, Szafir & Mutlu, 2012]. These EEG measurements are gathered from the frontal lobe which is known to manage attention, mental states and motor planning. FP1 region of the cortex which is known to manage learning, mental states and concentration (e.g., Gevins et al., 1998, Gentili et al., 2010 and Girouard et al., 2013). Therefore, we will use this following model for calculating cognitive engagement E_c.

$$E_c = \frac{\beta}{\alpha + \theta} \tag{3}$$

4.3.4 Emotional engagement

Research has shown that positive emotion is associated with gains in functional status post-stroke (Ostir et al., 2008). Therefore, the goal of the therapeutic exercise is to arouse the positive emotion of the patient. Emotional engagement E_e is defined as emotional involvement during the exercise. If the exercise can influence the patient's emotion, it means that the patient is emotionally engaged. If the patient is emotionally engaged, the dominant emotion will change due to different events of the game. Therefore, we define the indicator for emotional engagement as the ratio of time duration of dominant positive emotions and the time duration dominant negative emotions.

$$E_e = t_{positive}/t_{negative} \tag{4}$$

4.4 Smart learning mechanism

4.4.1 Stimulation strategies

Stimulation is needed when there is a decay of the engagement. As discussed in Chapter 2, stimulations have been categorized into four groups: motor, perception, cognitive and emotional stimulation. For instance, in the case motor stimulation is to be introduced, meaningful changes in the exercises should result in a more intensive involvement of motor functions of the patient. An exercise which exceeds the patient's capability is not a meaningful challenge. Consequently, a meaningful motor stimulation does not necessarily mean a higher difficulty level of the task, but it is the difficulty level that the patient can handle with effort. To characterize the patient's capabilities, a user profile recording their medical status (e.g. Fugl Meyer Assessment, Functional Independence Measurement, and Wolf Motion Function Test) can be used. These three assessments can show the patient's motor and cognitive abilities, which can indicate the most appropriate difficult level for the patient. In a typical robot assisted rehabilitation systems, four parameters of the motor stimulation (MP (i), i=1-4) can be defined and adjusted for a gamified therapeutic exercise, namely, (i) the assisting force of the robotic arm, (ii) the size of moving space, (iii) the required force exerted by the patient, and (iv) the required time to complete game task.

With regards to the perceptive stimulation, the system can adjust the visual, auditory and tactile feedback to increase the patient's sensory attention. For instance, parameters (PP (i), i=1-3), such as the resolution of the screen, the volume of the auditory feedback, and the intensity of the vibration can be adjusted respectively. In cognitive stimulations, three types of cognitive tasks are addressed by therapeutic exercises, that are training (i) the working memory, (ii) reasoning ability, and (iii) mental processing speed. Recalling a series of locations of items on the screen can be used to train working memory, in which the amount of items (CP (1)) can be adjusted. The difficulty level of the numerical reasoning task (CP (2)) can be adjusted to train reasoning ability. Exercises like identifying the same pictures in required time (CP (3)) can be used to train the processing speed. As for the emotional stimulations, integrating competition and cooperation features in the exercises can be used to influence the patient's positive emotion level. In the competition games the difficulty level (EP (1)) can be adjusted. In the cooperation games, the patient can communicate with other patients or physical therapist to complete game tasks together. The system can assign different part of the cooperation task (EP (2)) to the patients to stimulate them.

Stimulation strategy is defined as a combination of stimulations in the four aspects. Symbolically,

$$\text{stimulation strategy} = \sum_{n=1}^{4} i_n \times MP(n) + \sum_{n=1}^{3} j_n \times PP(n) + \sum_{n=1}^{3} x_n \times CP(n) + \sum_{n=1}^{2} y_n \times EP(n)\,,\ i_n, j_n, x_n,\ and\ y_n = 0\ or\ 1 \quad (5)$$

When the stimulations are needed, the system applies a stimulation strategy by adjusting a bundle of parameters in the game exercise.

The concrete manifestation of stimulations and how they can be addressed by the parameters in the game exercises are listed in Table 4.1. Motor stimulations and perceptive stimulations

Table 4.1 Kinds of stimulations to maintain engagement

Stimulations	Adjustable items	Game exercises	Parameters in the game exercise
Introducing motor challenge	Assistance level	Any game exercise	Assisting force by the robotic arms
	Range of motion	Any game exercise	Size of the moving space
	Required force by the fingers	Any game exercise	Threshold of the force sensor on the user interface
	Movement velocity	Any game exercise	Time to complete tasks
Adjusting sensory feedback	Visual feedback	Any game exercise	Resolution of the screen
	Auditory feedback	Any game exercise	Volume of the auditory feedback
	Tactile feedback	Any game exercise	Intensity and magnitude of the vibration feedback
Introducing cognitive challenge	Working memory task	Recalling a series of locations of items on the screen	Amount of items
	Reasoning task	Numerical reasoning task	Difficulty level
	Processing speed task	Identifying same pictures in required time	Required time
Involving competition and cooperation features	Competition	Competing against opponent in the game	Difficulty level
	Cooperation	Cooperating with others in the game	Different tasks assigned

are realized through user interface, so they can be applied in any game exercise.

4.4.2 Reasoning model of the smart learning mechanism

The objective of the SLM is to make suggestions on the most suitable stimulation strategies based on patterns of the effects of the stimulation strategies on the engagement levels. We argue that supervised learning is more suitable for this purpose than unsupervised machine learning. Though unsupervised learning may be considered to explore hidden structure in the data on the relationship of stimulations and their effect on engagement. However, since this data can be clearly labelled by the parameters of the input (i.e. change of the engagement levels) and output (i.e. stimulations and their parameters), supervised learning is preferred to be used in our smart learning mechanism. Supervised learning methods, such as the error back-propagation supervised learning algorithm are very efficient for many non- linear real time problems, which makes them suitable to classify the effect of stimulation strategies and make personalized recommendations for to simulate patients The system offering this learning capability should be able to reason about stimulation strategies, and match them to the case at hand. Further details on the system and implementation aspects will be given in the next section.

In order to learn the effects of stimulation strategies, in the first stage, the system applies pre-programmed stimulation strategies, and the changes of engagement level are recorded. Then, in the next stage, these known effects are used to train the learning mechanism. In the third stage, the system uses the trained learning mechanism to make suggestions on stimulations to apply. In the last stage, the new effects of the stimulation strategies are used to refine the trained learning mechanism.

The learning mechanism has two possible operation modes, which are (i) regression and (ii) classification. In classification, inputs are divided into two or more classes, and the learner must produce a model that assigns unseen inputs to one or more of these classes. In regression, the outputs are continuous rather than discrete. In this mode, the learning mechanism learns the relationship between the dependent variables (which are the changes of the parameters in the game exercise) and the independent variables (which are the changes in the engagement level). Then, the trained learning mechanism is used to predict the changes of the parameters according to the changes in the engagement level. While in classification mode, stimulation strategies are sorted as different classes. Each class represents a combination of different stimulations. The learning mechanism learns the relationships between the changes of engagement levels and the applied different stimulation strategies. Afterwards, the trained learning mechanism is used to predict suitable combination of stimulations in different situations (e.g. particular pattern of decrease in the engagement level, or specific profile of the patient). Based on the prediction of the SLM, the parameters of the game exercise are adjusted.

In the first stage, the program uses a direct mapping to apply stimulation strategies, which means stimulations are applied according to which engagement level decreases. The parameters in the game exercise are adjusted according to the stimulation strategies. After the parameters are adjusted, the patient has to deal with the new changes in the game exercise. It may involve: (i) change of the difficulty level of the motor tasks, (ii) change in the patient's sensory feedback, (iii) different cognitive tasks, or (iv) change in the competition or cooperation feature in the game exercise. These changes have the potential to stimulate and re-engage the patient, which result in a change in the engagement levels. Therefore, after the stimulations are applied, the changes in the engagement levels are recorded as the effects of the stimulation strategies.

In the next stage, the data collected from the first stage are used to train the learning mechanism. As shown in Figure 4.4, the inputs of the learning mechanism are the patient's profile and the changes of engagement level. The outputs of the learning mechanism are different in regression mode or classification mode. In regression mode, the outputs are the changes of the parameters. While in classification mode, the outputs are a combination of stimulations. The reason to learn the patient's profile is that when another patient with similar profile uses the system, the learning mechanism can recommend the most suitable stimulation strategies, which have been proven to be effective with other patients. For a patient with the

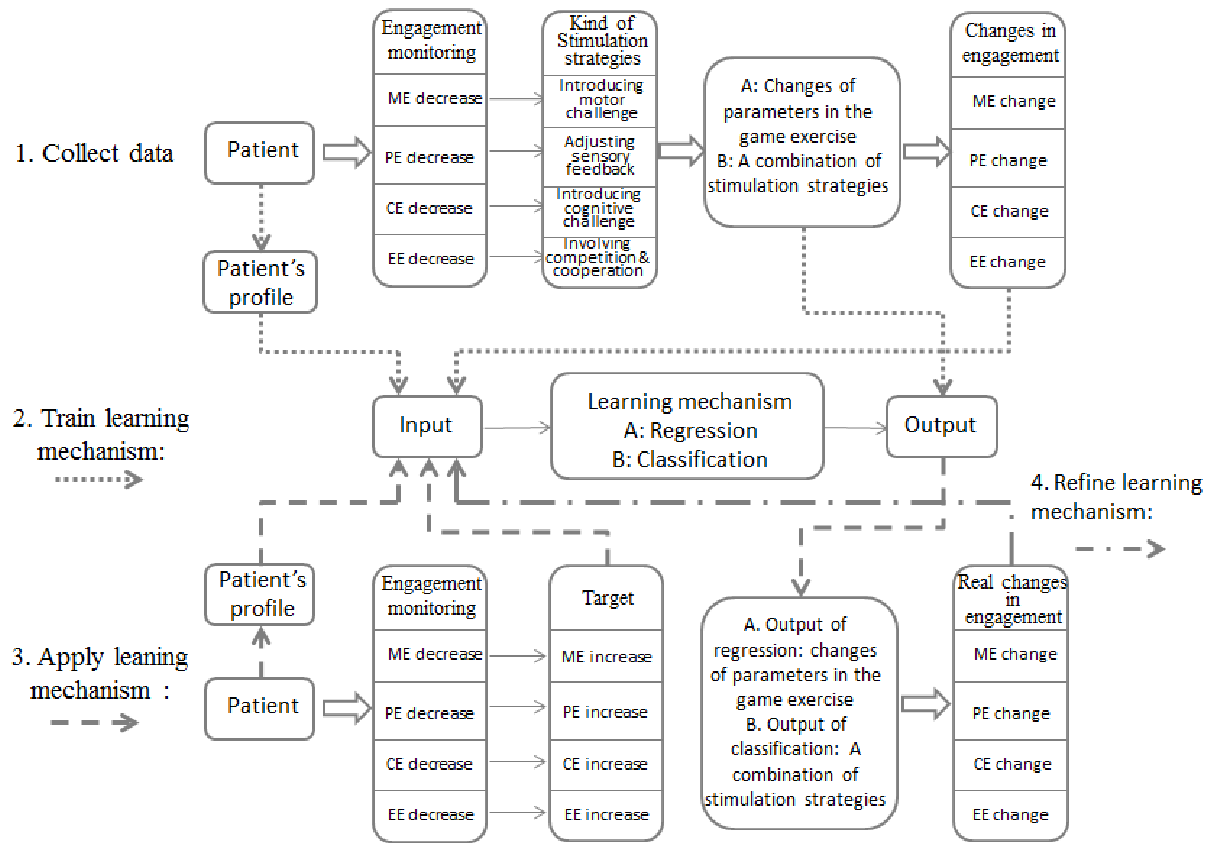

Figure 4.4 The reasoning scheme of the SLM

same patient's profile, the outputs of the learning mechanism mainly depend on the changes in terms of the target engagement level.

In the third stage, the target and the patient's profile are inputted to the learning mechanism to make recommendations for the most suitable stimulation strategies. The target is set by the system with the objective of increasing that aspect(s) of engagement level which are decreasing. The learning mechanism is expected to make decision on the changes of the parameters or the combination of stimulations. After the stimulations are applied, the real changes of the engagement level are recorded. The real changes and the applied stimulation strategies are used as one more case to train the learning mechanism. This way, the learning mechanism can learn the relationship of the input and the output in more cases, so that it can be more accurate to suggest the most suitable stimulations to apply.

4.5 Form of realization of the smart learning mechanism

As described above, the two possible operation modes, i.e., regression and classification, can be realized by using different methods. Artificial neural networks (ANN) have been widely used in fitting regression and recognizing patterns. In the current literature, a number of quantitative models including multilayer perceptron neural networks (MLPNNs), combined neural networks (CNNs), mixture of experts (MEs), modified mixture of experts (MMEs), probabilistic neural networks (PNNs), recurrent neural networks (RNNs), and support vector machines (SVMs) are being used in disease diagnosis cases to assist human decision makers (e.g., Kordylewski et al., 2001, Kwak and Choi, 2002 and Übeyli, 2009a). MLPNNs are the most commonly used feed-forward neural networks due to their fast operation, ease of implementation, and smaller training set requirements (e.g., Subasi, 2007, Kocyigit et al.,

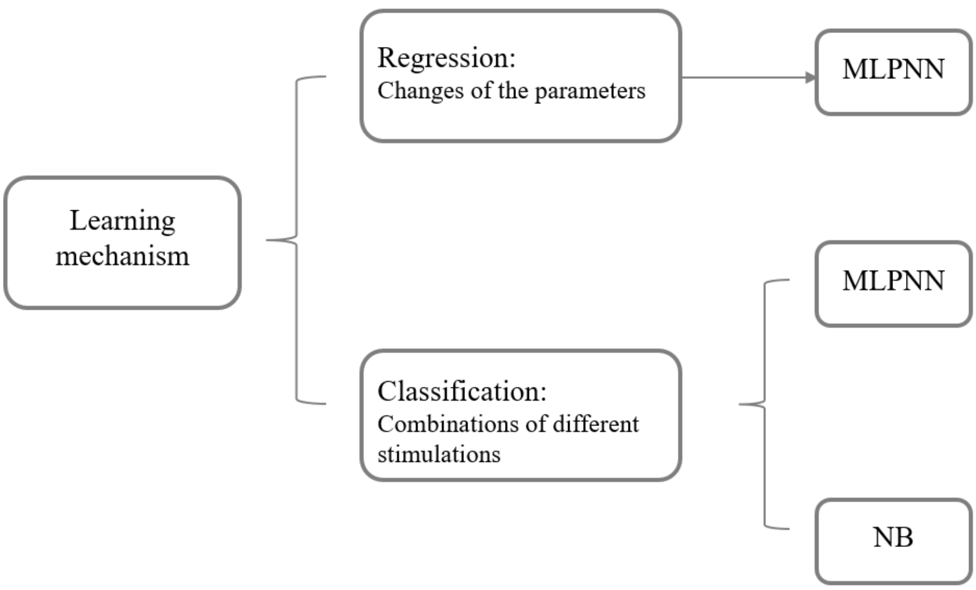

Figure 4.5 Computational methods applied in the learning mechanism

2008 and Übeyli, 2009b). Therefore, we have decided to apply MLPNN in both regression and classification modes. It should be mentioned that there exist many other supervised learning algorithms that can be used for classification, such as the support vector machine, naive bayes, discriminant analysis, and nearest neighbor algorithms. Having compared their characteristics, we came to conclusion that naive bayes (NB) can be a good alternative algorithm for ANN. Naive bayes classifier normally uses less training data than other classifiers when accurate classification is required. Therefore, in addition to using MLPNN, we also explored the potential application of naive bayes (Figure 4.5).

For regression with MLPNN, we used a two-layer-feed-forward network with sigmoid hidden neurons (10 neurons) and linear output neurons. It was trained with the most common Levenberg-Marquardt back-propagation algorithm, which is also more reliable in solving nonlinear inverse problems. The trained MLPNN learning mechanism was expected to fit the changes of parameters according to the inputs. For classification with MLPNN, we used a two-layer feed-forward network, with sigmoid hidden neurons (10 neurons) and softmax output neurons. This network was trained with scaled conjugate gradient back-propagation, which consumes less memory, because there are more classes of the stimulation strategies in the output. In this case, the trained learning mechanism was expected to classify the inputs into different classes, which are combinations of different stimulations. These two ANNs and the NB were all set up in MATLAB. Their accuracy were compared and evaluated in the next section.

4.6 Validation of feasibility

The feasibility of the proposed concept is investigated from two aspects. First the feasibility of measuring the proposed engagement indicators will be studied by exploring the requirements and identifying potential technologies capable to measure the parameters of the indicators. The second aspect of this feasibility study aims to explore which machine learning techniques could be used to capture the relationships between stimulation strategies and their effect on different aspects of engagement. The result of this feasibility study will provide a guideline to the technical implementation of the engagement enhancement rehabilitation system.

4.6.1 Validation of the feasibility of the indicators

Engagement by its nature is neither time triggered nor event triggered phenomenon. This means that it does not require strict time synchronization protocols that is typical for most cyber-physical systems. Changes in the engagement of the user during an exercise are not expected to happen as a sudden event or at a specific time, it is more likely to be a gradual process where decay in the intensity of the indicators represents the loss of engagement and motivation. Nevertheless, time based synchronization of signals and data is an issue, when multiple devices are used to determine the indicators of engagement. Therefore, synchronization is an important aspect of the validation of the feasibility of indicators.

1) Motor engagement indicator

The indicator of motor engagement requires the measurement of EMG signal and the speed of motion of the upper limbs. The EMG potential of the electrical source of the muscle membrane is about –90 mV. EMG potentials range between 50 μV and up to 20 to 30 mV, depending on the muscle under observation. Typical repetition rate of muscle motor unit firing is about 7–20 Hz, depending on the size of the muscle (eye muscles versus seat (gluteal) muscles), previous axonal damage and other factors. Bio-signal measurement devices used in medical applications are able to measure 8-256 channels, with a sample rate of 2048-16384 Hz, and total noise filtering of 0.8-2 μV_{RMS}. These devices, however, have a cost price in the range of 2000-15000keuro, and they require professional knowledge for their setup. Commercial EMG devices, such as a MYO[2] armband, has 8 channels to measure muscle activities of the lower or upper arm, with a sampling rate of 128 Hz. As in our indicator we are using the root mean square of the EMG signal, which has to be sampled at a minimum of 32 samples per second (Florimond, 2009), 128Hz sample rate is expected to be accurate enough for monitoring motor engagement.

In order to explore the requirement for measuring the velocity of the motion, i.e. the second parameter of motor engagement indicator, we have studied the paper of Rosen et al. (2005). They have measured the kinematics and dynamics of human motion during daily activities, including gross position actions (e.g. arm reach to head level), fine manipulation actions (e.g. moving an object at the waist level), and combined gross and fine manipulation (e.g. picking

Table 4.2 EMG devices and features

Device	Channels	Sampling rate	Range	Kinematic sensing
DELSYS Trigno Lab	16	1926 Hz	40 meters	Accelerometer
NORAXON Desktop Direct Transmission System	32	1500/3000 Hz	30 meters	
BioRadio	8	Up to 16000 Hz	10 meters	
BIOPAC Mobita	32	Up to 2000 Hz	10 meters	Accelerometer
MYO armband	8	128 Hz	10 meters	Accelerometer, magnetometer, gyroscope

[2] https://www.myo.com/

up a phone on a wall). For gross activities, they found that the angular velocities of the arm joints are in the range of -10 to +10 degree/sec for the arm joints, up to 20 degree/sec for the elbow. The angular acceleration is in the range of -110 to +80 degree/sec^2. For fine motor movement, the value of angular velocity is in the range -5 to +5 degrees/sec with a typical angular acceleration in the range of -70 to +70 degrees/sec^2. Due to the large angular acceleration, the actual value of the angular velocities can only be approximated between two sample measurements when digital devices are used with a fixed sample rate. This means that measuring the actual values of the angular velocities is only possible if the sampling of the EMG signal and the arm movement velocity is absolutely synchronized and measured with the same sample rate. This implies that the proposed indicator cannot be used for measuring the instantaneous value of motor engagement. It is, however, can be used by using the moving average of the measured parameters. Since MYO is integrated with a 9 axis IMU, that can be used to measure the speed of motion of the body parts, where the arm band is placed.

2) Perceptive engagement indicator

The control mechanism of human's visual attention focusses on perceiving meaningful elements of visual information and ignores others of low relevance. The spatial acuity of the eyes is only detailed in 2° region of the fovea, while the rest only produces a peripheral view with less details. To keep the image in focus the eyes move with a saccadic motions (10-100ms) followed by a fixation of 200-300ms (Snowden et al. 2006). During the saccadic motion no visual information is perceived and cognitively processed (Duchowski 2003). Feasibility of measuring the perceptive engagement requires an analysis of the eye-tracking technologies and computer vision algorithms. To track the motion of the eyes, the spatial resolution of typical eye tracking technologies is determined by the degrees of accuracy by which the horizontal and vertical eye movements are measured. This typically is in the range of 0.5-1 degrees. It means that in a standard training setup with a screen size of 27" at a viewing distance of 60 cm, the accuracy of eye tracking is around 0.5cm or 16px for a Full HD screen. The temporal resolution of eye tracking technologies is also a relevant factor. It is determined by the sampling rate (i.e. in the range of 30-200Hz) and the latency (i.e. 20-50ms). This implies that eye tracking technologies can track fixations, but may miss rapid saccades (that are smaller than 30ms) of the eye movement. However, tracking of visual attention may reliably done by executing eye tracking. The EYETRIBE[3] is then selected because it can meet the above requirements.

The second parameter of the visual engagement indicator is the location of content change of in the screen, which supposed to attract the attention of the user. To track the changes of the screen content several computer vision algorithms can be considered, such as Continuously adaptive mean shift (CAMShift), Kanade-Lucas-Tomasi (KLT), or Kalman filtering. These

[3] http://theeyetribe.com/

algorithms provide a reliable solution for tracking object changes on the screen and making an estimation of expected changes of motion in real time.

3) Cognitive engagement indicator

The parameters of the cognitive engagement indicator, i.e. alpha and beta waves, can be measured by EEG that is capable to capture the electrical activity of the brain. EEG signal has to be sampled at a minimum of 128 samples per second, they are measured from peak to peak and normally range from 0.5 to 100 μV in amplitude (Teplan, 2002). The power spectrum of theta (4-8 Hz), alpha (8-12 Hz) and beta waves (12-30Hz) can be derived by applying Fourier transform on the raw EEG signal. Although the spectrum is continuous, ranging from 0 Hz up to one half of sampling frequency, the brain state of the individual may make certain frequencies more dominant.

Table 4.3 EEG devices and features

Device	Channels	Sampling rate	Resolution
Neuroscan SynAmps	64,128, or 256	20000 Hz	24 bit
Neuroscan Siesta	32	1024 Hz	16 bit
BIOPAC Mobita	32	2000 Hz	24 bit
ENOBIO 32	32	500 Hz	24 bit
Emotiv EPOC	14	128 Hz	14 bit

To measure cognitive engagement, Table 4.3 gives an overview of popular devices with various technical specifications. As opposed to event related potential analysis, power spectrum analysis does not have high demand on the spatial and temporal resolution as well as on the voltage resolution of the signal measured by EEG device. Since engagement is not event related, therefore, the temporal resolution is not a relevant factor of the measurement. As far as the spatial resolution is concerned, the frontal lobe can be measured by all devices listed in the Table 4.3. The voltage resolution represents the conversion of the analogue signal to digital data. Considering specs of the most cost effective solution for our research, the EMOTIV EPOC[4], the error of the voltage resolution is 0.51 mV for the 16bit measurement. Within the expected range of measurements, the EPOC is expected to have 0.5% error.

4) Emotional engagement indicator

Tracking and monitoring the emotional engagement raises many challenges in terms of the feasibility of the proposed concept. Our concept aims to monitor facial expressions in order to track the emotions that are externalized by the user. Reliable monitoring of unexpressed emotions is not possible with facial tracking, but it is also difficult with other technologies

[4] https://emotiv.com/

such as heart rate monitoring and galvanic skin response. Heart rate monitoring can detect decrease in heart rate (HR), which is typically associated to happiness, relaxation, boredom. Low heart rate variation (HRV) shows a relationship between anxiety, and emotional stress (Dishman, et al. 2000). Using heart rate as engagement indicator is difficult as both HR and HRV may be associated to both negative and positive emotions (e.g. boredom and happyness). Galvanic skin response has the same problem. Though there is a relationship between sympathetic activity and emotional arousal, one cannot identify the specific emotion being elicited. Fear, anger, startle response, orienting response and sexual feelings are all among the emotions which may produce similar GSR responses.

Technologies for tracking the facial expressions during a training or gaming has become feasible due to the proliferation of computer vision algorithms and their applications, such as Insight[5]. These technologies are able to identify specific landmarks and features of the face, read micro-expressions in real time and predict components of emotions with probabilistic functions.

4.6.2 Validation of the feasibility of the smart learning mechanism

The computer simulations discussed in this section were conducted to explore the feasibility of the machine learning algorithms identified for implementing the SLM subsystem. This section will investigate the prediction performance of MLPNN for regression mode, MLPNN for classification mode, and NB for classification mode. At this stage of the research no real data was available to test the performance of these algorithms, therefore data were generated based on the following rules: i) different stimulations have different effects on engagement levels, thus generate different relationships between the inputs and outputs for different stimulations; ii) the effects of the same stimulation may vary for each individual case; therefore we introduced four kinds of weights, namely, large, middle, small and positive & negative weights to simulate different range of deviations by generating random numbers in different ranges; iii) stimulations applied towards a certain objective may also influence engagement levels in other aspects, for instance motor stimulation, may positively or negatively affect cognitive engagement.

Since the accuracy of learning mechanisms depends on the complexity and the sensitivity of the model it needs to learn and the deviations in the data, we compared the results from different learning mechanisms with different amounts of outputs and different ranges of variations in the data. For regression mode, we tested the learning mechanism with 4, 6 and 12 outputs of parameters under different weights respectively, since there were 12 parameters to predict. While for classification mode, we tested the learning mechanism with 6 classes, 12

[5] http://sightcorp.com/insight/

classes, 24 classes and 48 classes under each weight, because each class represents combination of different stimulations.

1) **Learning mechanism for regression**

The factors influencing the learning have been defined for the use of MLPNN in regression mode as follows:

$$\text{patient's profile} + \text{changes in the engagement level} \rightarrow \textit{changes in the stimulation}\ \text{parameters}$$

Table 4.4 Simulated data for regression

Items	Label	Simulated data
Patient's profile	PR1	Random (1-10)
	PR2	Random (1-10)
Motor stimulations	MP1: Assisting force by the robotic arms	Random (1-5)
	MP2: Size of the moving space	Random (1-5)
	MP3: Threshold of the force sensor on the user interface	Random (1-5)
	MP4: Time to complete tasks	Random (1-5)
Perceptive stimulations	PP1: Resolution of the screen	Random (1-5)
	PP2: Volume of the auditory feedback	Random (1-5)
	PP3: Intensity and magnitude of the vibration feedback	Random (1-5)
Cognitive stimulations	CP1: Amount of items	Random (1-5)
	CP2: Difficulty level	Random (1-5)
	CP3: Required time	Random (1-5)
Emotional stimulations	EP1: Difficulty level	Random (1-5)
	EP2: Different tasks assigned	Random (1-5)
Weights	Large range	Random (1-10)
	Middle range	Random (5-10)
	Small range	Random (7-10)
	Positive & negative	Random (-5-5)
Changes in the engagement level	MC: changes in motor engagement	$\mathrm{MC}(\mathrm{PC}, \mathrm{CC}, \mathrm{EC}) = (\mathrm{PR1} + \mathrm{PR2}) \cdot (\sum_{i=1}^{4} a_i \cdot w_i \cdot MP_i + \sum_{j=1}^{3} b_j \cdot w_j \cdot PP_j + \sum_{n=1}^{3} c_n \cdot w_n \cdot CP_n + \sum_{m=1}^{2} d_m \cdot w_m \cdot EP_m)$ (Note: a, b, c and d are constants in each function. If they are 0, it means certain stimulation does not influence certain engagement level. The symbol w represents weight.)
	PC	
	CC	
	EC	

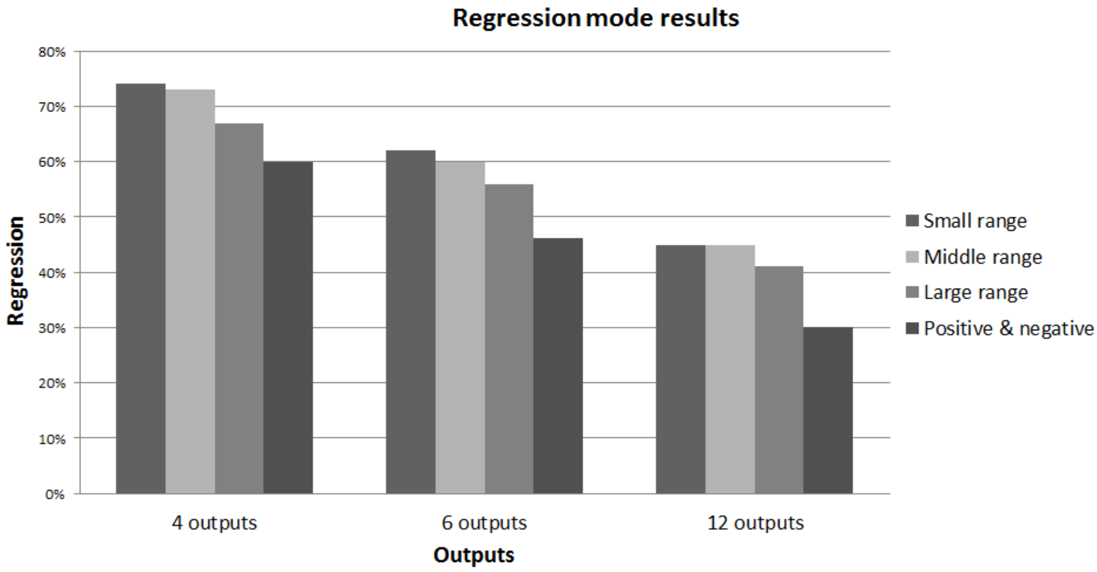

Figure 4.6 Comparison of the regression mode results

The inputs are the patient's profile and changes in the engagement level. The outputs are the changes in the stimulation parameters. The amount of outputs represents the amount of stimulations. The goal is to investigate the sensitivity of the learning mechanism to the amount of outputs and the deviations. The simulated data are shown in Table 4.4. The data consist of 500 samples, for which the patient's profiles were generated as random number from 1 to 10. The changes in the twelve parameters of the four aspects of stimulations were also generated as random numbers from 1 to 5. The large range weights were generated as random numbers from 1 to 10, representing a large deviation in the effects of the stimulation for different patients; middle range weights in the range of 5 to 10; small range of weights with values from 7 to 10; positive & negative weights from -5 to 5, which means certain stimulation may have positive effects for some patients, but negative effects for others. As for the changes in the engagement levels, we created different functions to calculate based on the patient's profiles.

The data presented in Table 4.4 were used to train three MLPNNs with 4 outputs, 6 outputs and 12 outputs. Early stopping was used to improve generalization of the MLPNN. The data were divided into three subsets. The first subset was the training set containing 70% of the data which were used to compute the gradient and update the network weights and biases. The second set was the validation set, which was comprised of 15% of the data. Increase in the error on the validation set triggers early stopping of the training process to avoid overfitting. The other 15% of the data were used to test the trained MLPNNs. The regression mode results are shown in Figure 4.6.

The regression value R is an indication of the relationship between the outputs (calculated by the MLPNN) and the targets (expected outputs). If R = 100%, it indicates that there is an exactly linear relationship between the outputs and the targets. If R is close to zero, then there is no linear relationship between the outputs and the targets. Higher R means that the results of the MLPNN are more accurate. Therefore, in our case, when MLPNN with 4 outputs was used under the conditions of small and middle range, the accuracy was bigger than 70% that were reasonably reliable.

2) **Learning mechanism for classification**

The factors influencing the learning have been defined in classification mode as follows:

$$\text{patient's profile} + \text{changes in the engagement level} \rightarrow \textit{different classes}$$

The rules for creating the simulated data were the same as in regression mode. Data related to this process are shown in Table 4.5. Patient's profile and weights were also the same as in regression mode. Concerning the changes in the engagement levels, we generated similar functions as in the regression mode to calculate the changes based on the patient's profiles and the weights. There were 480 samples of the data with 10 samples for each class. Exactly 90% of the data were used to train the learning mechanism with either MLPNN or NB. The other 10% of the data (one sample in each class) were used to test the trained learning mechanism. In addition, we tested the learning mechanism with outputs of 6 classes, 12 classes, 24 classes, and 48 classes respectively. The results generated by NB and MLPNN are shown in Figure 4.7 and 4.8.

Table 4.5 Simulated data for classification

Items	Label	Simulated data
Patient's profile	PR1	Random (1-10)
	PR2	Random (1-10)
Weights	Large range	Random (1-10)
	Middle range	Random (5-10)
	Small range	Random (7-10)
	Positive & negative	Random (-5-5)
Changes in the engagement level	MC: changes in motor engagement	$\mathrm{MC(PC, CC, EC)} = a \cdot w_a \cdot PR1 + b \cdot w_b \cdot PR2 + \mathrm{c}$ (Note: a, b and c are constants in each function, and w represents weight.)
	PC	
	CC	
	EC	
Stimulation strategies	Different classes	S1, S2, S3…S6…S12…S24…S48

The classification with NB had a better performance than that with MLPNN mainly for two reasons. Primarily, as the number of outputs increase, the accuracy of the classification with MLPNN decreases. In contrast, the number of outputs does not have an obvious impact on the accuracy of the classification with NB. There was even an increase in the performance of NB with 48-outputs under the weights of small and middle range. More importantly, classification with NB was less sensitive to the deviation in the data. If the weights had negative deviations, the accuracy of 24-outputs and 48-outputs MLPNN were less than 10%, while the performances of all the NBs were more than 60% accurate.

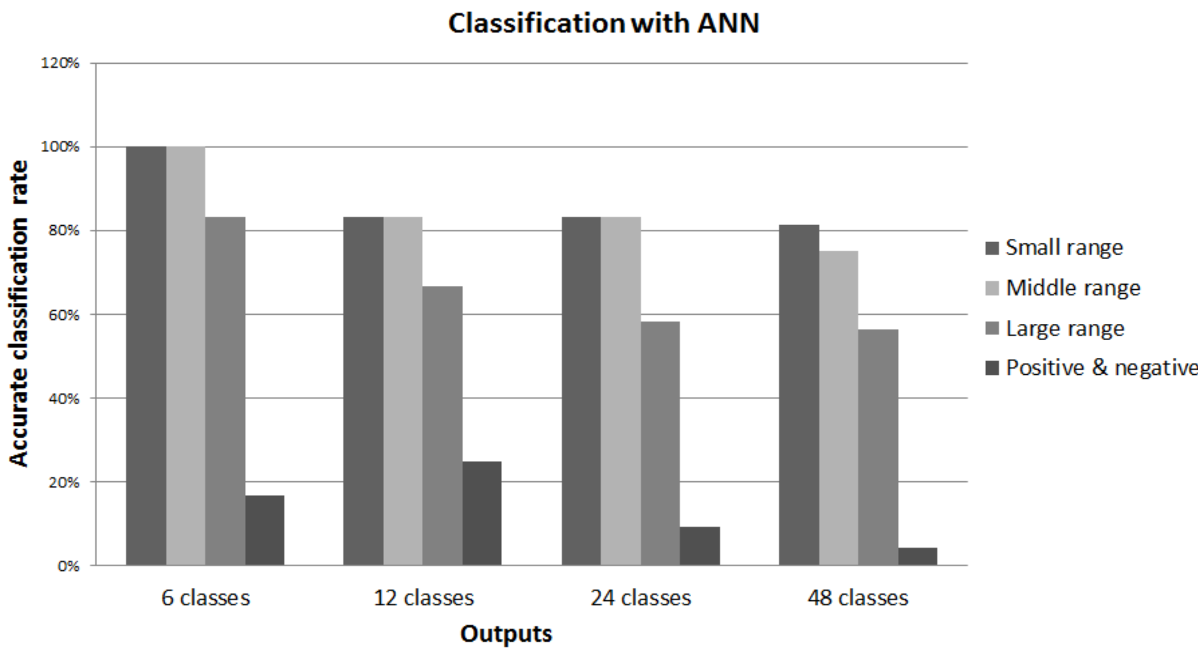

Figure 4.7 Comparison of the results of classification with MLPNN

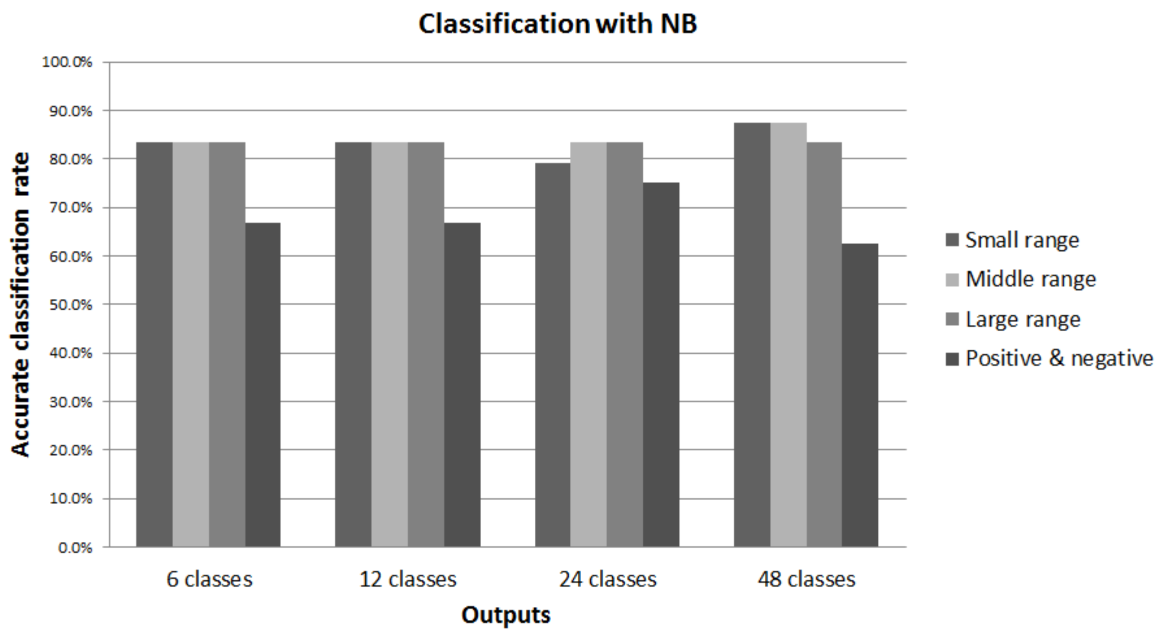

Figure 4.8 Comparison of the results of classification with NB

4.7 Discussion

In this chapter, we have identified the indicators for motor, perceptive, cognitive, and emotional engagement. During the training exercise, these indicators will be monitored by the biosignal tracking devices, such as EMG device, eye tracking system, EEG device, and facial expression analyzing system. Before this system is implemented, the feasibility of measuring the engagement indicators and the expected performance of the smart learning mechanism has been investigated. Our feasibility study has shown that commercially available biosignal tracking devices have the needed technical specification to realize our concept for monitoring motor, perceptive, cognitive and emotional engagement. As far as the implementation of the learning mechanism is concerned, we have made a study with artificially generated data. Although the magnitude of the generated data are not the same as the real data, the relationships between the input data (i.e. patient's profile and changes in the engagement level) and output data (i.e. changes in the stimulation strategies) are more important, which is what the proposed learning mechanism is expected to learn. A relative large variance in the simulated data has been introduced to simulate variances of the real data. The computer simulation showed that the three methods applied in the learning mechanism can learn the simulated relationships at different accuracy. High accuracy means that the implemented learning mechanism can make suggestions on the most suitable stimulation strategies with the objective to maintain the patient's engagement during the training exercise.

Results also showed that naïve bayes for classification is the most promising to be applied in our learning mechanism even when there are both positive and negative deviations of the stimulation strategies in different patients. MLPNN for classification mode may be also applicable if there are no negative deviations in the data. In addition, some stimulations strategies may have the same effect in increasing the engagement. If the SLM classifies certain case to a different class but with the same effect, it should not be considered as an inaccurate classification, because the output of this stimulation strategy can achieve the goal of increasing the engagement. Therefore, the performance of the SLM for classification may increase considering the context of increasing the engagement.

However, MLPNN in regression mode had a relatively low accuracy in our study. This means that the suggested parameters of the exercise are different from expectations, which can cause problems in practice. For instance, the SLM may recommend parameters settings for an exercise difficulty, which may be too difficult for the patients. For this reason, we propose to use MLPNN in classification mode for these cases. The output of classification is the suggested combination of different stimulations, but no specific parameter settings are recommended. Knowledge of the most suitable combination of stimulations can be used by physical therapists set the proper settings of the game exercise or it can be implemented in a form of a combinatorial recommender mechanism that maps stimulation combinations to parameter settings.

4.8 Conclusions

This chapter proposed a method to capture and evaluate the actual engagement levels of the patient during training exercise by analyzing the indicators identified in different aspects. It presented a smart learning mechanism (SLM) that is able to learn the effects of the stimulation strategies which can maintain the engagement. The objective of the SLM is to make recommendations on the most suitable stimulation strategies to be apply during training exercises. A computer simulation has been conducted to validate the feasibility of the proposed learning mechanism. As the results demonstrated, classification mode is more suitable than regression mode for recommending stimulation strategies for individual patients. Naive Bayes (NB) enabled learning mechanism in classification mode performed better than the multilayer perceptron neural network (MLPNN), for the reasons that NB was less sensitive to the deviations in the inputs. NB's accuracy did not decrease as the amount of outputs increased. We concluded from this study that learning mechanism with NB are expected to classify the changes of engagement levels to classes defined as combinations of different stimulations. This means the proposed system can make accurate recommendations on the stimulations strategies to be applied. MLPNN in classification mode could be applicable if there are no negative deviations in the inputs. These two machine learning algorithms will be compared with real data in coming experiments.

In the next chapters, the implementation and prototyping of the proposed system is reported, and its testing in pre-medical experiments. The objective of these experiments is to validate the concept from three aspects: i) to prove if the identified indicators can represent the real engagement; ii) to validate the effectiveness of the stimulation strategies i.e. they are able to increase engagement; iii) to test the accuracy of the recommendations made by the SLM for the most suitable stimulation strategies.

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CHAPTER FIVE

RESEARCH CYCLE 4:

Implementation in a cyber-physical system framework

5.1 Objective of the prototype development

Research cycle 4 concentrated on the implementation of the cyber-physical augmentation part of the CP-SRS in the form of a testable prototype. This chapter discusses the related work, the manifestation of the prototype, and the results of its testing. Cyber-physical augmentation part of the CP-SRS consists of: (i) an engagement monitoring subsystem (EMS), (ii) a smart learning mechanism (SLM), and (iii) an engagement enhancement subsystem (EES) (Figure 4.1). In section 5.2, the architecture of the cyber-physical augmentation part of the CP-SRS is introduced. Section 5.3 discusses the operation flow. Section 5.4 provides technical information about the implementation of the EMS as a testable prototype. Section 5.5 presents the actions of validation of the functionality of the EMS and the results. Finally, Section 5.6 discusses the findings and concludes.

The main function of the cyber-physical augmentation part of the system is to enhance the patient's engagement by introducing interventions during rehabilitation exercises. In order to be able to determine when to introduce the interventions, the EMS should monitor patient's engagement level. Basically, when the patient's engagement level decreases, the system introduces interventions. This is reasoned out based on the engagement indicators. Therefore, the reliability of the indicators was an important concern. Different experiments have been designed to validate the effect of the four engagement indicators and the operation of the EMS as a whole.

5.2 Architecture of the CP-SRS

The cyber-physical augmentation part of the CP-SRS integrates the EMS, SLM, and EES subsystems. The EMS includes engagement monitoring devices and the related engagement analysis software. The SLM mainly consists of the learning mechanism, which is implemented in MATLAB. According to the concept introduced in Chapter 4, the inputs of the SLM are the personal profile and the engagement changes. The output of the SLM is the most suitable simulation strategies according to the learned content. Based on the suggestion from the SLM, the parameters of the exercise are changed by the EES.

The architecture of this cyber-physical augmentation part is shown in Figure 5.1. The architecture is arranged in four layers of hardware, software, cyberware, and service components. The lowest level includes commercialized hardware components capable to monitor the activities and physiological properties of the patients. In addition to operational reliability, the basic requirement for selecting these monitoring devices was that they should not distract the patients during the rehabilitation exercise. It means that the devices should be wireless and easy to wear. The devices should also be of low-cost to make them generally acceptable. According to these principles, the MYO, Eyetribe, Emotiv Epoc devices, and a sophisticated web-camera were selected to monitor the patient's muscle activities, eye movement, brain activities, and facial expressions of emotion, respectively. The technical specifications are presented in Table 5.1.

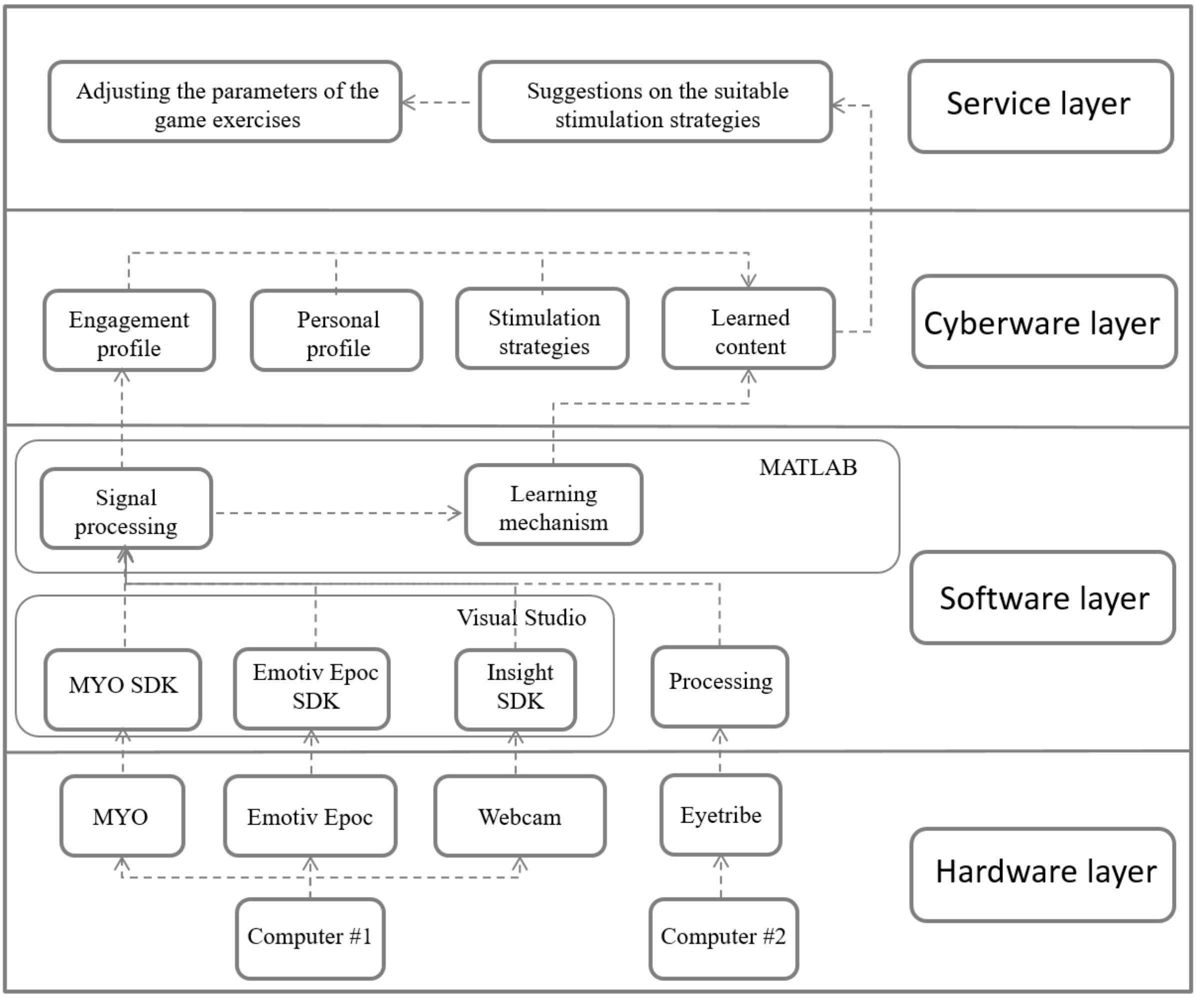
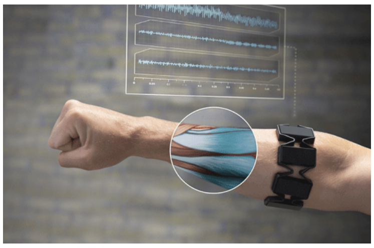
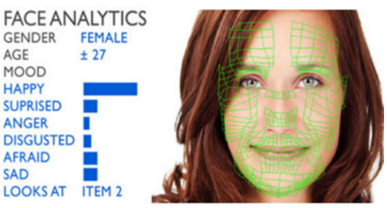


Figure 5.1 System architecture of the cyber-physical augmentation in the CP-SRS

The next level is the software layer, which includes third party software SDKs provided with the commercial hardware components, converts the measured signals into a time stamped data stream. The data is streamed via TCP/IP from Visual Studio and Processing to MATLAB that processes the data and interprets them as the actual engagement levels. The cyberware layer consists of the engagement profile, personal profile, stimulation strategies, and the learned content in the leaning mechanism. The fourth layer, includes the outcome of the cyber physical augmentation part of the CP-SRS, and is able to make suggestions on the suitable stimulation strategies to apply based on the learned content.

The cyber augmentation is also integrated with the rehabilitation robot. It provides a dynamic

Table 5.1 Technical specifications of the monitoring devices

Monitoring devices	Technical specifications
MYO 	• 8 medical grade stainless steel EMG sensors • Bluetooth • Sampling rate: 128 Hz • Cost: 199$
Eyetribe 	• Infrared sensor • Sampling rate: 30-75 Hz • Accuracy: 0.5: 30 • Latency:<16ms • Operating range: 45cm-75cm • Tracking area: 50cm×30cm at 65cm distance • Cost: 129$
Emotiv Epoc 	• 14 EEG channels (10-20 electrode location), • 2 references in P3/P4 locations • Bluetooth • Sampling rate: 128 Hz • Cost: 699$
Insight 	• Translate movements of facial muscles into universal facial expressions. Requirements: • Intel Core 2 Duo 2.0GHZ or better • 2GB RAM • 640×480 resolution webcam • Distance of user from the camera is appr. 60 cm

control for this part, and adjusts the physical parameters of the robot assisted training, such as the assisting force from the robotic arm, threshold of the force sensor on the user interface, size of the moving space, and so on, in accordance with the applied stimulation strategies. Based on this dynamic setting, the robot subsystem adjusts the exercises and assists the patient accordingly.

5.3 Operation flow

As shown in Figure 5.2, the operation flow of the proposed cyber augmentation system comprises four groups of operations. These are: (i) preparation, (ii) monitoring, (iii) suggesting stimulation, and (iv) applying stimulation. During the preparation operations, the physical therapist assists the patient in (i) putting on, (ii) starting, and (iii) calibrating the devices, as well as (iv) starting the monitoring program to record the patient's status.

There is a calibration process completed, by which the patient's engagement level is calibrated before the exercise. Multiple approaches can be applied to calibrate the measurement of indicators for each aspect of the engagement. Calibration for maximum engagement aims to create situations, in which one or more patient's functions (i.e. motor, perceptive, cognitive, and emotional) are fully engaged. The maximum values of

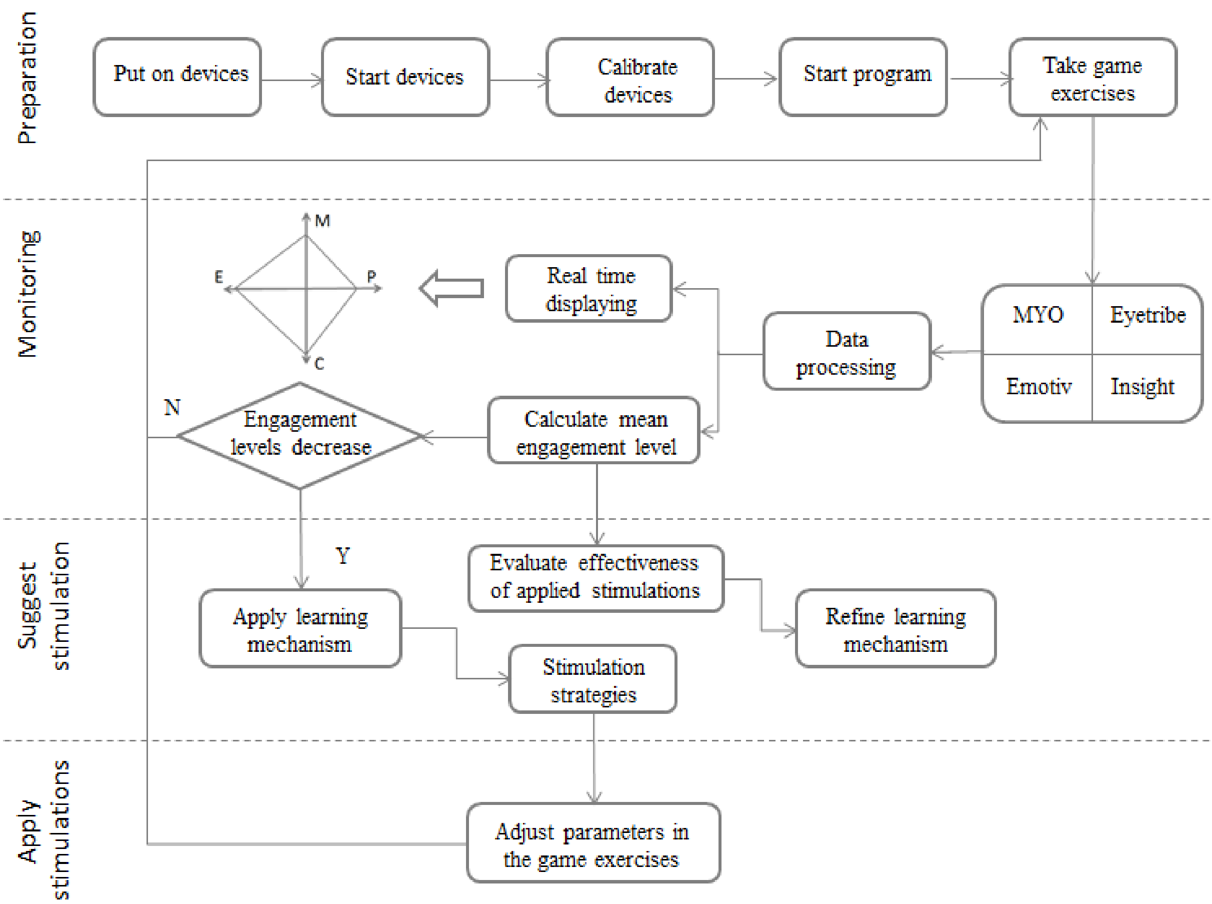


Figure 5.2 The four operational stages included in the operation flow

engagements are then used as the goal of therapeutic exercises, and interventions/stimulations are introduced when large deviations from this goal is measured. Another approach that is applied as an alternative is calibration against the regression functions of motor, perceptive, cognitive and emotional engagements. In this approach, it is assumed that there is a characteristic relationship between the indicator of the engagement and the engagement itself. Having multiple measured points explored in the calibration process about the engagement, the regression function is approximated. During the calibration process, the patient is required to complete a several tasks that tend to be boring, or engaging from the aspects of motor, perceptive, cognitive, and emotional aspects, respectively. The result of the calibration is recorded in the patient’s engagement profile for each of the four aforementioned aspects. These calibrated values are then used as a threshold value to evaluate the patient’s engagement levels during the exercises and as relative response to different stimulation strategies.

In the monitoring phase the patient’s engagement levels are tracked during the therapeutic exercises. The measured signals are filtered, processed and interpreted as engagement levels according to the indicators introduced in Chapter 4. Details of the filtering, signal processing and engagement interpretation methods are reported in Sub-sections 5.4.2 -5.4.6. The signal and data processing unit calculates the mean of the engagement is using a simple moving average, in which 10 seconds of previous data is used in the calculation. The mean of the engagement is displayed in a diagram implemented in MATLAB, as well as it is used the basis for making a decision about the introduction of stimulation strategies. If the mean engagement level decreases in any aspects, the trained learning mechanism recommends the stimulations.

In the phase of suggesting stimulation strategies, two parallel processes are implemented that are running parallel. The first process is a reasoning mechanism that aims to identify the most appropriate stimulation strategy for increasing engagement. The second process aims to refine the knowledge captured by the learning mechanism by retraining with extending and resampling the data. As it was introduced in the previous chapter, the learning mechanism were realized using naive bayes or neural network. To implement NB based learning mechanism the following steps have been applied: 1) converting the data set into a frequency table, which aims to represent the parameters of the patient profile and the changes of engagement 2) create likelihood table by finding the probabilities of different kinds of stimulations based on the input, i.e. the patient profile/change of engagement, and 3) applying Naive Bayesian equation to calculate the posterior probability for each class of stimulation strategies. The class with the highest posterior probability is the outcome of prediction. The neural network based classification are trained with the same input and outputs, and then makes suggestions based on the new input.

In the last phase, the stimulations are applied and the patient continues with the adjusted game exercise. The game exercise should be involved with either motor tasks or cognitive tasks or both tasks, depending on the goal of the training. Then the parameters of the games can be adjusted according to the suggested stimulation strategies, such as the assisting force from the robotic arm, size of the moving space, difficulty of the cognitive tasks and so on. Additionally, after the stimulations are applied, the effectiveness of the stimulation, or the actual changes in the engagement level, is evaluated and used to refine the learning mechanism to make it more accurate. Moreover, when a new patient begins to use this system, the learning mechanism can also give recommendations of the exercise to take based on the knowledge it has learned.

5.4 Implementation of the EMS

5.4.1 Overview of the EMS

As shown in the sequence diagram of the EMS (Figure 5.3), the system reads data from five sources, namely, EEG signals from Emotiv Epoc, emotion by analyzing the facial expressions, EMG signals from MYO, eye movement from Eyetribe, and content changes on

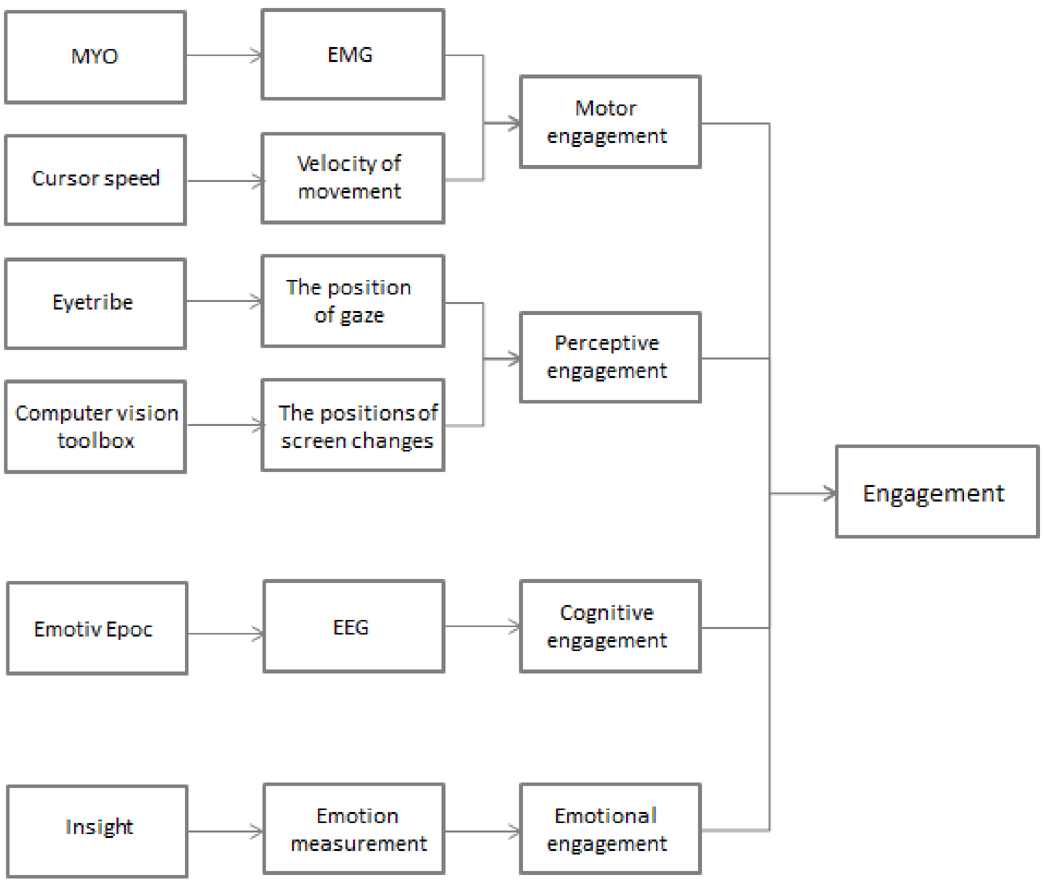


Figure 5.3 Data sources and the monitored variables for evaluating engagement

the screen. This data is streamed to MATLAB in parallel. The MATLAB program then interprets these data into engagement according to the equations (1) -(4) demonstrated in the following subsections. The mean engagement levels are calculated in every 10 seconds, the results are displayed.

Figure 5.4 shows the variables and their sources for calculating the engagement level in the four aspects. The data are stored in an array which contain the information needed to interpret

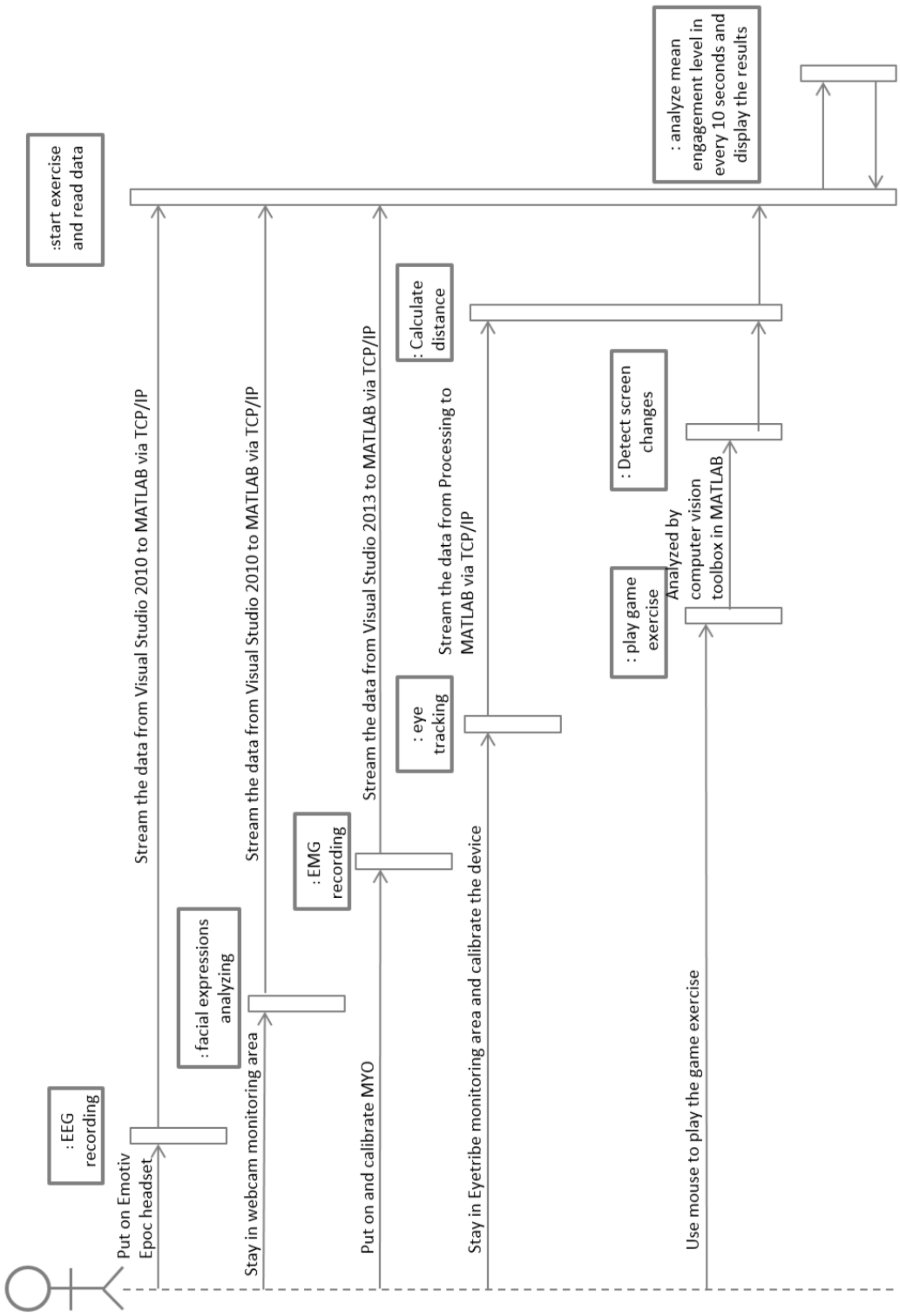


Figure 5.4 Sequence diagram of the EMS

the engagement and the unix timestamp of the system to synchronize the streams of data. Details about processing each variable are discussed in the following subsections.

5.4.2 Motor engagement monitoring

As we discussed in Chapter 4, we used the normalized EMG as the indicator for evaluating motor engagement.

$$\mathrm{E_m} = \frac{\mathrm{EMG}_{RMS}}{velo ctiy} \quad (1)$$

MYO armband (Thalmic Labs) consists of eight EMG sensing modules that can be strapped onto user's forearm. These EMG signals can be interpreted as different hand gestures that can be translated into various types of computerized input via Bluetooth. There is also a combination of a gyroscope, an accelerometer, and a magnetometer to detect the arm motion.

We used MYO as a low-cost, wireless, and easy-to-use device to monitor the muscle activities on the upper arm. MYO was put on the subject's upper arm, with one EMG sensor right on the bicep. Visual Studio 2013 was used to read the data from MYO and stream the data to MATLAB via TCP/IP in real time. The data consisted of EMG signal and the corresponding time. The sample rate was 200Hz. The EMG signals were filtered using a bandpass filter (20 Hz - 500 Hz). Maximum voluntary contraction (MVC) was used to normalize the data (Vera-Garcia et al., 2010). Before the experiment, each participant was required to do isometric contractions of the biceps brachii for three times. The maximum values of each repetition are averaged to compute the MVC. The data acquired from the experiment was compared to the MVC and were rescaled to percentage of the MVC. In MATLAB, these data were used to calculate RMS.

As for the velocity of movement, the moving speed of the cursor was applied as the velocity of movement, since the movement of the cursor reflected the patient's movement. The positions of the cursor were read in Processing together with the unix timestamp of the system time. Then these data were streamed to MATLAB via TCP/IP. In MATLAB, the velocity of the movement was estimated by dividing the distance between two cursors by the time interval of one second.

5.4.3 Perceptive engagement monitoring

Perceptive engagement ($\mathrm{E_p}$) is evaluated by analyzing patient's gaze (PG), the position of the system cursor (PSC), and the position of the content change (PCC) in the video game. PG was monitored by the Eyetribe. PCC was identified by comparing the screen contents at different times. PSC was read in Processing program. Let d_{v1} be the distance between PG and PCC, and d_{v2} the distance between the PG and PSC. If there were multiple content changes, then d_{v1} was the average distance between PG and multiple PCCs. The system evaluated the visual engagement by comparing the sum of d_{v1} and d_{v2}.

$$E_p = d_{v1} + d_{v2} \quad (2)$$

In this case, the cursor was always one of the content changes in the screen. Therefore, we can only use d_{v1} to represent the perceptive engagement. This distance is also an indicator of the reaction time of the patient. If the distance becomes bigger, it means that the patient becomes slower in reacting to the game tasks. The Eyetribe was used to monitor the position of gaze on the display unit. It relies on infrared illumination and uses advanced mathematical models to determine the point of gaze. The sample rate was 30 Hz. We used Processing to read the eye tracking data and PSC. The data also contained system time in the unit of unix timestamp. These data were streamed to MATLAB via TCP/IP.

In MATLAB, example of Motion-Based Multiple Object Tracking[6] was used to detect the moving objects in a video. The input video was made by capturing the area of the game on the screen using ScreenCapture tool[7]. The unix timestamp of the system time was also read in MATLAB with screen changes. Then the two timestamps read from MATLAB and Processing were used to synchronize these two signals so that d_{v1} can be calculated.

5.4.4 Cognitive engagement monitoring

Cognitive engagement (E_c) is considered to be proportional to the level of concentration performing cognitive tasks.

$$E_c = \frac{\beta}{\alpha + \theta} \quad (3)$$

Emotiv EPOC, a headset with 14 nodes, was used to monitor the EEG signal. The EEG measurements were gathered from AF_3, AF_4, F_3, F_4, FC_5, and FC_6 on the frontal lobe which is known to manage attention, mental states and motor planning. The sampling rate was 128 Hz. Similar to MYO, Visual Studio 2010 was used to read the data from the headset and streamed and stored in MATLAB. We adopted the processing method from Freeman's study [28]. The power spectrum was calculated using a fast Fourier transformation. Bandwidth powers of α (8-12Hz), β (13-30Hz), and θ (4-7Hz) were calculated by combining the bin powers in these three bandwidths. Then bandwidth powers were divided by total power (0-80Hz) to produce percent power. E_c was first computed over a 20-s period and then updated every 2s using a moving 20-s window.

5.4.5 Emotional engagement monitoring

The indicator for emotional engagement (E_e) is the ratio between time duration when positive emotion is dominant and the time duration when negative emotion is dominant.

$$E_e = T_{positive} / T_{negative} \quad (4)$$

[6] http://nl.mathworks.com/help/vision/examples/motion-based-multiple-object-tracking.html
[7] http://nl.mathworks.com/matlabcentral/fileexchange/24323-screencapture-get-a-screen-capture-of-a-figure-frame-or-component

In our system, the emotion is monitored by Insight, which is one software that can measure the user's emotion based on facial expression and produces the likelihoods of the emotion in seven categories, namely, neutral, happiness, surprise, anger, disgust, fear, and sadness. Insight was run in Visual Studio 2010. So we used the same method as with MYO to send the results of Insight to MATLAB via TCP/IP.

5.4.6 Test setup of the EMS

Due to the computation capacity of a regular computer, two computers were used for implementing the prototype. Basic information of these two computers was shown in Table.5.2. As you can see in Figure.5.5, computer #1 ran the game, and Eyetribe, and MATLAB in its background. We selected several games from the Internet, with focuses on motor training and cognitive training. All the games were played with mouse in computer #1. Chrome was used for running the game. MATLAB interpreted the perceptive engagement level based on the measurement of the gaze from Processing and the measurement of screen

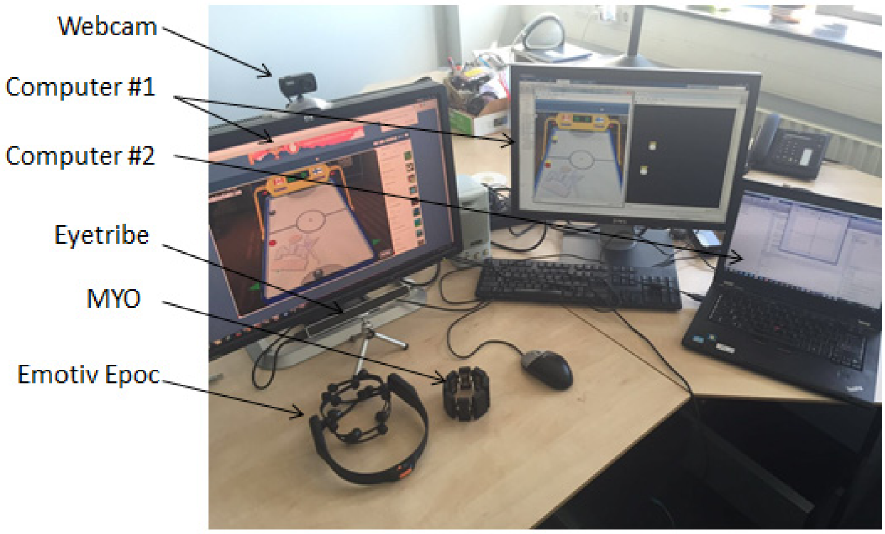


Figure 5.5 Overview of the prototype

Table 5.2 Properties of two computers used in the prototype

Computer	Operation system	Processor	Installed memory(RAM)	System type	Monitor type
Computer #1	Windows 7 Enterprise	Inter(R) Core(TM) i7-2770 CPU @3.40GHz	16GB	64-bit	HP LP2475w
Computer #2	Windows 7 Ultimate	Inter(R) Core(TM) i5-2520M CPU @2.50GHz	3GB	64-bit	Thinkpad Display

changes.

Computer #2 ran MATLAB, MYO, Insight, and Emotiv Epoc. The data from these three sources were streamed to MATLAB via TCP/IP from Visual Studio. The program in MATLAB interpreted these data as motor engagement, cognitive engagement, and emotional engagement. Together with the data sent from MATLAB in computer #1 via TCP/IP, the MATLAB program in computer #2 were able to represent all the four levels of engagement in real time.

5.5 Validation of the functionality of the EMS

5.5.1 Objective

In this pre-medical experiments, the goal was to characterize the range and accuracy of the engagement indicators by influencing the subjects into different engaged states. The reliability of the indicators was an important issue. We expected that healthy subjects may provide a more consistent sample set, which allows us to see if the selected indicators of engagement can be used. Five healthy subjects were recruited in four experiments, which were designed and conducted to individually validate system modules of motor, perceptive, cognitive and emotional engagement monitoring. Different setups were created to mimic the situations in which the subject was in engaged, unengaged, or neutral engagement state. The prediction of the measurement in each setup is demonstrated in Figure 5.6. Our assumption was the measurement of the indicator for the motor and cognitive engagement would be higher and the measurement of the indicator for perceptive engagement would be lower in the engaged state than that in the neutral and the bored state. Due to the small sampling, Friedman Test,

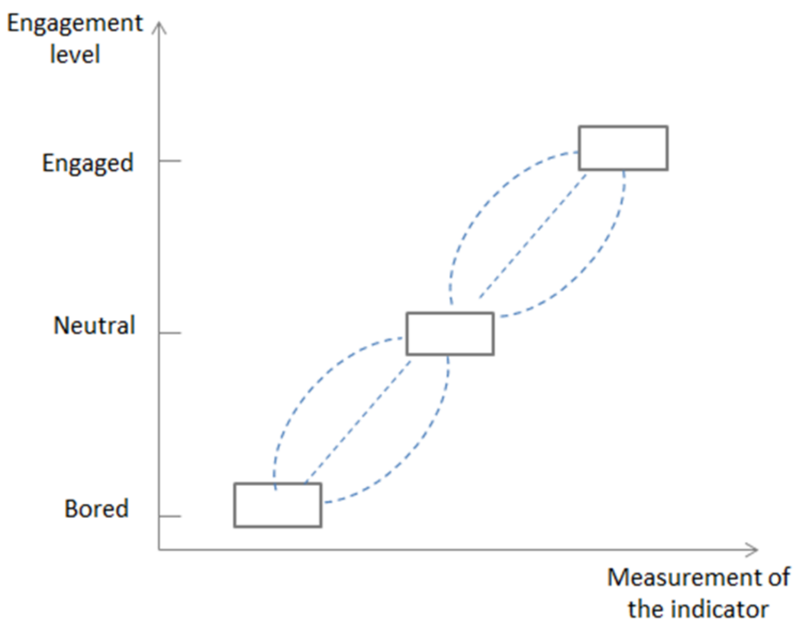


Figure 5.6 Prediction of the measurement in different setups

non-parametric method of analysis, was applied in each experiment to see if the results were consistent for all the subjects.

5.5.2 Experiment to validate indicator of motor engagement

1) Design of the experiment

The objective of this experiment was to validate the indicator for motor engagement, which was correlated with RMS of EMG divided by the velocity of the movement. We investigated and compared the measurements of the indicator in the created engaged and unengaged state. When the subjects were making the movement with attention and effort, the level of their motor engagement was supposed to be higher. Therefore, in the experiment mimicking the engaged state, the subjects were required to follow a strict accuracy requirement that needed the subject's attention. Whereas in the created unengaged state, instead of making active movement, the subjects were passively moved by the experimenter. We also investigated the influence of velocity of the movement by requiring the subjects to move at different speeds.

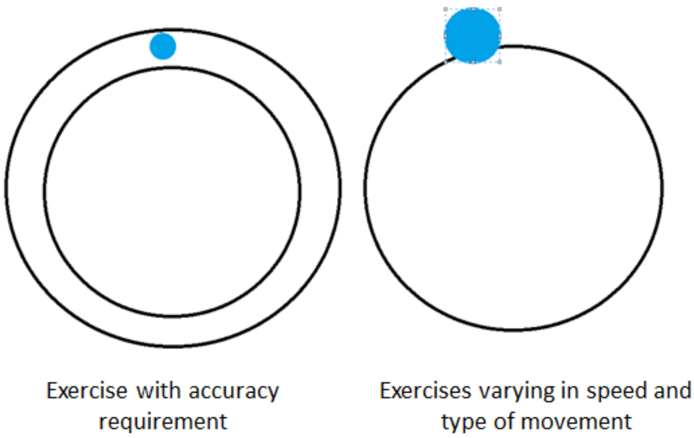


Figure 5.7 The picture for the motor exercises displayed on the screen

In this experiment, the exercise was displayed on the screen for the subjects (Figure 5.7). All the five subjects were required to use their right arm to do different exercises, in which they controlled the computer mouse to drag the object (the small solid circle) to track the given circle. During each exercise, MYO armband was put on the middle of the upper right arm of the subject to measure the EMG signals. There were three variables in different exercises (Table 5.3). The first one was accuracy requirement. In the exercise requiring accuracy, the subject had to move the solid circle in the area between two given circles. The second one was speed requirement. The subject was required to move at three speeds respectively. At high speed, the subject had to complete each circle in about 3 seconds, while at medium and low speed, the time of completing a circle

Figure 5.8 The equipment used in the passive exercises

was 5 seconds and 10 seconds respectively. The speed was controlled by the subjects. The third variable was the type of movement, active or passive. In the active movement, the subject moved voluntarily, while in passive movement, the subject was moved by the experimenter to move using the equipment shown in Figure 5.8. The subject put their right hand on one of the handles, and the experimenter grasped the other handle to drive the subjects to complete the exercise. The mouse in the middle of the equipment was also controlled by the experimenter by another hand.

Table 5.3 Independent variables in the exercises for validating motor engagement

Exercises	Accuracy	Speed	Type of movement
Exercise 1	Accurate	No requirement	Active
Exercise 2	No requirement	3 seconds to complete	Active
Exercise 3	No requirement	5 seconds to complete	Active
Exercise 4	No requirement	10 seconds to complete	Active
Exercise 5	No requirement	3 seconds to complete	Passive
Exercise 6	No requirement	5 seconds to complete	Passive
Exercise 7	No requirement	10 seconds to complete	Passive

In the exercise with accuracy constraints, the subject was required to move the solid circle in the area between two given circles without speed requirement. In the second to fourth exercise, the subject was required to move the solid circle to track the big circle at high speed, medium speed and low speed respectively but without accuracy constraints. In the fifth to seventh exercise, the experimenter drove the subject to track a big circle at three speeds without accuracy requirement. Each exercise lasted one minute. The order of the exercise was random for different subjects.

2) Results

The mean of RMS of EMG and the velocity of the movement were calculated in every second. The typical patterns of the indicator of motor engagement, that is the RMS of the EMG signal divided by velocity, in all the seven exercises are shown in Figure 5.9. Boxplot of the measurement of all the subjects in different setups was shown in Figure 5.10. In the box, the central line is the median, the circle is the mean, and the edges of the box are the 25th and 75th percentiles.

A Friedman Test was conducted to test for differences between different setups. There was a statistically significant difference in the measured indicator depending on different setups, $\chi 2(2) = 19.736$, $p = 0.003$. Post hoc analysis with Wilcoxon signed-rank tests was conducted with a Bonferroni correction applied. Due to the reason that Bonferroni corrections are overly conservative, only one comparison between the active exercise with accuracy requirement and active exercise with a high speed. Post hoc analysis showed there was a significant difference

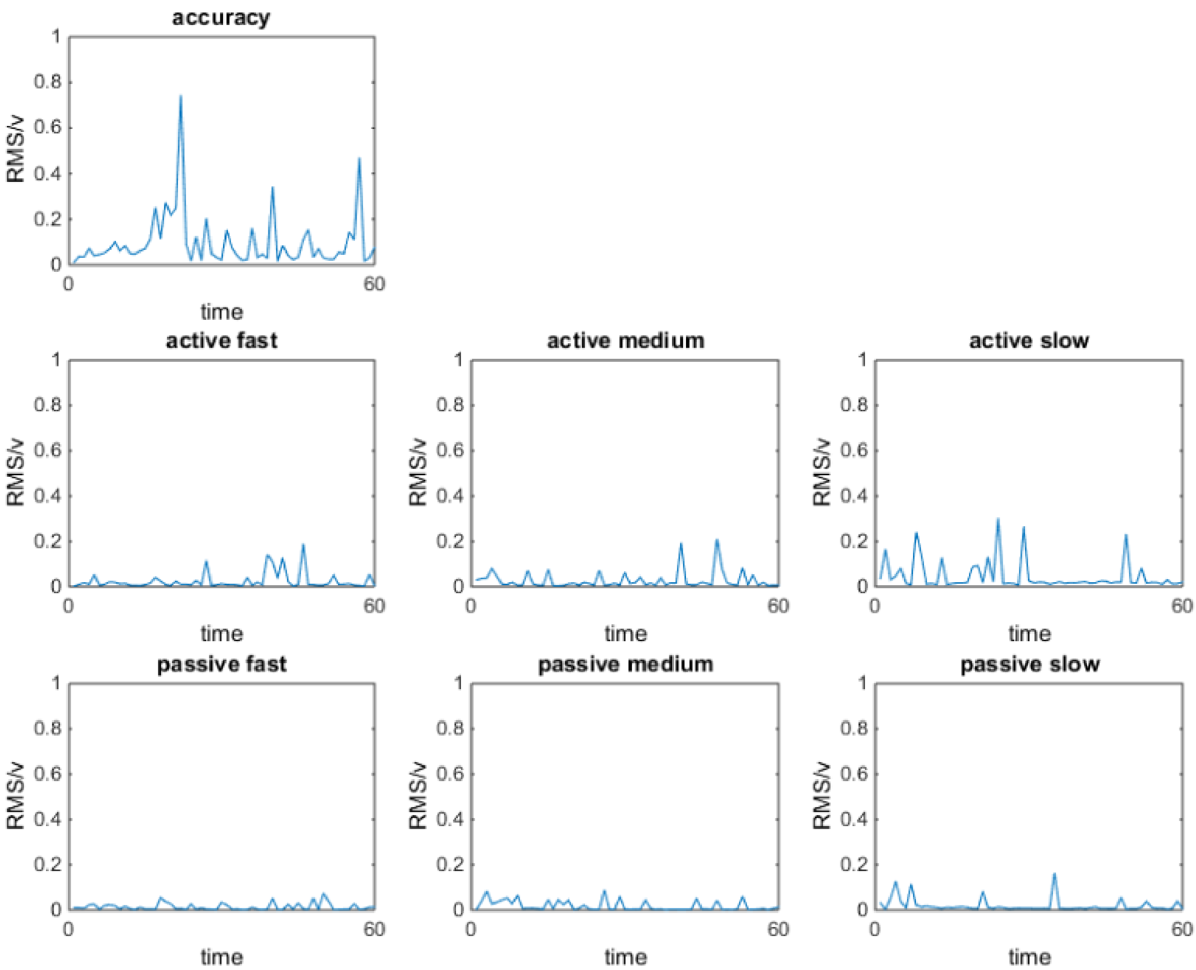


Figure 5.9 Typical pattern of the motor indicator in different exercises

in the measurement between these two exercises (Z=-2.023, p=0.043). Median (IQR) motor engagement for the exercise with accuracy requirement, the exercise with active movement at a high speed, the exercise with active movement at a medium speed, the exercise with active movement at a low speed, the exercise with passive movement at a high speed, the exercise with passive movement at a medium speed, the exercise with passive movement at a high speed, were 0.23 (0.14 to 0.3), 0.08 (0.035 to 0.12), 0.07 (0.045 to 0.1), 0.08 (0.06 to 0. 125), 0.03 (0.015 to 0.07), 0.06 (0.03 to 0.085), and 0.03 (0.02 to 0.085), respectively.

The sensitivity and the specificity of the indicator for motor engagement were also analyzed. Two data sets from exercise 1 and exercise 7 were used. When the measurement of one subject in exercise 1 was the biggest among the seven setups, it was recognized as a true positive; when the measurement of one subject in exercise 7 was the smallest among the seven setups, it was recognized as a true negative. The analysis showed that the sensitivity was 100% and the specificity was 86.7%, which means the indicator was able to distinguish the motorly engaged and unengaged setups.

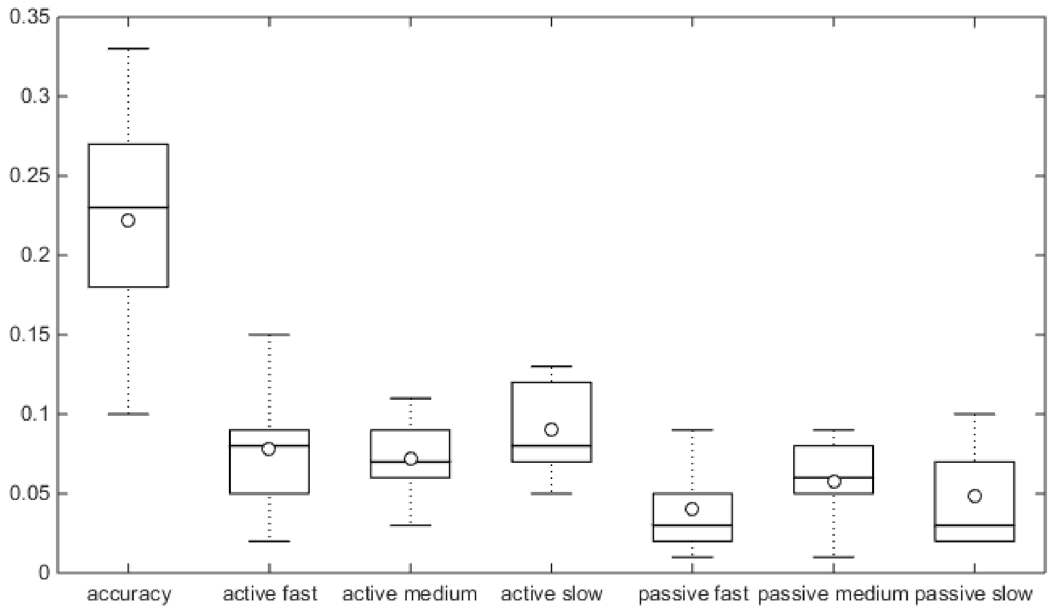


Figure 5.10 Boxplot of the measurement of all the subjects in different setups

5.5.3 Experiment to validate indicator of perceptive engagement

1) **Design of the experiment**

The objective of this experiment was to validate the indicator for perceptive engagement, which was characterized by the distance between the focus of the subject's gaze and the content changes on the screen. According to the definition of the perceptive engagement, when the subject was following the content changes on the screen, he/she was regarded to be engaged perceptively. Therefore, in the simulated engaged state, the subject was required to follow the content changes all the time. While in the simulated unengaged state, the subject was asked to get fixated on non-changed part of the screen.

In this experiment, the picture for the exercise was shown on the screen (Figure 5.11). During each exercise, the first object was always moving in the given circle on the screen. The subjects were required to look at the first object and follow its location until the second object appeared on the screen. Then the subjects were asked to look at the second object until it disappeared from the screen. The second object stayed at the same position during its appearance. A controlled time of appearance was used as independent variable of this experiment. When the second object appeared for a short time (i.e. 1 second) it was

Table 5.4 Independent variables in the exercises for validating perceptive engagement

Exercises	Duration of the second object on display
Exercise 1	1 second
Exercise 2	3 seconds
Exercise 3	5 seconds
Exercise 4	9 seconds

regarded as a screen change by comparing the two frames of the screen in MATLAB. When it appeared on the screen for longer time (e.g. more than 3 seconds), it was not considered as a screen change, but as a loss of attention. The gaze of the subjects was monitored by Eyetribe, which was put in front of the subject. The Eyetribe was calibrated for the subject before the exercise.

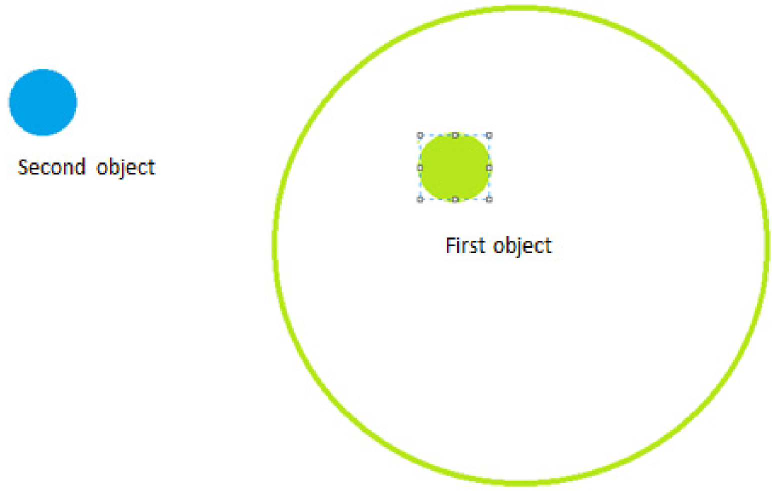


Figure 5.11 The picture for the perceptive exercise

There were four exercises in this experiment. Each exercise lasted one minute. The order of the exercise was random for different subjects. In the first exercise, the second object stayed on the display for one second, and the interval between its appearances was 9 seconds. In the second exercise, the second object stayed on the display for 3 seconds, and the interval was 7 seconds. In the third and fourth exercise, the second object stayed on the screen for 5 seconds and 9 seconds respectively, and the interval was 5 seconds and 1 second respectively. Therefore, in the first exercise, the subjects had full perceptive engagement, and the indicator for perceptive engagement was expected to increase in the other exercises.

2) Results

The mean of the distance between the subject's gaze and the screen changes was analyzed in every second. Typical patterns of the indicator in different exercises were shown in Figure 5.12.

In the typical patterns, we can see that in the first exercise, since the subject was perceptively engaged all the time, the distance was between 1cm and 6cm in the whole exercise. While in the second setup, when the second object stayed longer at the same position on the screen, the subject got fixated on the non-changed content. As the first object moved while the subjects were fixated, the distance between the focus of the subjects' gaze and the location of the first object has increased in the corresponding time period. As the second object appeared longer in the third and fourth exercises, the distance remained high for a longer duration.

Boxplot of the measurement of all the subjects in different setups was shown in Figure 5.13. In the box, the central line is the median, the circle is the mean, and the edges of the box are the 25th and 75th percentiles.

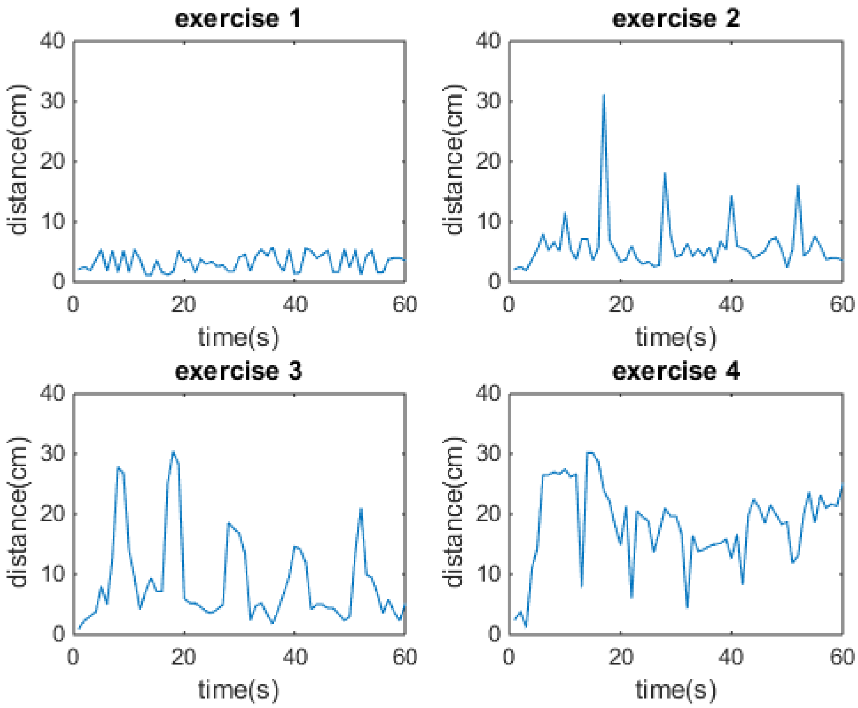


Figure 5.12 Typical patterns of the distance in different exercises

A Friedman Test showed that there was a statistically significant difference in the measured indicator depending on different setups, $\chi2(3) = 15.00$, $p = 0.002$. Post hoc analysis with Wilcoxon signed-rank tests was conducted with a Bonferroni correction applied. Similar as in the analysis above, only one comparison between exercise 1 and exercise 2 was conducted. Result showed a significant difference in the perceptive engagement between these two

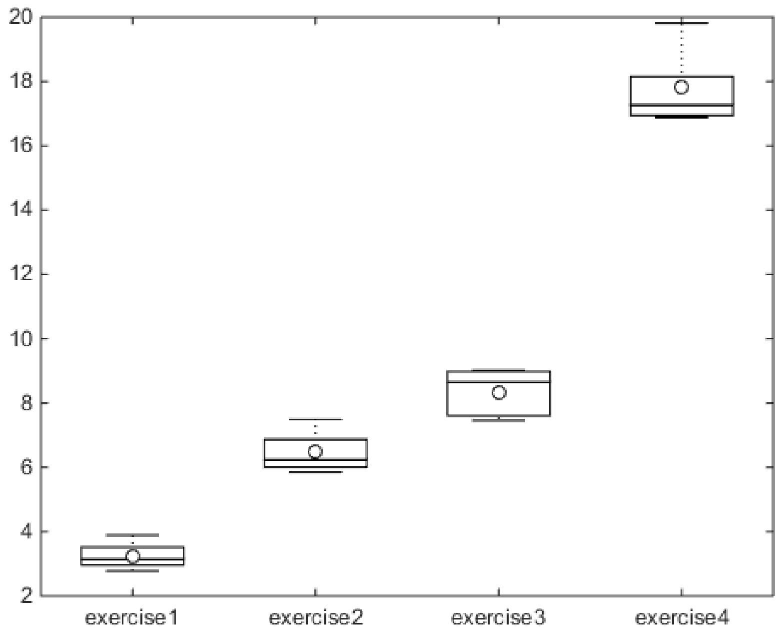


Figure 5.13 Boxplot of the measurement of all subjects in different setups

exercises (Z=2.023, p=0.043). Median (IQR) perceptive engagement for exercise 1, exercise 2, exercise 3, exercise 4, were 3.14 (2.87 to 3.71), 6.23 (5.93 to 7.18), 8.65 (7.54 to 9.00), and 16.91 (17.26 to 18.98), respectively. Separate Wilcoxon signed-rank tests were conducted as the Post Hoc Tests. However, no significant differences were found between different setups.

The sensitivity and the specificity of the indicator for perceptive engagement were analyzed. Two data sets from exercise 1 and exercise 4 were used. When the measurement of one subject in exercise 1 was the biggest among the four setups, it was recognized as a true positive; when the measurement of one subject in exercise 4 was the smallest among the four setups, it was recognized as a true negative. The analysis showed that the sensitivity was 100% and the specificity was 100%, which means the indicator was able to distinguish the perceptively engaged and unengaged setups.

5.5.4 Experiment to validate indicator of cognitive engagement

1) Design of the experiment

The objective of this experiment was to validate the indicator of cognitive engagement, which was defined in formula (3). Our assumption was that when the subject is doing the cognitive tasks intensively with effort, the indicator for the cognitive engagement is higher. Therefore, in the artificially created cognitively engaged state, the subject was involved with challenging cognitive tasks. While in the artificially created unengaged state, the subject was involved with less intensive and less challenging cognitive tasks.

In the experiment of cognitive engagement, all the 5 subjects were asked to play a cognitive game, Corsi block task (Figure 5.14), in which the subjects were required to remember order of the blocks that got marked, then used the computer mouse to click them in the same order. There were two independent variables in different exercises. The first one was difficulty of the cognitive tasks. The second one was the intensity of the cognitive tasks.

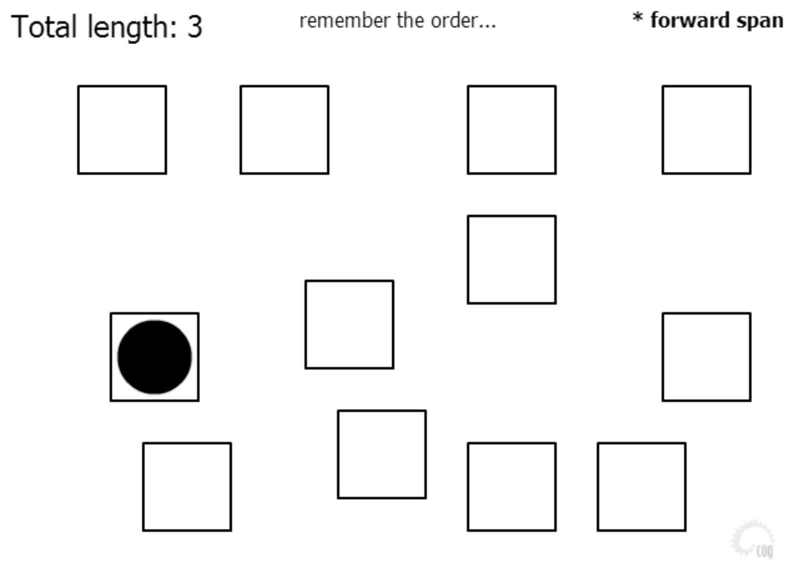


Figure 5.14 Corsi block task

In the first exercise, the subjects were required to complete 10 challenging tasks. During the first exercise, the subject can only play the next level with more blocks to remember, if he/she completed two tasks at the current difficulty level. The cognitive task was always challenging for the subject in this way. When the subject completed 10 tasks, the exercise stopped. While in the second exercise, the subject was required to play 10 tasks at the easiest level (3 blocks to remember) during 2 minutes. In the third and fourth exercise, the subject was required to complete 5 and 1 task at the easiest level respectively during 2 minutes. After the subject completed the task in the second to the fourth exercise, in the rest of the time, the subject was asked to move the mouse between different blocks, but without doing any cognitive tasks. The aim of this requirement was to make the subject to make similar movement during each exercise to eliminate the influence of the movement on the measurement. The order of the exercises was random for different subjects.

Table 5.5 Independent variables in the exercises for validating cognitive engagement

Exercises	Amount and difficulty of the cognitive tasks
Exercise 1	10 challenging tasks
Exercise 2	10 easy tasks
Exercise 3	5 easy tasks
Exercise 4	1 easy task

2) Results

The results were analyzed from the 6 locations, AF_3, AF_4, F_3, F_4, FC_5, and FC_6. We found that there was a clear tendency in the data from AF_3 to represent cognitive engagement of the subjects, but no clear tendency in the data from the other five locations. So the results analyzed from the data of AF_3 were presented below. Typical patterns of E_c were shown in Figure 5.15. Boxplot of the measurement of all the subjects in different setups was shown in

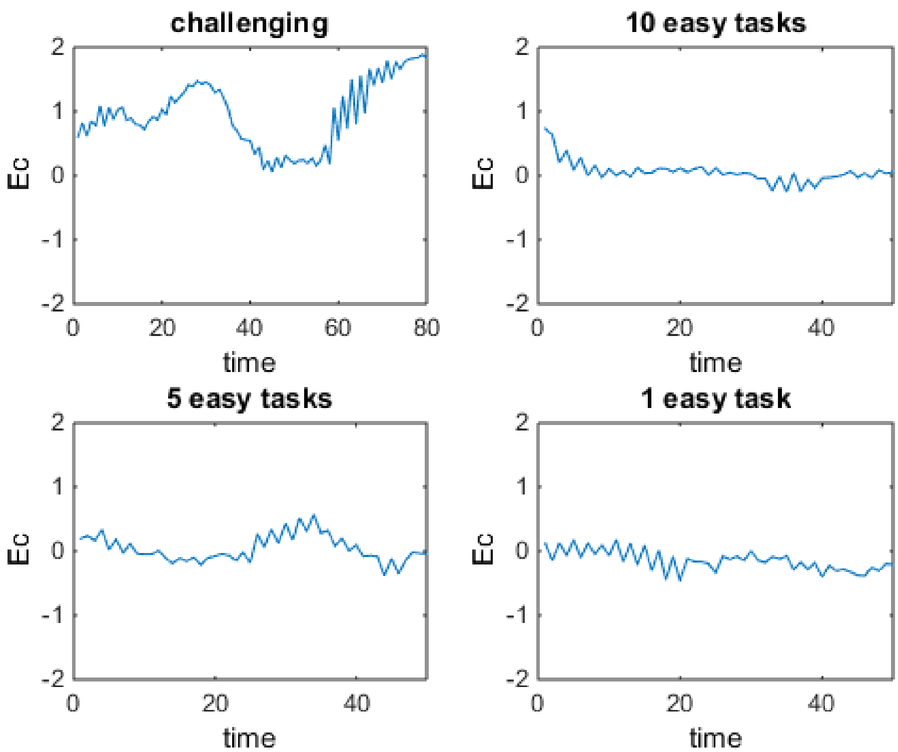


Figure 5.15 Typical patterns of RMS of E_c

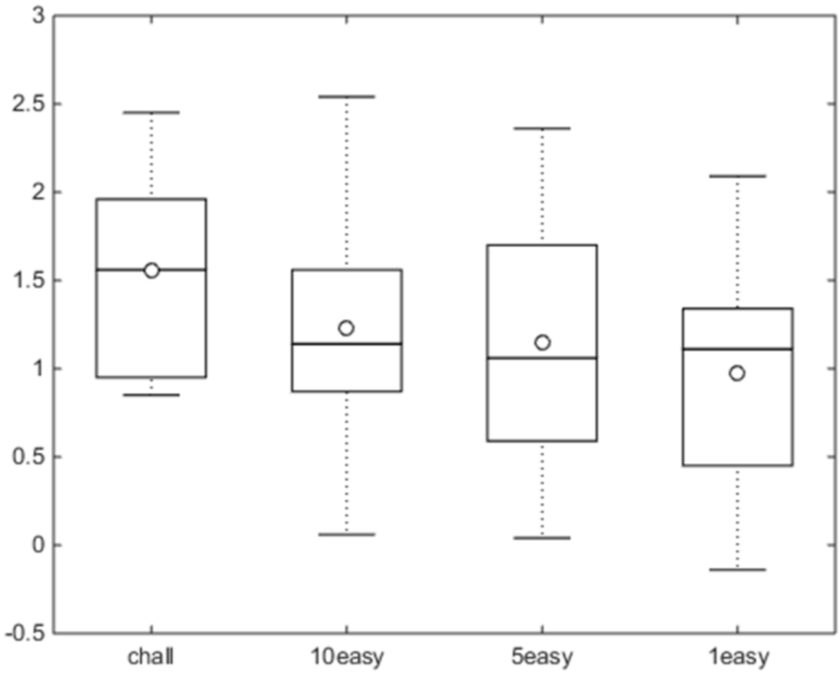


Figure 5.16 Boxplot of the measurement for all the subjects in different setups

Figure 5.16. In the box, the central line is the median, the circle is the mean, and the edges of the box are the 25th and 75th percentiles.

A Friedman Test showed that there was a statistically significant difference in the measured indicator depending on different setups, $\chi2(3) = 10.92$, $p = 0.012$. Post hoc analysis with Wilcoxon signed-rank tests was conducted with a Bonferroni correction applied. According to our hypotheses, two comparisons were conducted, between exercise 1 and exercise 2, and between exercise 2 and exercise 3, resulting in a significance level set at $p < 0.025$. However, no significant difference was found in these two pairs, between exercise 1 and exercise 2 ($Z=-1.214$, $p=0.225$), between exercise 2 and exercise 3 ($Z=-1.214$, $p=0.225$). Median (IQR) perceptive engagement for exercise 1, exercise 2, exercise 3, exercise 4, were 1.56 (0.90 to 2.21), 1.14 (0.47 to2.05), 1.06 (0.32 to 2.03), and 1.11 (0.16 to 1.72), respectively.

The sensitivity and the specificity of the indicator for cognitive engagement were analyzed. Two data sets from exercise 1 and exercise 4 were used. When the measurement of one subject in exercise 1 was the biggest among the four setups, it was recognized as a true positive; when the measurement of one subject in exercise 4 was the smallest among the four setups, it was recognized as a true negative. The analysis showed that the sensitivity was 60% and the specificity was 80%, which means the indicator was able to distinguish the cognitively engaged and unengaged setups.

5.5.5 Experiment in emotional aspect

1) Design of the experiment

According to our definition of the emotional engagement, the subject is emotionally engaged when the rehabilitation exercise can influence the subject's emotion. The indicator for emotional engagement was the ratio of the time duration when positive emotion (happiness and surprise) was dominant with the time duration when negative emotion (anger, disgust, fearful, and sad) was dominant. The objective of this experiment was to validate if the emotion analyzed by Insight can reliably measure the subject's emotion. If the emotions analyzed by Insight can match the emotions indicated by the subject, it can be inferred that the indicator for emotional engagement will be measured correctly using Insight. To achieve the objective, the subjects were required to complete a questionnaire in which they had to reflect their emotions in the given moments during each exercise. Then the emotions reflected by the subjects were compared to the emotions measured by Insight.

During this experiment, each subject was required to play three online games (Figure 5.17). In Air hockey, the subjects had to play against the computer. They were expected to use the hockey stick (the one below), which was controlled by the

Air hockey

Connect

Cooking

Figure 5.17 Online games

Table 5.6 Questionnaire----emotion at given moments during different game exercises

Please fill in your emotion at each moment during the game you just played. You can choose one of the following emotions: neutral (😐), happy (😃), surprised (😯), anger (😠), disgust (😩), fearful (😨), sad (😞), or other (name it).								
Air hockey		Time (s)	Connect		Time (s)	Cooking		Time (s)
Moments	Emotion		Moments	Emotion		Moments	Emotion	
Beginning	Neutral	0	Beginning	Neutral	0	Beginning	Neutral	0
Score first goal	Surprised	19	Finding pairs fast	Neutral	25	Slicing the meat	Neutral	150
Lose first goal	Anger	12	Struggling finding pairs	Anger	52	Finish slicing	Happy	230
Pass first level	Happy	54	Computer gives you a hint	Happy	86	Marinating the chicken	Bored	320
Score behind the component	Fearful	65	One minute left	Fearful	300	Finishing marinating the vegetables	Bored	340
Lose at a level (if any)	Anger	103	Finished the task in time (if you did)	No		Heating the kebab	Bored	470
End	Motivated to return	120	Cannot finish in time	Relaxed	360	End	Relaxed	570

mouse, to shoot the hockey in the opposite goal. The subjects were required to play the first two components in this game. In the game Connect, the subjects had to connect the same two objects with the mouse and finish in four minutes. In the Cooking game, the subjects were required to move the mouse to cook kebab according to the game instructions. The order of these three games were random for different subjects. These games were controlled by the mouse. During each game, the subject's emotion was analyzed by Insight.

After each game, the subject was required to fill in a questionnaire in Table.5.6. The questionnaire of each exercise was given to the subject separately after each exercise. In the questionnaire, the subject had to choose one of the emotions from a list of Emoji faces[8], including neutral (😐), happy (😃), surprised (😯), anger (😠), disgust (😩), fearful (😨), sad (😞), or other (named by the subject), at each given moment during the exercise, while the time of each moment was filled in by the experimenter. During the exercise, the experimenter recorded the time at each moment in the questionnaire. After the exercise, the emotion analyzed by Insight at each moment was identified, which was then used to be compared with the emotion reflected by the subject at the same moment. The result of one subject was shown in Table.5.6.

[8] http://unicode.org/emoji/charts/full-emoji-list.html

2) Results

The mean of emotion measured by Insight was calculated in every second. The dominant emotion in each second, which means the highest value of the seven emotions at that moment, was identified. The analyzed dominant emotions of the same subject who filled in the questionnaire above were shown in Figure 5.18. Then these analyzed emotions were compared with the results of the questionnaires. We found that the overall accuracy of the emotions analyzed by Insight was 56%. However, the accuracy was 68% for four subjects, who seemed to express their emotions explicitly. For the other subject, although he indicated in the questionnaire that his internal emotion changed during the games, neutral emotion was the dominant emotion for 86% of the time. Moreover, Insight was found to be more accurate in identifying happiness, with an accuracy of 82%, much higher than the negative emotions, such as anger, disgust, and fearful. It may because that the subjects tend to express positive emotion more easily and naturally than negative emotions.

Then the proportion of the emotion at each moment was analyzed. The most dominant three emotions at each moment in each game were shown in Table 5.7. We found that although the dominant emotion identified by Insight was not the same as the emotion indicated by the subject at some

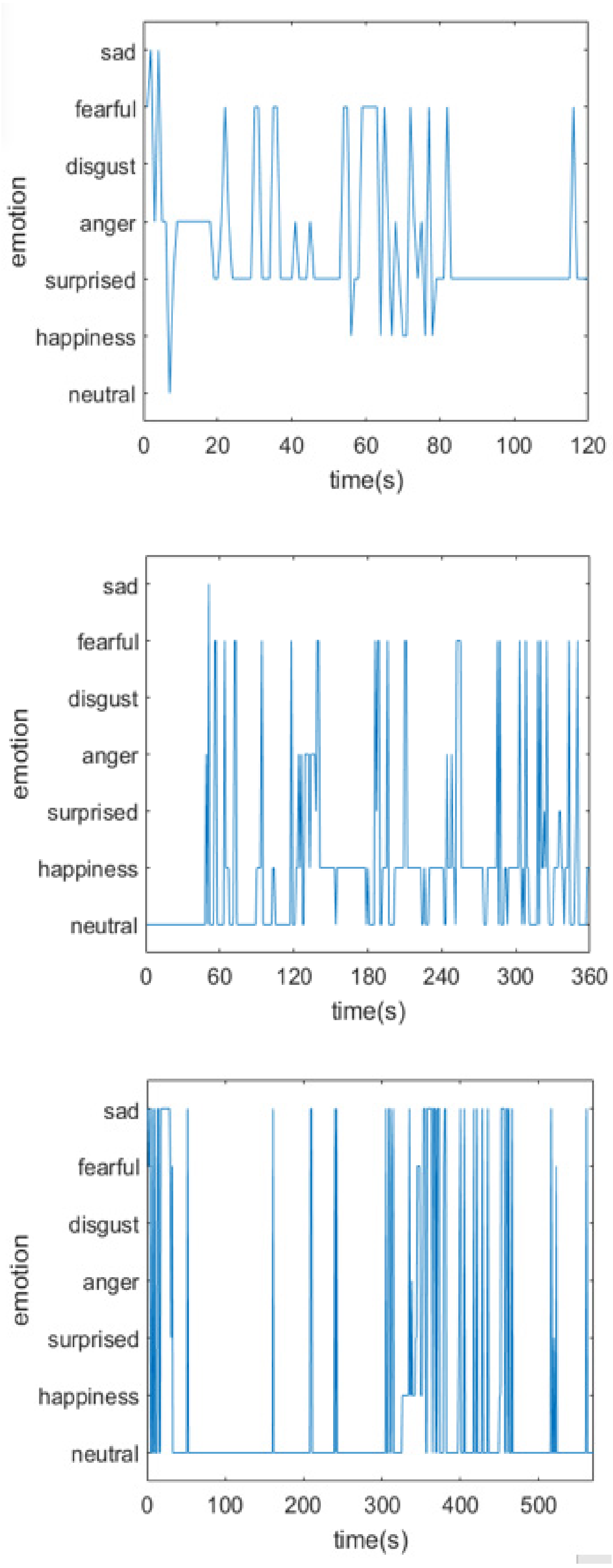


Figure 5.18 Typical patterns of emotion analyzed by Insight in each game (From left to right: Air hockey, Connect, and Cooking)

Table 5.7 Proportion of the components of emotion at each moment

Air hockey						
Beginning	neutral	33%	fearful	62%	surprised	1%
Score first goal	neutral	2%	surprised	98%	others	0%
Lose first goal	neutral	25%	happy	49%	surprised	9%
Pass first level	neutral	3%	happy	94%	others	3%
Score behind the component	neutral	21%	surprised	36%	fearful	41%
Lose at a level	surprised	41%	happy	10%	anger	3%
End	surprised	39%	happy	27%	anger	6%
Connect						
Beginning	neutral	97%	surprised	2%	others	1%
Finding pairs fast	neutral	73%	surprised	13%	fearful	6%
Struggling finding pairs	neutral	25%	anger	33%	sad	19%
Computer gives you a hint	happy	89%	fearful	10%	others	1%
One minute left	happy	46%	surprised	14%	fearful	25%
Cannot finish in time	neutral	85%	happy	6%	fearful	6%
Cooking						
Beginning	neutral	87%	surprised	6%	sad	1%
Slicing the meat	neutral	93%	anger	4%	sad	3%
Finish slicing	neutral	52%	happy	26%	surprised	7%
Finish marinating the chicken	neutral	36%	happy	62%	others	2%
Finish marinating the vegetables	neutral	8%	fearful	1%	sad	88%
Heating the kebab	neutral	2%	anger	5%	sad	91%
End	neutral	13%	happy	41%	sad	37%

moments, the emotion indicated by the subject exist in the most dominant three emotions at some moments, such as “lose at a level” in Air hockey, “one-minute left” in Connect, and “finish slicing” in Cooking. Using the most dominant three emotions identified by Insight was found to improve the accuracy to 89% in matching the emotion indicated by the subjects. Therefore, the most dominant three emotions can be used in analyzing the indicator for emotional engagement. The indicator for emotional engagement can be refined as:

$$\mathrm{E}_e=\frac{T_{p1}*w_1+T_{p2}*w_2+T_{p3}*w_3}{T_{n1}*w_1+T_{n2}*w_2+T_{n3}*w_3} \tag{5}$$

(T_{p1}: time duration when positive emotion is the dominant emotion, T_{p2}: time duration when positive emotion is the second emotion, T_{p3}: time duration when positive emotion is the third emotion; T_{n1}: time duration when negative emotion is the dominant emotion, T_{n2}: time duration when negative emotion is the second emotion, T_{n3}: time duration when negative emotion is the third emotion; w_1, w_2, and w_3: weights are different for the top three emotions, here they are 0.5, 0.3, and 0.2 respectively.)

These results indicated that Insight was able to identify the subject's emotion reliably using the most dominant three emotions identified by Insight. Therefore, the refined indicator for emotional engagement can distinguish the situation when the subject is in a positive emotion and the situation when the subject is in a negative emotion.

5.6 Discussion and conclusions

5.6.1 Discussion of the work and results

The results have shown that there were significant differences in the measured indicator between different setups in the experiments of the motor, perceptive, and cognitive aspects, which has achieved the objective of the experiments to test if the proposed indicators can reflect the expected results in different setups.

Regarding the motor engagement, it was found that there was a significant difference between the active exercise with accuracy requirement with the active exercise with a high speed. However, the results showed that there is only small difference between the active exercise without accuracy requirement and passive exercise. This indicated that movement with accuracy requirement requires the subjects to pay much more attention and effort to complete the task. Active movement without accuracy requirement does not engage users on high level. Therefore, voluntary movement during rehabilitation training does not necessarily mean the patients are engaged. Other measures of the engagement in the perceptive, cognitive, and emotional aspects are also needed to have a comprehensive and accurate view on patients' engagement.

As for the experiment in the perceptive aspect, the results showed a significant difference in the perceptive engagement between the created engaged state and created neutral state, and there were also recognizable differences between other exercises. Experiments are still needed to be conducted to measure the indicator of perceptive engagement with real patients in the future.

In the cognitive aspect, no significant difference was found between exercise 1 and exercise 2, and between exercise 2 and exercise 3, which may be caused by the small sample size. Also, no clear difference was found between the exercises with different cognitive loads. It may because after the subject completed the required cognitive tasks during the third and fourth exercise, the subject's attention was diverted when doing the mundane movement from block to another block, according to some subjects. This diverted attention can lead to subject's cognitive action which was represented by the measurement. Therefore, this may be the explanation that there was no difference in the measurement between the exercise with more intensive cognitive tasks and less cognitive tasks.

In the emotional aspect, the subjects may be subjective in answering the questionnaires. But their answer should reflect their emotion at the moment, at least the emotion they believe they were in. Since it is difficult, if not impossible, to detect the subject's internal emotion, we believe this is the best way to monitor the emotion in this context. However, the current results from the Insight was not accurate enough to measure the subject's emotion. In the future, maybe it is a good idea to profile the engaged and unengaged facial expressions based on the results from the Insight, and then use a machine learning technique to classify the facial expressions into different engaged states.

The primary reason of monitoring the engagement from motor, perceptive, cognitive, and emotional aspects is to provide a comprehensive understanding of the engaged states of the patients in the context of rehabilitation. Moreover, the ultimate goal of the CP-SRS is to enhance the patient's engagement during rehabilitation training. Based on monitoring the engagement, the SLM can make suggestions on a suitable stimulation strategy in order to enhance the engagement in the aspects which have decreased.

Although the experiment has shown promising results with these healthy subjects, it is too early to draw conclusion if the identified indicators are able to represent the real engagement level of real stroke patients. Problems may occur in a real environment with stroke patients. For instance, there might be abnormality in the EMG or EEG measurement due to spasm or lesions in the region of the cortex where the EEG is measured from. Experiments with real stroke patients are still needed to validate the accuracy of the refined indicator because post-stroke patients may have different facial expressions due to muscle paralysis. Moreover, a trade-off between cost and accuracy could be reached if the indicator is not reliable. For instance, if the overall accuracy of facial expression analysis by Insight with real patients is low, then the CP-SRS could function accurately without including the Insight.

5.6.2 Conclusions

This chapter introduced the implementation and validation of the EMS. The proposed EMS can read the data from four sources, namely, MYO, Eyetribe, Emotiv Epoc, and Insight, to analyze the subject's motor, perceptive, cognitive and emotional engagement during the exercise. Experiments were conducted to test if the identified indicators can reflect the expected results in different setups, which were created to mimic the situations in which the subject was in different engaged states. The results have shown that there were significant differences in the measured indicator between different setups in the experiments of the motor, perceptive, and cognitive aspects. Therefore, it is promising to use the identified indicators to evaluate the engaged states of the patients during rehabilitation. Then, in the next step, based on monitoring and evaluating the engagement level during the exercise, the effectiveness of the stimulation strategies in enhancing the engagement and the accuracy of the suggestions from the SLM on the most suitable stimulation strategies will be investigated

5.7 References

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CHAPTER SIX

RESEARCH CYCLE 5:

Validation of the functionality of the stimulation strategies and smart learning mechanisms

6.1 Objective of this chapter

This chapter focuses on the validation of the functionality of the proposed stimulation strategies and the smart learning mechanisms (SLMs). Two aspects were considered in the validation study: (i) validation of the effectiveness of the applied stimulation strategies (SSs), and (ii) validation of the accuracy of the classifying suggestions of the SLM. In this chapter the functionality of the applied learning mechanisms (the neural network-based SLM and the Naive Bayes-based SLM) is validated using real life data, with the objective of evaluating and comparing the actual effects of the SSs. The next section introduces the completed within-subject experiment. Section 6.3 analyzes the effects of applying various SSs individually and in combination. After that, the results of the ANOVA investigation are presented, which was done to see if there was any significant difference between the effects of the different SSs. Section 6.4 tests the accuracy of the suggestions made by the SLMs. To achieve this, the data from the experiments were used to train, validate, and test the two learning mechanisms.

6.2 Setup and conduct of experiments

6.2.1 Kinds and implementation of stimulations

A stimulation strategy (SS) is defined as a combination of stimulations in the motor, perceptive, cognitive, and emotional aspects. When stimulation is needed, the system applies a particular SS by adjusting a bundle of parameters in the game exercise. In total, there are 12 stimulations in the four considered aspects. The concrete manifestations of the available stimulations in the current prototype, and how they can be changed by adapting the parameters in the game exercises are listed in Table.6.1. For instance, introducing motor challenge is a form of stimulation in motor aspect. In the practice it means that the speed of the pointer of the system can be adjusted to a lower level so that it then requires faster

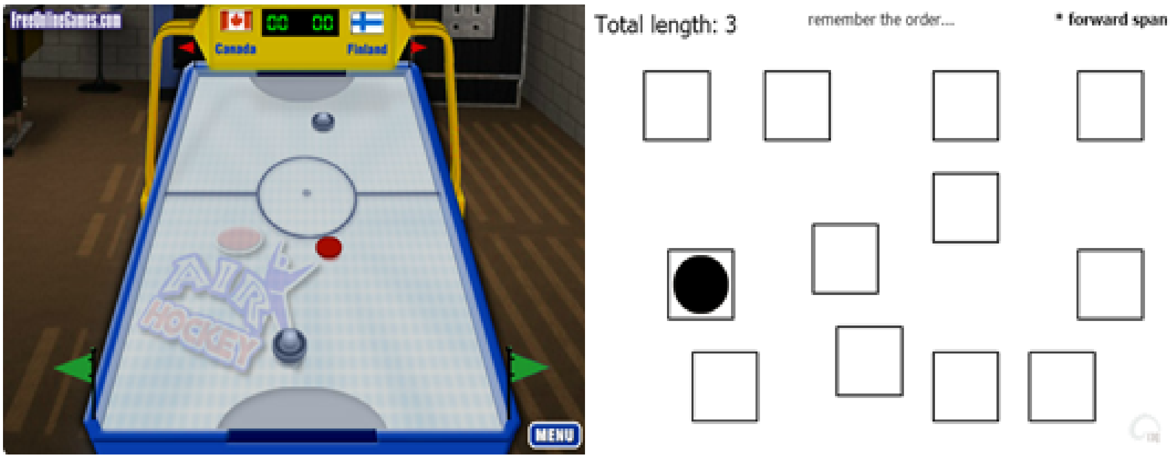
Table 6.1 Kinds and implementation of stimulations

Stimulations	Adjustable items	Parameters in the game exercise
Introducing motor challenge	Movement velocity	Pointer speed of the mouse (PS)
	Range of motion	Displayed size of the visual image of the game (DS)
Adjusting sensory feedback	Visual feedback	Displayed size of the visual image of the game (DS)
	Visual feedback	Resolution of the screen (RS)
Introducing cognitive challenge	Working memory task	Amount of items to memorize (AM)
Involving competition feature	Competition	Performance of the opponent (game computer) (PO)

movements from the patient. Since all of the game exercises are displayed on the screen, another adjustable item is the range of motion of the patient, and the related adaptable parameter is the displayed size of the visual image of the game. If the displayed size of the visual image is enlarged, the participant has to make bigger movements with the computer mouse to complete the task. The displayed size of the visual image can also influence the perceptive engagement of the participant. With regards to the perceptive stimulations, the contents of the sensory (visual) feedback can also be adjusted. Therefore, a combination of motor SS and perceptive SS can be achieved by adjusting the size of the displayed image. In the case of the working memory task, the cognitive challenge is that the patient is supposed to memorize multiple items during the game exercises. It has been found that increase of the competitive nature of game exercises can increase the patient's emotional involvement. The corresponding parameter is the performance of the opponent (i.e. the game computer) or the level of difficulty of the game.

6.2.2 Experiment design

To test the effectiveness of different SSs, a within-subject experiment was designed. In this experiment, 18 healthy participants (8 men and 10 women: aged 32.1 $\pm$ 7.7 years) were recruited to complete the two game exercises. The sampling strategy was convenience sampling. The first experiment focused on a motor task. As shown in Figure 6.1, this was an Air hockey game, and the participants had to play against the computer. They were expected to use the hockey stick (the lower one), which was controlled by the mouse, to shoot the hockey in the opposite goal. The second experiment focused on a cognitive task. This was a Corsi block game, and the participants were required to remember the order of the blocks that was marked, then to move the computer mouse to the right blocks, and click them in the same order. It was assumed that the effects of SSs on engagement of healthy participants are similar to the effects on the engagement of stroke survivors.



Air hockey

Corsi block task

Figure 6.1 The selected tasks: using (a) the Air hockey game and (b) the Corsi block game

During the exercise, all adjustable stimulations were applied individually in order to test their individual influence. Complementing this, combinations of stimulations were also applied to test their combined influence. The appropriate stimulations for this game exercise were identified as shown in Table. 6.2. Each setting of game exercise lasted for two minutes. In the case of the Air hockey game, SS1, SS2, and SS3 were the stimulations in motor, perceptive, and emotional aspect, respectively. SS4 was a combination of the SSs in motor and perceptive aspects, while SS5 was a combination of the SSs in motor, perceptive, and emotional aspects. Similarly, in the case of the Corsi Block game, SS1, SS2, and SS3 were the stimulations in motor, perceptive, and cognitive aspect, respectively. SS4 was a combination of motor and

Table 6.2 Suitable SSs in the two game exercises

Game exercises	Original settings	SS1	SS2	SS3	SS4	SS5
		Motor	Perceptive	Emotional	Motor & Perceptive	SS3 & SS4
Air hockey	DS: small PS: high RS: 1920 X1200 PO: easy	DS: small PS: low RS: 1920 X1200 PO: easy	DS: small PS: high RS: 1280 X800 PO: easy	DS: small PS: high RS: 1920 X1200 PO: hard	DS: large PS: high RS:1920 X1200 PO: easy	DS: large PS: high RS:1920 X1200 PO: hard
Game exercises	Original settings	SS1	SS2	SS3	SS4	SS5
		Motor	Perceptive	Cognitive	Motor & Perceptive	SS3 & SS4
Corse block	DS: small PS: high RS: 1920 X1200 AM: three blocks to remember	DS: small PS: low RS: 1920 X1200 AM: three blocks to remember	DS: small PS: high RS: 1280 X800 AM: three blocks to remember	DS: small PS: high RS: 1920 X1200 AM: increasing number of blocks to remember	DS: large PS: high RS: 1920 X1200 AM: three blocks to remember	DS: large PS: high RS: 1920 X1200 AM: increasing number of blocks to remember

perceptive stimulations, while SS5 was a combination of motor, perceptive, and cognitive stimulations. Since there was no reliable method to eliminate the interplay of SS on the next applied SSs, the order of the SSs was random for each participant with the aim of reducing the interplay to a minimal level.

6.2.3 Calibration of the engagement profile

The indicators of the four types of engagement were monitored by the EMS during the exercises. Before doing the exercise, the participant's engagement profile was calibrated in motor, perceptive, cognitive, and emotional aspects. This is referred to as the calibration phase. The participant was required to complete a task in four engaged situations. These situations were specifically created so as to get the participants fully engaged in motor, perceptive, cognitive, and emotional aspects. This resulted in a calibrated engagement profile for them, which was used as a reference value concerning the participant's engagement levels.

The four tasks used for calibrating the personal engagement profiles are shown in Figure 6.2. It has been discussed in Chapter 5 that the engagement levels related to these four created engaged tasks are supposed to be higher than that in the created unengaged situations. Specifically, in the case of the motor task it has been shown that when the participant was involved in the movement with accuracy requirement task, he/she had to complete the task with more attention and effort. The research data underpins that this resulted in a higher motor engagement. During the calibration of motor engagement, the participants were required to move the solid circle within the area between the two given circles, as shown in the first subfigure of Figure 6.2. In the case of the perceptive task, the engagement has been shown to be the highest when the participant followed the content changes on the screen all the time. During the calibration of perceptive engagement, the participants were required to look at the solid object and follow its movement within the big circle, as shown in the second subfigure of Figure 6.2.

In the case of the cognitive task, the engagement has been shown to be the highest when the participant was involved in a personally matched, challenging cognitive tasks. During the

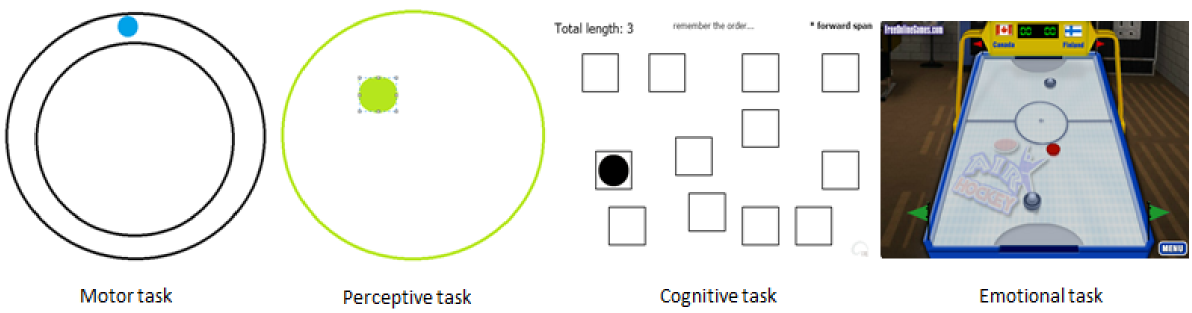


Figure 6.2 The four tasks used in calibrating the engagement profiles

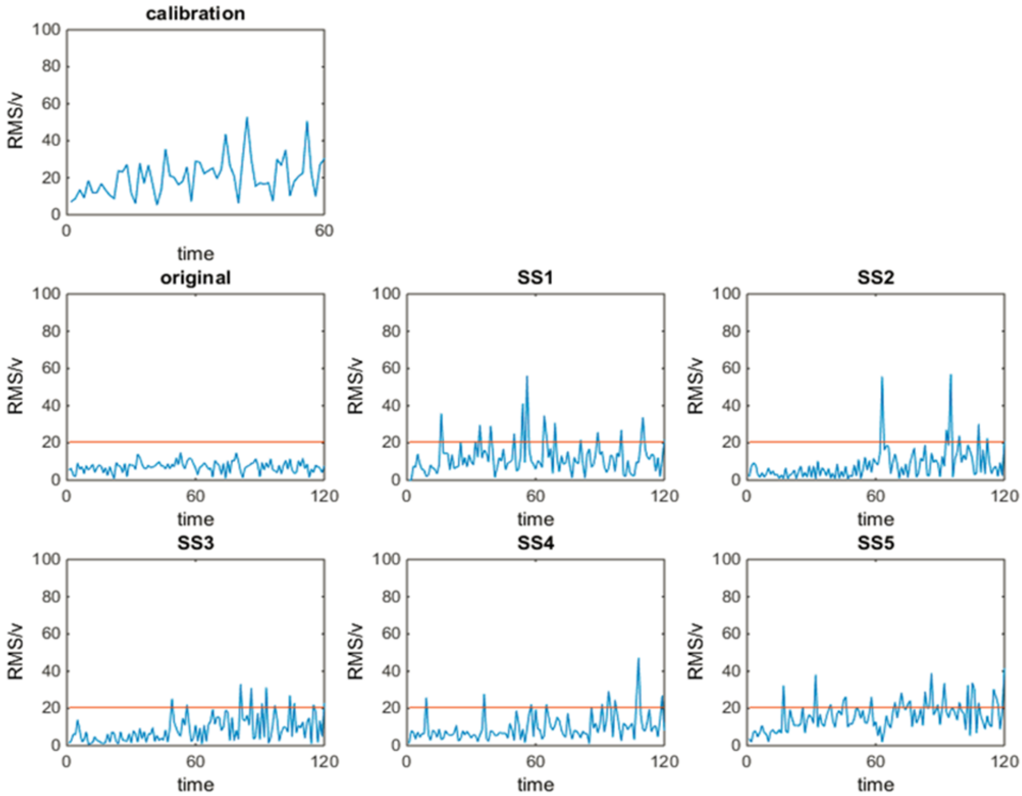
calibration of cognitive engagement, the participants were required to complete the task at a given difficulty level, then to move to the next level and play the game with more blocks to remember. In the case of the emotional task, first the participants played against the computer at the easiest level. On this level of challenge, it was guaranteed that the participants could win and enjoy the easy scoring. At a higher level of challenge, it was not guaranteed. The emotional engagement was measured as the ratio between the duration of time when this positive emotion was dominant and the duration of time when negative emotion was dominant. It was our observation in our previous experiment that the emotional engagement indicator was more accurate at mapping the emotion of the participants when the most dominant three emotions analyzed by Insight were used. This explains why the emotional engagement indicator was calculated using Equation (5) in Chapter 5.

Each task lasted for one minute in the calibration phase. The mean of the measurement during this one minute was recorded as the reference value in the participants' engagement profile. After finishing the calibration phase, the true experimental exercise began. First, the participant played the game with the original settings. Then, different SSs were applied and the changes were recorded. After the completion of the exercises, the mean of engagements in the four aspects were analyzed and compared with the reference value in the engagement profile. The effects of the various stimulation strategies on the output values were observable practically in all cases. Below we discuss the concrete effects of stimulation strategies on the different aspects of engagement.

6.3 Analyses of the effects of stimulation strategies

6.3.1 The effects on motor engagement

The mean of RMS of EMG and the velocity of the movement were calculated in 0.33s. The typical patterns of the motor engagement indicator in all of the settings after applying SS are shown in Figure 6.3. Since engagement is not a momentary construct, the mean of the indicator was used during each setting to characterize the actual level of motor engagement. Then, the actual level values were compared to the reference level values, which were included in the profiles in the calibration phase. The reference value, which was the mean of engagement level during task execution in the calibration phase, is indicated as a straight line in each setting in the typical patterns. In the case of the Air hockey game, the participants were moving all the time, while in the case of the Corsi block game the participants stopped moving when the next task was displayed. This explains why the motor engagement indicator remained zero several times in each setting of the Corsi block exercise. This means, the Corsi block exercise was not an optimal exercise from the aspect of motor training. Consequently, we used only the data related to the Air hockey game, when we analyzed the effects of the SSs on the motor engagement.



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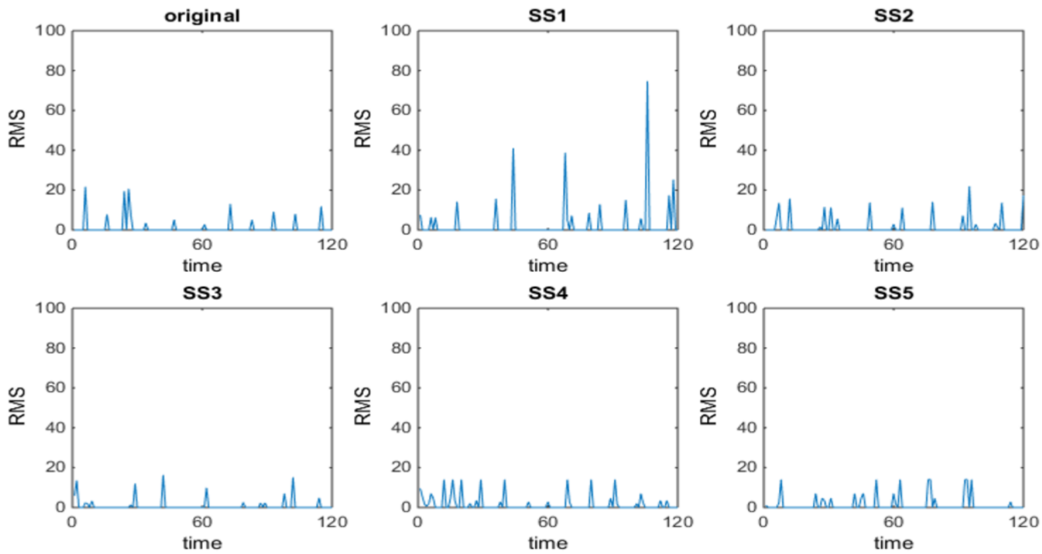


b

Figure 6.3 Typical patterns of the motor engagement indicator: (a) in the Air hockey game, and (b) in the Corsi block game

The boxplot of the motor engagement indicator is shown in Figure 6.4 in each setting of the Air hockey exercise. In the box, the central line is the median, the circle is the mean, and the edges of the box are the 25th and 75th percentiles. Since our intention was to analyze the differences in the actual level of motor engagement under different settings, a within-subject ANOVA was used to investigate the effectiveness of each SS. Based on the result from the

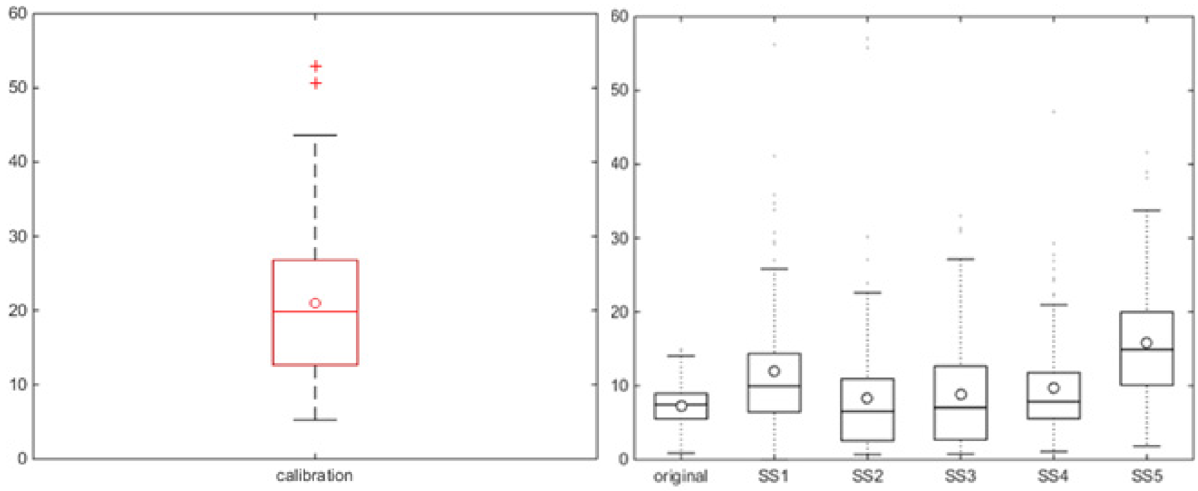
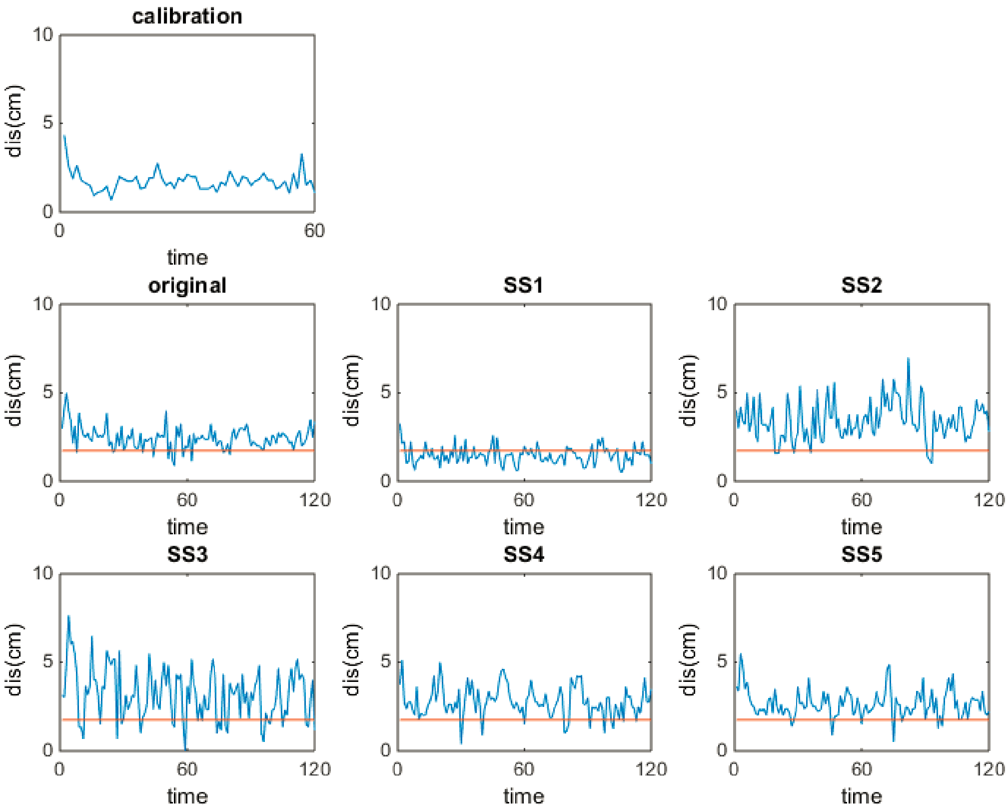


Figure 6.4 Boxplot of the measurement of the motor engagement considering all participants in the Air Hockey game

within-subject ANOVA, Mauchly's test indicated that the assumption of sphericity had been violated, $\chi^2(14) = 36.653$, p<0.05, therefore, degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity ($\epsilon = 0.603$). The mean of the indicator differed statistically significantly between different settings in Air hockey game (F (3.017, 51.290) = 29.911, p < 0.0001). Post hoc tests using the Bonferroni correction, the most common method, revealed that there was significant difference in the motor engagement between the original setting (-0.667±0.114) and SS1 (0.333±0.140) (p<0.0001), between the original setting and SS4 (0.611±0.118) (p<0.0001), between the original setting and SS5 (0.111±0.159) (p=0.024), between SS1 and SS2 (-0.722±0.109) (p=0.001), between SS1 and SS3 (-0.833±0.090) (p<0.0001), between SS2 and SS4 (p=0.002), between SS2 and SS5 (p<0.0005), between SS3 and SS4 (p<0.0001), and between SS3 and SS5 (p=0.001). However, there was no significant difference between other pairs. Therefore, we could conclude that SSs which involved motor stimulation were validated to be able to increase the motor engagement, and increasing the displaying size of the game, the combination of motor and perceptive stimulation, was the most efficient SS in increasing motor engagement.

6.3.2 The effects on perceptive engagement

In the part of the experiment dedicated to perceptive engagement, the mean of distances between the positions of participant's gaze and the positions of screen change were calculated in every second. The typical patterns of the indicator of perceptive engagement in all of the settings after applying SS are shown in Figure 6.5. The boxplot of the perceptive engagement indicator is shown in Figure 6.6 in each setting of the Corsi block exercise. Within-subject ANOVA for the perceptive engagement was conducted in the same way as in the case of the motor engagement.



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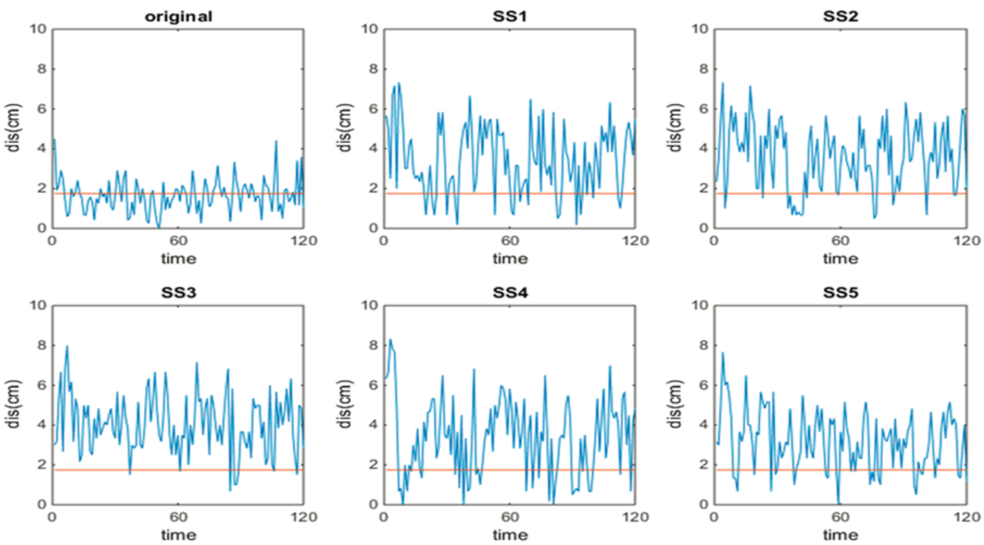

b

Figure 6.5 Typical patterns of the perceptive indicator: (a) in the Air hockey game, and (b) in the Corsi block game

The within-subject ANOVA with a Greenhouse-Geisser correction explored that mean of the indicator differed statistically significantly between different settings in the Air hockey game ($F\ (2.538,\ 43.148) = 12.926$, $P < 0.0001$). Post hoc tests using the Bonferroni correction revealed that there was significant difference in the perceptive engagement between the original setting (-0.722±0.109) and SS1 (0.444±0.166) (p<0.0005), between SS1 and SS2 (-0.833±0.121) (p=0.001), between SS1 and SS3 (-0.778±0.101) (p=0.001), between SS1 and SS4 (-0.389±0.143) (p=0.011), and between SS2 and SS5 (-0.389±0.164) (p=0.027). However, there was no significant different between other pairs.

In the Corsi block game, a within-subject ANOVA with a Greenhouse-Geisser correction determined that mean of the indicator differed statistically significantly between different settings in Air hockey (F (2.153, 9.568) = 14.067, P < 0.0001).Post hoc tests using the Bonferroni correction revealed that there was significant difference in the perceptive engagement between the original setting (0.111±0.137) and SS2 (-0.667±0.162) (p=0.001), between the original setting and SS3 (-0.611±0.164) (p=0.001), between SS1 (0.611±0.183) and SS2 (p=0.002), between SS1 and SS3 (p=0.003), between SS1 and SS4 (-0.222±0.129) (p=0.002), and between SS1 and SS5 (-0.278±0.135) (p=0.009).

There was no significant difference between other pairs. Based on the above results we can

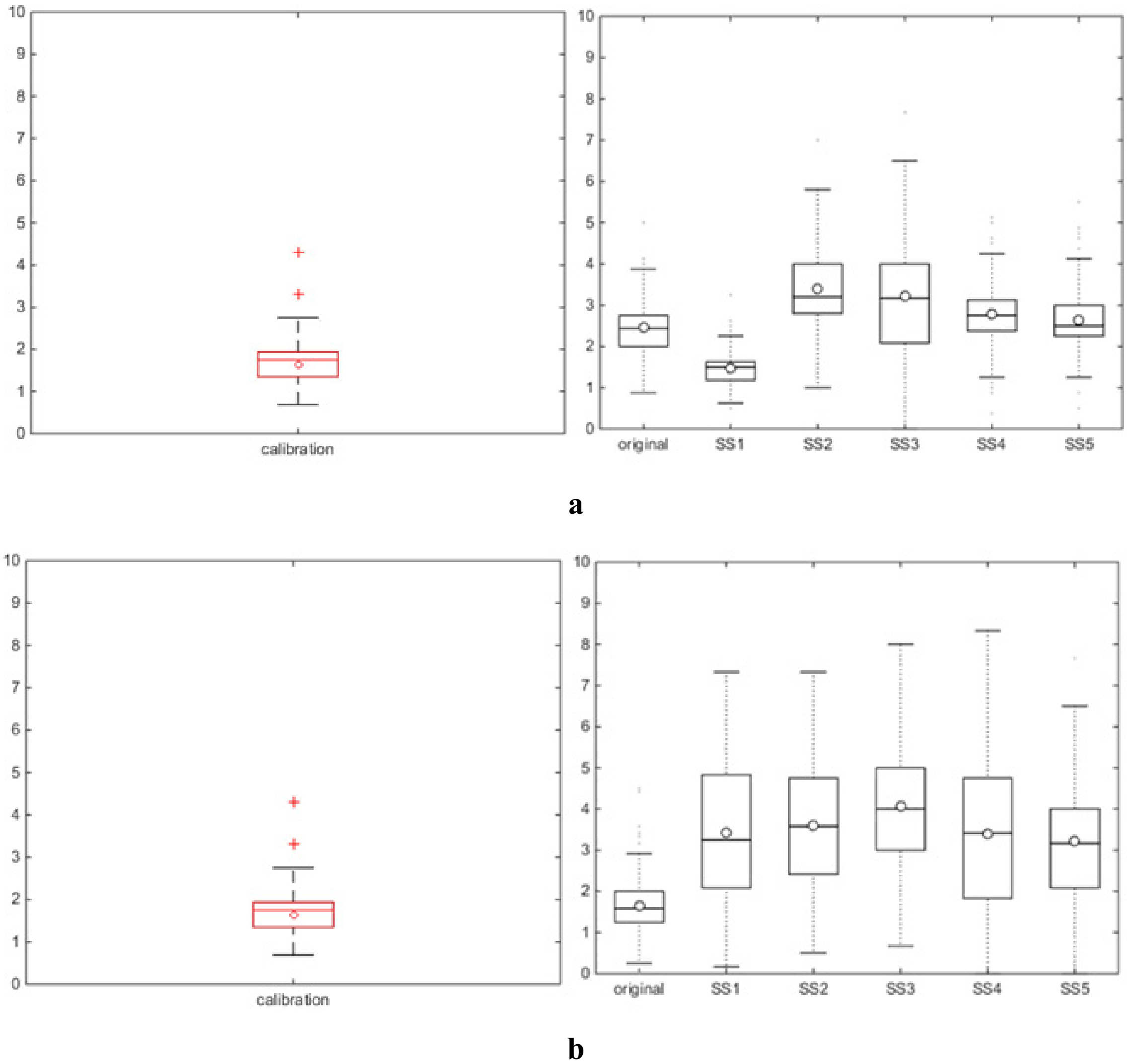

Figure 6.6 The boxplot of the perceptive engagement considering all subjects: (a) in the Air hockey game, and (b) in the Corsi block game

conclude that decreasing the pointer speed of the mouse as a motor stimulation was able to increase the participant's perceptive engagement, while SSs, such as decreasing the resolution of the screen, increasing the level of competition, or increasing the difficulty level of cognitive task seemed to have the opposite effect. For maintaining a high level of perceptive engagement, it is reasonable to set the resolution of the screen to a high level and the pointer of the mouse to a low speed.

6.3.3 The effects on cognitive engagement

The mean of indicator for the cognitive engagement were calculated in every second. The typical patterns of the cognitive engagement in all of the settings after applying SS are shown in Figure 6.7. The boxplot of the indicator in each setting in the two game exercises is shown in Figure 6.8. Within-subject ANOVA for the cognitive engagement was conducted in the same way.

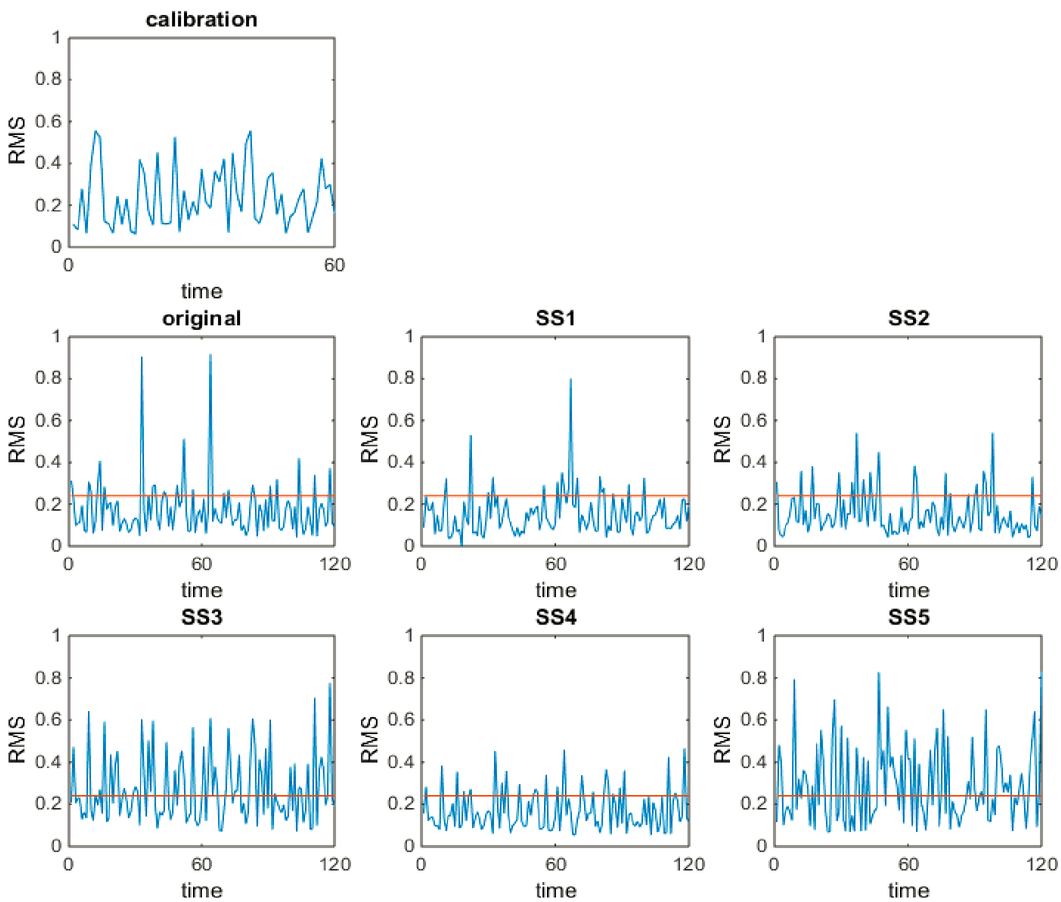

Figure 6.7 a. Typical patterns of the cognitive engagement indicator in the Air hockey game

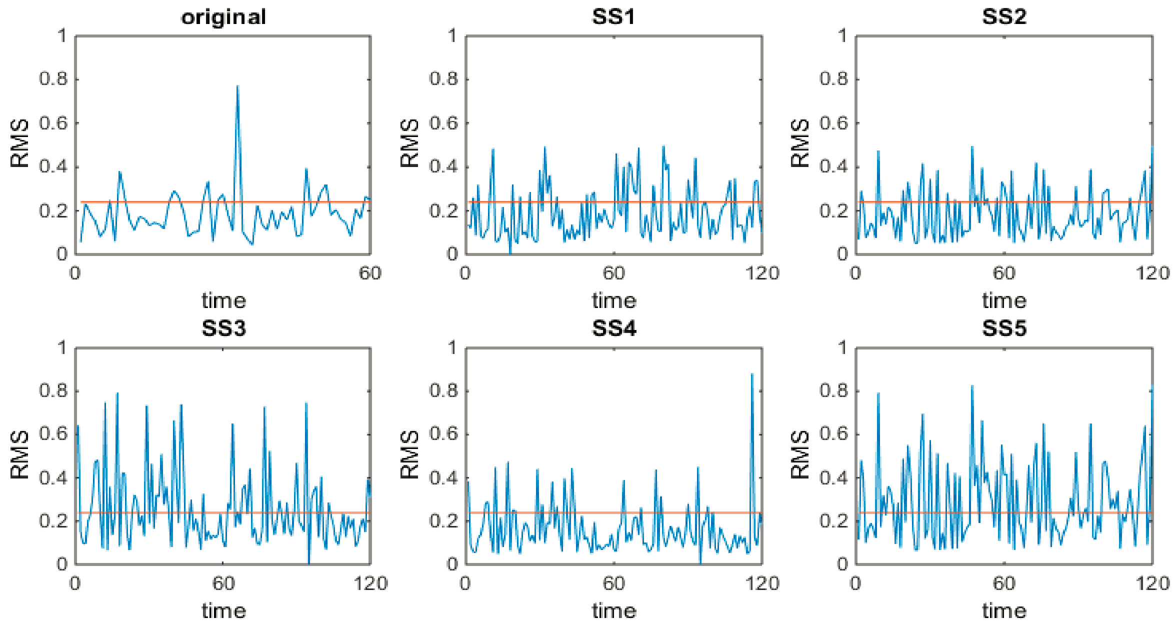

Figure 6.7 b. Typical patterns of the cognitive engagement indicator in the Corsi Block game

Related to the Air hockey game, a within-subject ANOVA suggested that there was a significant difference in the mean of the indicator between different settings, Wilk's Lambda = 0.164, $F (5, 13) = 13.230$, $p<0.0005$. Post hoc tests using the Bonferroni correction revealed that there was significant difference in the cognitive engagement between the original setting (-0.111±0.137) and SS3 (0.389±0.641) ($p=0.048$), between the original setting and SS5 (0.778±0.101) ($p=0.002$), between SS1 (-0.333±0.140) and SS3 ($p=0.012$), between SS1 and SS5 ($p<0.0005$), between SS2 (-0.389±0.143) and SS5 ($p<0.0005$), between SS3 and SS4 (-0.333±0.114) ($p=0.026$), and between SS4 and SS5 ($p<0.0005$). There was no significant difference between other pairs.

In the case of the Corsi block game, a within-subject ANOVA suggested that there was a significant difference in the mean of the indicator between different settings, Wilk's Lambda = 0.048, $F (5, 13) = 51.338$, $p<0.0005$. Post hoc tests using the Bonferroni correction revealed that there was significant difference in the cognitive engagement between the original setting (0.111±0.111) and SS3 (0.889±0.076) ($p<0.0005$), between the original setting and SS5 (0.833±0.090) ($p=0.04$), between SS1 (-0.444±0.121) and SS3 ($p<0.0005$), between SS1 and SS5 ($p<0.0001$), between SS2 (-0.278±0.158) and SS3 ($p<0.0001$), between SS2 and SS5 ($p<0.0001$), and between SS3 and SS4 (0.000±0.213) ($p=0.041$). There was no significant difference between other pairs.

Therefore, we could conclude that SSs that involve emotional stimulation and cognitive stimulation were able to increase the participant's cognitive engagement significantly, while other SSs did not have these significant effects.

6.3.4 The effects on emotional engagement

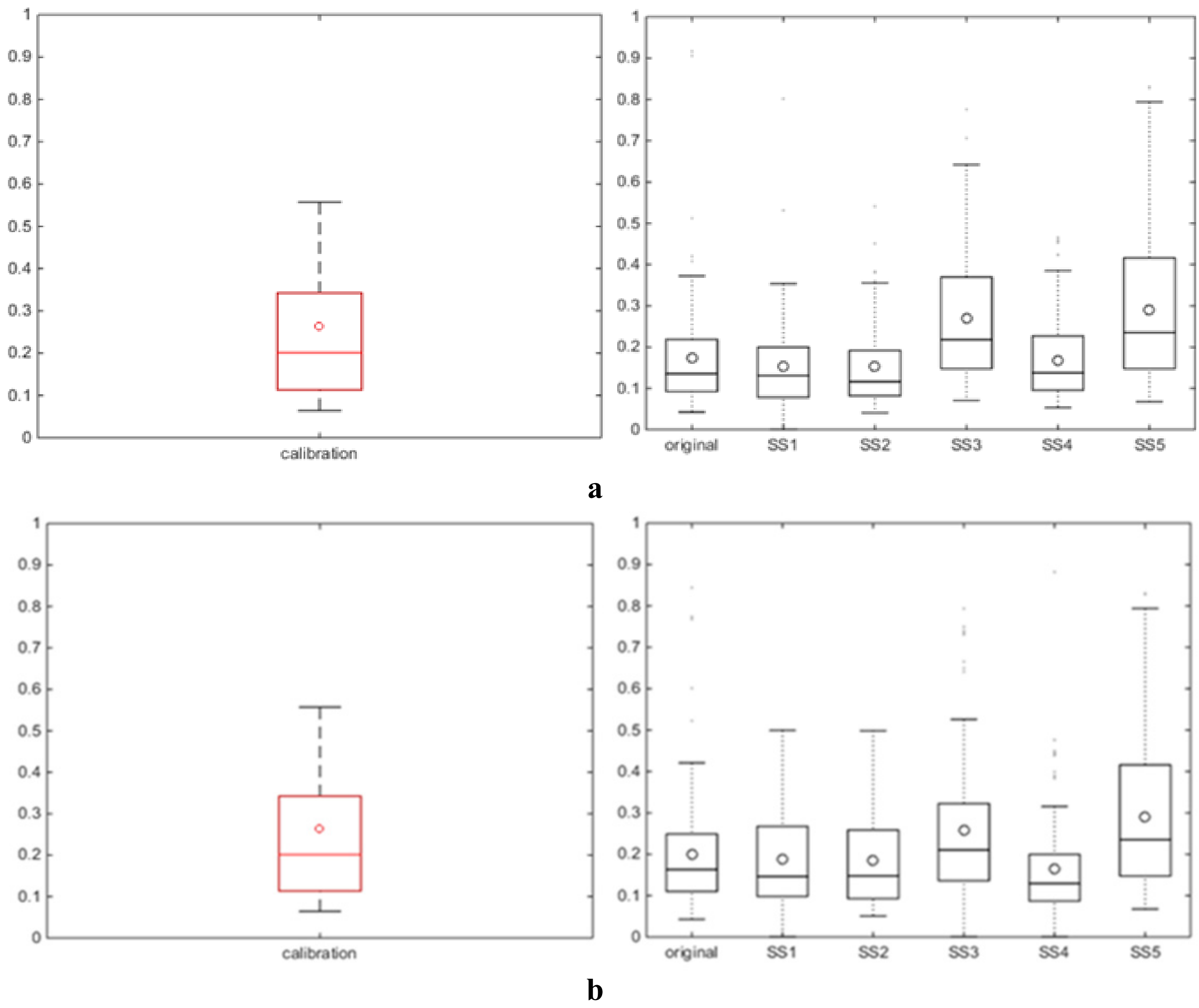

Figure 6.8 Boxplot of the cognitive engagement considering all participants, (a) in the Air Hockey game, and (b) in the Corsi Block game

The indicator for the emotional engagement was calculated in each setting. The pattern of the most dominant three emotions during the Air hockey exercise with SS1 is shown in Figure 6.9. In this setting, the emotional engagement was calculated as follows:

$$\mathrm{E}_e = \frac{T_{p1} * w_1 + T_{p2} * w_2 + T_{p3} * w_3}{T_{n1} * w_1 + T_{n2} * w_2 + T_{n3} * w_3}$$

$$= [(happy + surprised) * 0.5 + (happy_2 + surprised_2) * 0.3 + (happy_3 + surprised_3) * 0.2] \div [(anger + disgust + fearful + sad) * 0.5 + (anger_2 + disgust_2 + fearful_2 + sad_2) * 0.3 + (anger_3 + disgust_3 + fearful_3 + sad_3) * 0.2]$$

$$= 0.75$$

The within-subject ANOVA for the emotional engagement was conducted in the same way as above. In the case of the Air hockey game, a within-subject ANOVA suggested that there was a significant difference in the mean of the indicator between different settings, Wilk's Lambda = 0.151, F (5, 13) = 14.579, p<0.0005. Post hoc tests using the Bonferroni correction revealed that there was significant difference in the emotional engagement between the original setting (-0.611±0.118) and SS3 (0.389±0.164) (p=0.001), between the original setting and SS5 (0.578±0.219) (p<0.0005), between SS2 (-0.389±0.183) and SS3 (p=0.005), and between SS2 and SS5 (p=0.041). There was no significant difference between other pairs. The mean and standard deviation in other settings were SS1 (-0.222±0.191) and SS4 (-0.222±0.207).

In the case of the Corsi block game, a within-subject ANOVA suggested that there was a significant difference in the mean of the indicator between different settings, Wilk's Lambda = 0.139, F (5, 13) = 16.142, p<0.0005. Post hoc tests using the Bonferroni correction revealed that there was significant difference in the emotional engagement between the original setting (-0.778±0.101) and SS1 (-0.056±0.189) (p=0.026), between the original setting and SS3 (0.278±0.135) (p<0.0005), between the original setting and SS5 (0.778±0.101) (p<0.0005), between SS1 and SS5 (p=0.020), and between SS4 (-0.278±0.158) and SS5 (p<0.0005). However, there was no significant difference between other pairs. The mean and standard deviation in SS2 was -0.056±0.206.

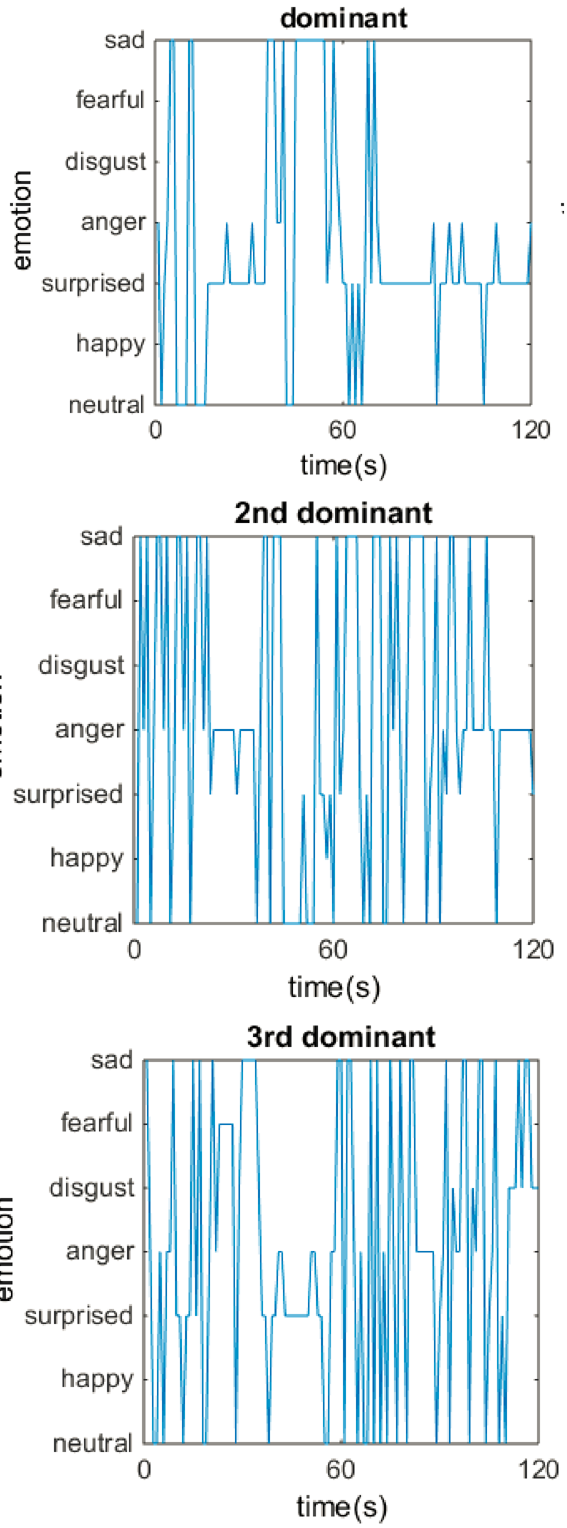

Figure 6.9 The most dominant three emotions in SS1 in Air hockey

Therefore, we could conclude that in both games, the combinations of three stimulations were the most effective SSs in increasing the emotional engagement. Individual stimulations, such as setting the pointer speed of the mouse at a low level, introducing cognitive challenge, and increasing the level of competition, were also able to increase the participant's emotional engagement significantly.

6.3.5 Conclusion on the effects of the proposed stimulation strategies

Based on the results of the within-subject ANOVA in each aspect, the effects of each SS can be evaluated. This requires a comparison of the results with the data in the original setting in both game exercises. This was done and concluded in Table 6.3. The results indicated that: (i) the tested motor, cognitive, and emotional stimulation was validated to be effective in terms of increasing the engagement in the motor, cognitive, and emotional aspects, (ii) it is reasonable to set the resolution of the screen at a high level and the pointer of the mouse at a low speed in order to achieve a high level of perceptive engagement, (iii) SSs that involved cognitive stimulation or emotional stimulation were able to concurrently increase the engagement in the cognitive and emotional aspect, (iv) all of the SSs had similar effects on cognitive engagement and emotional engagement in both game exercises, and (v) the participants tend to express positive emotions to the changes of the game exercise according to the effects of the SSs on the emotional engagement.

Although several SSs showed positive effects on engagement, it could be noticed that the engagement of the participants could reach the reference value (generated in the calibration phase) only in one or two SSs in each of the aspect. This can be quantitatively shown by comparing the engagement level values in each SS with the reference value. This may be explained by the fact that the participants focused only on one single aspect of the task execution in the calibration phase. This was not the case in the experimental set ups. It could result in full engagement in that aspect. However, the tasks completed in the calibration phase would become boring for a longer time because of their mundane nature. Therefore, the

Table 6.3 The effects of the proposed stimulation strategies on engagement

Game exercise	SS	Motor engagement	Perceptive engagement	Cognitive engagement	Emotional engagement
Air hockey	SS1	+	+	(-)	(+)
	SS2	(-)	(-)	(-)	(+)
	SS3	(-)	(-)	+	+
	SS4	+	(+)	(-)	(+)
	SS5	+	(+)	+	+
Corsi block	SS1	\	(+)	(-)	+
	SS2	\	-	(-)	(+)
	SS3	\	-	+	+
	SS4	\	(-)	(-)	(+)
	SS5	\	(-)	+	+

+: significant positive effect; -: significant negative effect;
(+): positive effect but not significant; (-): negative effect but not significant
\: not considered

Table 6.4 Input and output the SLM

Input						Output
Participant number	Game exercises	Engagement level				Stimulation strategy
		ME	PE	CE	EE	
1-18	1: Air hockey 2: Corsi block	1: bigger than 1.2× reference value 2: (0.8~1.2) × reference value 3: less than 0.8× reference value				1:SS1 2:SS2 3:SS3 4:SS4 5:SS5

engagement level in the calibration could also be used as the reference value for a full engagement. Nevertheless, it has to be emphasized, that the calibration tasks were not suitable for training exercise.

6.4 Set up of smart learning mechanisms and the provided suggestions

In the validation described in the subsection, all the data from the above experiments were used to train, validate and test a neural network (NN-based) and a Naive Bayes (NB-based) smart reasoning mechanisms, whose implementation was described in Chapter 4. The trained learning mechanism was expected to classify the inputs into different classes of SSs. Here the term 'class' refers to kinds of different SSs. The inputs and outputs of the SLMs are shown in Table 6.4. Important aspect of validation, the accuracy of the output generated by the two above mechanisms will be discussed in the next section.

In order to conduct a within-subject analysis, the engagement level during each setting was normalized using the participant's own reference value. In this normalization procedure, which also extracted features from the data in order to train the SLM, the following rules were applied:

1) If the mean engagement increased with more than 20% of the reference value, then the engagement level was represented as 1.

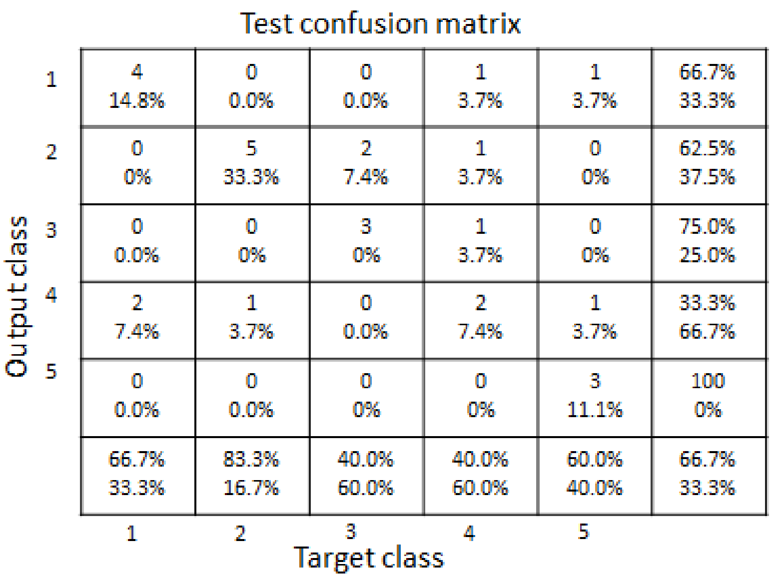

Figure 6.10 Test confusion matrix of classification by NB based SLM

2) If the mean engagement did not change significantly, i.e. remained between (0.8~1.2)× reference value, then the engagement level was represented as 0.

3) If the mean engagement decreased with more than 20% of the reference value, then the engagement level was represented as -1.

As for the NN-based SLM, a two-layer feed-forward network was used It contained sigmoid hidden neurons (10 neurons) and *softmax* output neurons. This network was trained with scaled conjugate gradient back-propagation. 70%, 15%, 15% of the data from the exercise were used to train, validate, and test the NN based SLM respectively. Likewise, 85% of the data were selected randomly to train the NB based SLM. And 15% of the data were used to test the trained learning mechanism. The accuracy of the suggestions made by these two SLMs was compared. For the NB-based SLM, the accuracy of suggestions for the test data set was 66.7% (Figure 6.10). For the NN-based SLM, the accuracy of classification in the test data set was 70.4%, and the overall accuracy is 70.0% (Figure 6.11). The results showed that

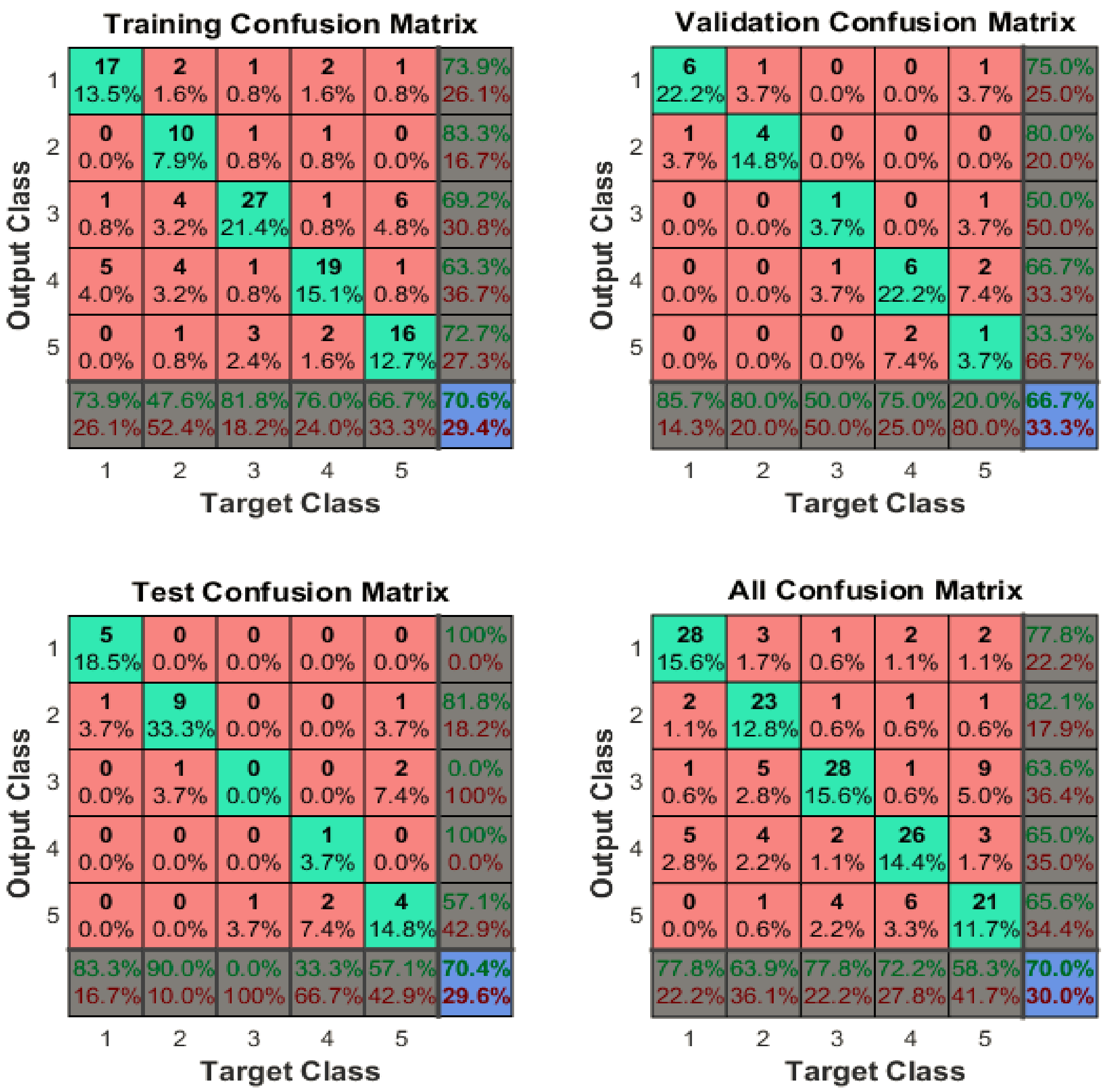

Figure 6.11 Confusion matrix of classification by NN based SLM

the suggestions made by the NN-based SLM were slightly more accurate than the suggestions made by the NB-based mechanism.

6.5 Discussions of the accuracy of the suggestions made by SLMs

It has been shown by the analysis of effects of SSs that it is possible to influence the engagement level of the participants by adjusting a bundle of parameters of the games exercises. The proposed stimulations in the motor, cognitive, and emotional aspects were validated to be effective in increasing the corresponding engagement; and perceptive engagement can be increased by applying SS1. Furthermore, the applied SSs were found to have effects not only on the corresponding aspect but also on the other aspects, so it was essential that the SLM can learn the effects of different SSs on different participants. Based on the learned knowledge, the results suggested that NN based SLM and NB based SLM can have an accuracy of about 70% to make suggestions on which is the appropriate SS to apply.

Although the accuracy was about only 70%, according to Table 6.3, some SSs have the same significant effects on the engagement level. For instance, SS1, SS4, and SS5 all have a significant positive effect on motor engagement. Therefore, there are possibilities that the SLM classifies some cases to a different class of SS which has the same significant effect as the correct class. Based on this criterion, misclassifications can be further divided into two categories. The first category includes the cases in which the SLM classifies into a different class with the same significant effect on the engagement that has decreased. The second category includes the cases in which the SLM classifies into a different class with different effects or not significant effects on the engagement. In this context, the first category is not inaccurate classification because the classified SS can have the same significant effect in increasing the engagement, which is goal of the SLM.

Corrected test confusion matrix by NN based SLM

Output class \ Target class	1	2	3	4	5	
1	5 18.5%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
2	1 3.7%	9 33.3%	0 0.0%	0 0%	1 3.7%	81.8% 18.2%
3	0 0.0%	1 3.7%	0 0%	0 0.0%	2(2) 7.4%	66.7% 33.3%
4	0 0%	0 0%	0 0.0%	1 3.7%	0 0.0%	100% 0%
5	0 0.0%	0 0.0%	1(1) 3.7%	2(2) 7.4%	4 14.8%	100 0.0%
	83.3% 16.7%	90.0% 10.0%	100% 0.0%	100% 0%	85.7% 14.3%	88.9% 11.1%

Corrected test confusion matrix by NB based SLM

Output class \ Target class	1	2	3	4	5	
1	4 14.8%	0 0.0%	0 0.0%	1(1) 3.7%	1 3.7%	83.3% 16.7%
2	0 0%	5 33.3%	2 7.4%	1 3.7%	0 0%	62.5% 37.5%
3	0 0.0%	0 0%	3 0%	1 3.7%	0 0%	75.0% 25.0%
4	2(1) 7.4%	1(1) 3.7%	0 0.0%	2 7.4%	1 3.7%	66.7% 33.3%
5	0 0.0%	0 0.0%	0 0%	0 0%	3 11.1%	100 0%
	83.3% 16.7%	83.3% 16.7%	40.0% 60.0%	60.0% 40.0%	60.0% 40.0%	77.8% 22.2%

Figure 6.12 Corrected confusion matrix of the test data set

Then, all the misclassification cases were analyzed to investigate the amount of the first category misclassification. The results are shown in Figure 6.12. The number in bracket indicates the number of cases that belong to the first category. The accuracy of classification of the test data set by the NN-based SLM was 88.9%, and the accuracy by the NB based SLM was 77.8%. Having considered the context of increasing the engagement, the accuracy of suggestions made by NN-based SLM was significantly higher than that of NB-based SLM. Therefore, it can be concluded that both the NN-based and NB-based SLM were able to learn the effects of the SSs on the engagement, and NN-based SLM was more appropriate to be applied in this context because some misclassifications can have the same effect in increasing the participants' engagement.

6.6 Conclusion

In this chapter, a complex experiment was conducted to validate the effectiveness of the SSs with regards to increasing the participant's engagement and the accuracy of the suggestions made by the SLM. In the two exercises, which were done with two different games, five different SSs were applied. The participants' engagement was evaluated in each setting and compared with the engagement in the original setting to identify the effects of the applied SSs. The within-subject ANOVAs suggested that: (i) Tested motor stimulation, cognitive stimulation, and emotional stimulation was validated to be effective in increasing the engagement in the motor, cognitive, and emotional aspect respectively; (ii) To achieve a high level of perceptive engagement, it is reasonable to set the resolution of the screen at a high level and the pointer of the mouse at a low speed; (iii) SSs that involved cognitive stimulation or emotional stimulation were able to increase the engagement in the cognitive and emotional aspect at the same time; (iv) All the SSs had similar effects on cognitive engagement and emotional engagement in both game exercises; (v) The participants tend to express positive emotions to the changes of the game exercise according to the effects of the SSs on the emotional engagement.

Then these data from the experiment were used to train a NN and NB based SLM respectively. Since several SSs had the same significant effect in increasing the engagement, if the SLM classified certain cases into the class with the same significant effect, it should not be considered as misclassification in this context because it can achieve the goal of increasing the engagement. After correction, the accuracy of the suggestions made by NN and NB based SLM for the test data set were 88.9% and 77.8% respectively. Therefore, considering the context, NN based SLM was more suitable to be applied in the system than NB based SLM. This result indicated that there was a pattern in the applied stimulation and its effects on the engagement for each participant, so that the SLM is able to identify and learn the different effect on each individual. In the future, more SSs or combinations of SSs should be tested for the purpose of validating if the SLM can be accurate in predicting new effective combination of SS. For instance, if the SLM is not confident to classify a case in SS A or SS B, then the combination of the SS A and SS B can be applied. Then the effects of this combination of SSs can be analyzed in order to validate the prediction of the SLM.

The results from the two aspects demonstrated that the proposed CP-SRS is able to enhance the engagement of the participants by monitoring the participant's status and applying personalized interventions during the training session. Future rehabilitation system should monitor the patient's status in real time and introduce interventions during training when the engagement of the patient decreases. Additionally, the interventions should be personalized according to the different patients' situations so that the intervention can be meaningful for the patient and may probably have a positive effect on their recovery. In this sense, learning capability of the system is essential to provide personalized interventions. Furthermore, future system should consider a comprehensive scope of patient's status, such as motor, perceptive, cognitive, and emotional. As shown in the results, some SSs have positive effects on certain aspects, but negative on the others. As far as stroke patients are concerned, some may have serious impairment in their motor ability, while some need to improve in their cognitive capability. Therefore, future rehabilitation systems should be capable not only to deliver motor therapy, but also to facilitate efficient and patient-sensitive rehabilitation in cognitive, perceptive, and emotional aspects too.

CHAPTER SEVEN

CONCLUSIONS AND FUTURE WORK

7.1 Reflections on the findings

Since lack of engagement hinders the efficiency of recovery during stroke rehabilitation, this thesis aimed at using a cyber-physical solution to enhance and maintain the engagement during training exercises. As a new paradigm of computing, cyber-physical computing makes it possible to deeply penetrate into real life processes, such as a stroke rehabilitation process, to control the processes based on run-time acquired data, and to develop strategies for adaptation of the process, the activities of human stakeholders, and the operation of the cyber-physical system as a whole. In order to implement a first prototype of the physical and the cyber part of the cyber-physical solution, five research cycles were conducted in this PhD research.

In the first research cycle, a survey was conducted to understand the phenomenon of engagement in rehabilitation. Influencing factors of therapeutic engagement were identified based on various existing models of engagement. Based on studying the current state of the art of methodological enablers and several engagement enhancement systems, it was found as a major limitation that the currently used rehabilitation systems failed to deliver a comprehensive self-adaptive and personalized treatment. Moreover, although there were many enablers and systems that had been reported on engaging the patients, just few quantitative measures have been proposed to evaluate the level and status of patient engagement. Without specific measures, it was not possible to validate the related enablers and systems, and to sufficiently intensify the engagement of patients. Therefore, one of the objectives for the next RCs was to identify indicators that can reliably capture the engagement level.

In the second research cycle, an experimental investigation was conducted with an entry-level system comprising an upper limb rehabilitation robot integrated with gamification, in order to better understand the current limitation of gamification. The rationale behind this investigation is that gamification is the most common engagement enhancing method in the current practice. One of the findings was that the engagement of the patients decreased during the video game exercise as they became familiar with the exercise. Another important finding was that gamification alone is not enough to maintain a sufficiently high engagement of the patients. Although the video game fulfilled the requirements of providing immediate feedback to each patients, involve the patients in interaction, and pose a matching challenge to the patients, it could still not avoid becoming mundane exercising when playing for a long time. The abovementioned requirements pointed at factors that were identified and studied based on the previously proposed models of engagement. Current and next generation rehabilitation systems have to go beyond the paradigm of assistive robotics extended with gamification in order to be able to more intensely engage the patients during training exercises. Yet another influential finding was that the RMS of EMG signals correlated with the engagement level of the patients. This means that these signals can be used as one of the possible indicators of and representing the engagement level of the patients. Finally, we could draw as a conclusion that monitoring of the patients' status is essential for providing a personalized treatment.

In the third research cycle, new enablers for monitoring and enhancing the patients' status and engagement were investigated. The functional affordances and implementation opportunities offered by cyber-physical computing were studied, and an overall concept of a cyber-physical system orientated solution has been considered. Based on additional literature studies, a series of brainstorm sessions, and experimental investigations, a detailed concept of a cyber-physically stimulating rehabilitation system (CP-SRS) was derived. In the center of the interest were the reasoning and strategy development mechanisms of the target CP-SRS. The argumentation concerning the utility of the CP-SRS was that engagement of the patients can be maintained and influenced if the CP-SRS applies self-adaptive and personalized stimulations. The feasibility and prototyping of the target CP-SRS was positively judged with a view to utilizing the capabilities of smart cyber-physical systems, such as multi-sensor monitoring, smart learning, and strategy-based output adaptation. In the second part of this research cycle, the smart learning mechanism was developed and implemented as a prototype by using various adaptable commercial tools. The functioning of the proposed learning mechanism was tested and validated through a series of computer simulations.

In the fourth research cycle, the engagement monitoring subsystem (EMS) of the CP-SRS was implemented at a testable prototype level. EMS can monitor the patient's engagement level in the motor, perceptive, cognitive, and emotional aspects using MYO Armband, the Eyetribe, the Emotiv EPOC headset, and the Insight device respectively. Having the prototype of the EMS subsystem, we developed and conducted a series of experiments to validate the functionality of this implementation. In the experiments, different setups were used to mimic the engaged, normal, and unengaged situations. The results showed that the proposed indicators for evaluation motor, perceptive, cognitive, and emotional engagement were correct and able to distinguish different engaged statuses. The software part was fine tuned.

In the fifth research cycle, an experiment was conducted in order to validate the functionality of the stimulation strategies and learning mechanism. In the experimentation, different stimulation strategies were applied and the changes in the engagement levels were recorded. The analyses of the data demonstrated the effectiveness of several stimulation strategies in enhancing engagement, and more importantly, the learning mechanism was able to learn the relationship between the applied stimulation strategies and changes in the engagement level. This means that the learning mechanism is able to support a self-adaptive and personalized solution for different patients based on analyzing the data obtained in the monitoring and stimulation processes.

In a general sense, the essence of the implemented cyber-physical system is acquiring related information and assisting decision making based on learning. Putting everything together, this thesis demonstrated that a cyber-physically-based rehabilitation system is able to provide self-adaptive and personalized stimulations to enhance patient’s engagement by continuous monitoring and learning. Since the current assistive robotics-based systems, even with gamification or VR augmentation, cannot guarantee the patient’s engagement during training exercises, future rehabilitation systems should focus on delivering a comprehensive personalized training by including system features such as multi-sensor networking and smart learning. Then, the overall engagement in the training exercises can improve, and it in turn can make a significant contribution to the efficiency and successful outcome of rehabilitation programs in the case of very different patients.

Indicators have been identified in the four aspects, namely from the human perspective, motor, perceptive, cognitive, and emotional aspects, to evaluate the engagement level during the exercises. These indicators have offered a dexterous way for a quantitative assessment of the engagement status and level. This is an important step forward since most of the current engagement evaluation methods tend to be qualitative or subjective based on the therapists’ rating on the scales. Moreover, these indicators provide a comprehensive understanding of the engagement status compared with other evaluation methods. Additionally, these quantitative assessments of engagement also offered an opportunity to evaluate the effectiveness of the currently used engagement enhancing methods - in order to better understand the limitations of these methods. For instance, VR solutions may be more effective to engage the patients perceptively, but cannot increase the patient’s motor engagement.

In the engagement monitoring, commercial sensors were utilized, such as MYO Armband, The Eyetribe, Emotiv EPOC headset, and the Insight device. These commercially available physiological recording sensors are cost effective for the research. As more commercial products have been developed and released in the market as a result of the technology push, future research should take advantage of these products. Kinect and Wii have already been widely used in research, especially in rehabilitation to provide treatment with gamification.

Currently, these physiological sensors are also capable to contribute to research. Moreover, SDKs with these devices are usually available on the Internet, which simplifies the implementation. There is new trend that more and more VR devices are commercialized, so my vision is that future rehabilitation systems, especially systems for home rehabilitation, will benefit from this technology trend.

This thesis also presents an example in developing cyber-physical systems. The core of the developed system is the embedded learning mechanism, which is able to learn the differences in different situations for different patients, thus providing self-adaptive and personalized training. This system was implemented in MATLAB using the machine learning toolbox. As a powerful tool, MATLAB is very useful for future research in building adaptive systems with machine learning characteristic. The presented technical ideas of smart learning and adaptation strategy development can also be applied in other fields, such as automatic diagnosis, transport management, evacuation in buildings, and so on.

7.2 Propositions

In line with main objectives of the PhD research work, four propositions have been formulated that capture the main scientific contribution and results. Based on the content of the research work and thesis, additional four propositions have been derived, which projects out from these and other achievements, and puts them into a social, personal, and cognitive context. The propositions are as follow:

Proposition 1: *It has been found that the ratio of the root mean square of the measured EMG signal and the velocity of motion of the human limb is a reliable indicator of motor (function) engagement.* Δ

EMG signals represent the electrical potentials produced by skeletal muscles when they are neurologically activated. They can indicate the intensity of motor activities of a person. The root mean square gives a measure of the power of EMG signals. Since the amplitudes of EMG signals have correlation with the velocity of the movement of the human limb, we introduced the concept of normalized EMG, which has been defined as the root mean square of EMG divided by movement velocity. It has been found that this normalized EMG value is a reliable indicator of the motor engagement if the motion fulfils some precision requirements. When a patient makes effort to perform precisely in a rehabilitation exercise, he is ‘motorly’ engaged in the task up to the level, which is shown by the indicator.

Proposition 2: *The indicators introduced for measuring the motor, perceptive, cognitive, and emotional engagement should be considered together to determine an optimal stimulation strategy and should be interrelated in order to form a distinct measure.* Δ

Considering the influencing factors of therapeutic engagement in rehabilitation, it has been concluded that monitoring and analyzing the motor, perceptive, cognitive, and emotional engagement levels is necessary and sufficient for having a comprehensive and precise understanding of the overall engagement state of the patients. Therefore, these four attributes have to be considered together in order to determine an optimal stimulation strategy to maintain the engagement level when needed.

Proposition 3: *Though the motor, perceptive, cognitive, and emotional engagement indicators provide a robust basis for developing stimulation strategies, there is also a need for considering the personal profile of the patient.* Δ

Though the proposed indicators can capture and express the actual level and changes of engagement, they cannot consider the patients' interest, awareness, education, and abilities. These can be captured is a personal profile. When providing personalized stimulation strategies is aimed at, personal profiles can help figure out the expectable the effects and influences of the stimulation strategies on different persons. Therefore, personal profiles have significance in enhancing engagement in rehabilitation.

Proposition 4: *Neural network-based smart learning mechanism is able to learn the effects of the different stimulations strategies on different persons and to propose personalized enhancement.* Δ

A neural network-based learning mechanism can be taught to recognize the pattern between the input (i.e. the personal profile and the changes in the engagement) and the output (i.e. the applied stimulation strategy). In other words, the learning mechanism can learn the changes in the engagement level, which is caused by the applied stimulation strategies. Based on this relationship it is capable to find and propose the most suitable stimulation strategy in different situations.

Proposition 5: *Self-adaptive and personalized training in rehabilitation achieved by continuous monitoring and smart learning can significantly increase the efficacy of stroke rehabilitation.* Δ

Since every patient has a different personality and attitude, each of them needs personalized therapy. Research has shown that a self-adaptive and personalized training can enhance the patients' engagement level even in a long-duration rehabilitation process and facilitate brain plasticity. The current trend of exploiting the working principles and functional potentials of cyber-physical systems creates new opportunities for creation of smartly adaptive systems and for improving the recovery outcome for the stroke patients.

Proposition 6: *The identified engagement indicators can be useful not only for enhancing engagement, but also to understand the limitations of the current engagement enhancing methods.* Δ

This thesis has shown in what way the identified engagement indicators can be used to enhance engagement. They have also been used to evaluate the effectiveness of the current engagement enhancing methods by quantitatively assessing the changes in the engagement level due to various factors. The qualitative assessment the motor, perceptive, cognitive, and emotional aspects, in particular in their interrelationship, is a new contribution to the field of assisted stroke rehabilitation.

Proposition 7: *A cyber-physical system oriented solution can penetrate into the rehabilitation processes, which cannot be controlled otherwise.* Δ

In case of rehabilitation, various dimensions such as medical, social, personal, cognitive, exists. In each of these dimensions different processes are taking place. Based on their intense interaction with the embedding environment and the stakeholders, cyber-physical systems are able to penetrate deeply into these processes. As a result of this, a huge amount of various pieces of information can be detected, generated, pre-clustered, and used as a basis for run-time operation. This was not the case with traditional robot-assisted rehabilitation systems. The thesis has shown how a cyber-physical oriented learning, reasoning, and strategy planning mechanism can interact with rehabilitation exercises and patients, how it can monitor the patients' status on a perpetual basis, and how it can apply stimulation strategy in a self-adaptive manner. Without using the principles of cyber-physical computing, the implementation of the necessary control would bump into many obstacles.

Proposition 8: *Although the methodology developed for monitoring and enhancing engagement is dedicated for rehabilitation, this approach can be used in other fields as well, such as sports, driving, and education.* Δ

At conceptualization of the proposed cyber-physically supported engagement enhancement system, the needs, requirements, and application conditions of stroke rehabilitation were considered. This gives the flavor of the proposed implementation. However, the proposed methodology (including the underpinning theory, the computational procedures, methods, instruments, and the application criteria) can be adapted and then used to improve the engagement efficacy in other fields, such as sports, driving, and education. In these cases, the indicators of the user's status should be changed, but the same computation framework and resources can be applied.

Proposition 9: *S*
tudying engagement really needs engagement. Δ

This proposition is independent of the topic and results of the PhD research project.

Proposition 10: *Everything will be okay in the end - if not okay, then not yet the end.* Δ

This proposition is independent of the topic and results of the PhD research project.

These propositions are regarded as opposable and defendable, and have been approved as such by the supervisors prof. dr. Imre Horváth, dr. Zoltán Rusák and prof. dr. Linhong Ji.

7.3 Future research work

7.3.1 Immediate further research and development for enhancement of the proposed solution

Below we give a concise overview of the planned follow up research and development actions that are requested and made possible based on the current state of the research. In general, the research will be continued with a testable level prototype implementation of the proposed CP-SRS, including all hardware, software and cyberware elements reported in this thesis. In addition, various stimulation strategies will be elaborated and applied in medical testing of the proposed cyber-physical engagement enhancement system in some medical applications. The planned specific activities are as follows:

- *Integrating the cyber-physical augmentation part with the upper limb rehabilitation robotic system.*

  Due to the capacity of the PhD project, we made a decision to focus on the cyber part of the proposed CP-SRS. However, without the physical part, especially the assistive robot, the system cannot be utilized in clinical environment to deliver rehabilitation therapy. In the next step, the cyber-physical augmentation part will be integrated with the upper limb rehabilitation robot, as the concept of the whole CP-SRS was proposed in Chapter 4.

- *Implementation of a more elaborate and adjustable/adaptive physical part for other rehabilitation exercises*

  In this thesis, cyber solutions, such as continuous monitoring and smart learning, were studied to enhance the engagement during the training exercises. In the future, an adaptive physical part should be developed to suit the patient's personalized need. For instance, different physical parts of the system can be recruited to assist the patients according to their capability and rehabilitation prescription.

- *Comprehensive implementation of the CP-SRS, including context dependent engagement stimulating cyberware*

  In the current prototype, the games were selected from the available online video games. In the next step, the games should be designed, or selected in a systematic way, so that the movement exercises in the game are in line with the prescription which will be helpful to restore their motor ability. Moreover, patients can have more suitable games to choose according to their own interests and needs. Then the engagement stimulations can be implemented in the context of each game, which makes the training exercise more immersive.

- *Development of patient and program dependent stimulation strategies, in order to apply personalized run time interventions based on the suggestions from the learning mechanism.*

  In the future, run time stimulation strategies should be implemented after the development of the CP-SRS, such as adjusting assistive force, changing the threshold of the pressure sensor on the user interface, adjusting the velocity of the robotic arm. Then the system can apply the interventions to maintain and enhance engagement in real time based on the suggestions from the learning mechanism.

- *Refinement of the indicators, in particular the emotional engagement indicator*

  The experiments have shown the dominant emotion analyzed by the software is not always the real emotion of the user. In the future, the engaged and unengaged facial expressions can be profiled based on the analysis from the Insight, and machine learning technique can be used to classify the facial expressions into different engaged states during the training exercise.

7.3.2 Distant further research and development for exploitation of the proposed solution

After the CP-SRS is implemented, clinical experiments will be conducted to validate the usability and utility of the system. Experiments with real stroke patients are still needed to validate the accuracy of the refined indicators.

- *Large scale clinical experiments with real stroke patients*

  Although the experiments conducted so far has shown that the proposed engagement indicators are able to represent the real engagement level of healthy subjects, problems may occur in with real stroke patients. For instance, there might be abnormality in the EMG or EEG measurement due to spasm or lesions in the region of the cortex where the EEG is measured from. Therefore, further clinical study is needed to validate the effectiveness of the CP-SRS in enhancing engagement and improving recovery outcome.

- *Investigation of the phenomenon of long term engagement in rehabilitation programs*

  This thesis focused on enhancing short term engagement during rehabilitation exercises. However, it was pointed out that long term engagement during the whole rehabilitation program also needs to be maintained in order to achieve a successful outcome.

- *Investigation of the influencing factors and the context dependence of long term engagement*

  Further research should be conducted to study the influencing factors for long term engagement, which are different from those for short term engagement. Cyber-physical solution has been shown to be able to penetrate into the real life process of rehabilitation. With the method of multi-sensor networking, the comprehensive status of the patients during the rehabilitation program can be monitored and understood when the influencing factors are identified.

- *Development stimulation strategies for long term engagement*

  Stimulation strategies to enhance long term engagement should also be different from those of short term engagement. With the method of smart learning, the system will be able to apply suitable and personalized stimulation strategies according to their status in order to engage the patients during the program which can last for months.

7.3.3 Application of the proposed approach and system in other application fields

- *Sports*

  In many branches of sport, precise movement or coordination of the movement is very important to the athletes to improve their performances. However, sometimes, when the required movement is not precise enough, it is difficult to identify where they are doing wrong. Future research can be conducted to identify the indicators for evaluating the athlete's movement or status in different sport. Then the proposed approach of continuous monitoring can record the related indicators with sensors, and the smart learning mechanism can make suggestions on how to improve their performances by identifying the relationship between the indicators and good performance.

- *Education*

  Many researchers have studied the engagement in education. The indicators of engagement, such as perceptive, cognitive, and emotional engagement, can be monitored in education with the proposed method. Monitoring and intervention can be done on-line in a decentralized form. For instance, when the engagement level of a remotely located decreases, the system can collect information about the students individually and apply personalized stimulation to maintain and enhance their engagement, which can improve their learning efficiency.

- *Automatic diagnosis*

  Clinical studies have shown that technology–assisted rehabilitation has the same effect to improve patient's recovery as conventional therapy. However, current robotics cannot evaluate the patient's deficits, which makes the patients have to go back the physical therapist for assessment. The next step in rehabilitation is to study the indicators for evaluating the status of the patients. Then the smart learning mechanism can make suggestions on the prescription for the patients. Therefore, future research needs to be conducted to identify the indicators for evaluating the patient's deficits so that the technology-assisted rehabilitation system can achieve an automatic rehabilitation program

SUMMARY

CYBER-PHYSICAL SOLUTION FOR AN ENGAGEMENT ENHANCING REHABILITATION SYSTEM

1 Background

Stroke remains the most common cause of disability for adults. Stroke survivors often suffer from various impairments or disabilities concerning their motor, perceptual, and cognitive functions. Hemiplegia caused by stroke brings terrible burden on patients and their families, especially in the case of impaired upper extremity, because the lack of arm movement control unfavorably affects independence and the activities of daily living. Activity-based rehabilitation can help regain upper-limb motor functions. Rehabilitation can be made possible due to brain plasticity that refers to changes in neural pathways and synapses owing to changes in behavior, environment, neural processes, thinking, and emotions.

Normally, (i) acute, (ii) sub-acute, and (iii) chronic phases are distinguished as after-event pathophysiological states of patients. Stroke patients should receive different therapies and treatments according to their individual condition in each phase. However, rehabilitation in the chronic phase is often neglected because of the limited resources of healthcare systems. Research has shown that, even in the case of a chronic stroke, the motor function of the upper-limb can still be improved (Van der Lee et al., 1999), (Page et al., 2004). Evidence suggests that repetitive training (Kwakkel et al., 2007), (Krouchev and Kalaska, 2008), intensive use of the impaired limb (Wu et al., 1998), (Fisher & Sullivan, 2001), (Bach-y-Rita, 2003), task-specific motion practice (Bayona et al., 2005), and high patient motivation and engagement (Bach-y-Rita et al., 2002), (Wood et al., 2003), (Johnson et al., 2005), (Langhorne et al., 2011) are the factors influencing and the major opportunities for a brain plasticity-based motor recovery.

Robot assisted rehabilitation systems were introduced some 30 years ago with the goal to assist physical therapists in providing consistent, repeatable training to stroke patients. Though these systems show promising results in providing assistance in specific rehabilitation exercises (e.g. gait rehabilitation), they have limitations in upper limb rehabilitation, where task-oriented training exercises need to be practiced. It has been shown that patients must be actively engaged and must attempt to move in order to achieve positive outcome of robotic rehabilitation (Hogan et al., 2006), (Krebs et al., 2009). Recent research has focused on increasing patient engagement during rehabilitation exercise (Blank et al., 2014). However, there is no reliable solution to avoid mundane exercising that is prone to become a routine or even boring for the patients involved in current robotic rehabilitation. The motivation of this thesis is to develop a system that is capable to enhance the engagement of patients during robot assisted rehabilitation training of chronic stroke patients.

2 Research domain and problem

The first generation of the robot-assisted rehabilitation systems primarily includes robotic arms that assist the patients to do some motor exercises. Gamification of rehabilitation training is a proliferating approach of robot assisted stroke rehabilitation. The second generation of the robot-assisted rehabilitation systems includes assistive devices integrated with gamification or virtual reality that facilitates perceptive and cognitive training too. However, it is still not fully understood which factors (e.g. game difficulty, personal interest, game design, immersive environment) are the most influential on the engagement of patients, and how these factors can be managed by the system in order to maintain and enhance the patients' engagement. Using a prototype system in experiments, it has been shown that an upper limb rehabilitation robot integrated with only video games (Figure 1) cannot fulfill the expectations to maintain engagement of the participants on a high level. Therefore, the intention of the reported PhD research was the aggregation of specific knowledge and the development of a cyber-physical computing enabled system, which goes beyond the second generation of rehabilitation systems by penetrating into the physiological processes with the aim of maintaining and enhancing the engagement of patients in robot assisted stroke rehabilitation.

Figure.1 Upper limb rehabilitation robot integrated with video games

Engagement and stimulation of motor, sensory, and cognitive functions of patients are the primary goals of rehabilitation therapy. Since the patients are in different states, therapy programs personalized according to the individual needs of patients are needed. On the one hand, a personalized rehabilitation program requires insight into the actual engagement state and level of each patient during rehabilitation exercises and activities. On the other hand, it needs dedicated methods capable to select adequate engagement enhancing methods to maintain the engagement of patients. To get a proper insight in the actual engagement of patients, technologies capable to monitor and create computer representation of engagement are necessary. They should be able to convert and process signals obtained from monitoring devices of motor, sensory, and cognitive functions into meaningful computer representations. In this context, explorative research was conducted to identify what the most relevant, reliable and expressive indicators of engagement in completing motor, sensory, and cognitive functions were. To create reliable, consistent, and personalized models of patients' engagement, both data elicitation and information processing aspects were considered. In our research, selection of engagement enhancing methods went beyond trial and error approaches. Instead of these, we preferred rigorous studies and experimentation with enabling hardware and software technologies and eventually applying machine learning techniques in order to fulfill the largest number of functional and technical requirements and expectations. The latter implied the need for systematic investigations of the applicability of various machine learning techniques in the context of engagement enhancement.

According to the above analysis, the research problem of this PhD project was formulated as aggregation of specific knowledge and development of a cyber-physical computing enabled system, which goes beyond the current rehabilitation systems. By applying the principles of cyber-physical augmentation, it makes a robot assisted stroke rehabilitation capable to penetrate into the physiological processes of stroke patients with the aim of maintaining and enhancing their engagement at least on a short terms, i.e. during the rehabilitation exercises. In an ideal situation, a cyber-physical rehabilitation system would consist of a sophisticated physical part and a smart cyber part, which have balanced role and provide complementing functionalities for monitoring and enhancing engagement of stroke patients. However, conceptualization and implementation of such an ideal cyber-physical system is a huge challenge and goes beyond the possible scope and extent of a PhD study. It would involve both foundational and operative research, and hardware, software and cyberware development and integration.

These altogether were deemed to be too complex and ambitious to get addressed in this PhD project. Consequently, a decision was made that the research would primarily focus on the cyber-part of the system, which has anyway not been sufficiently addressed in the studied literature (Figure 2). With the

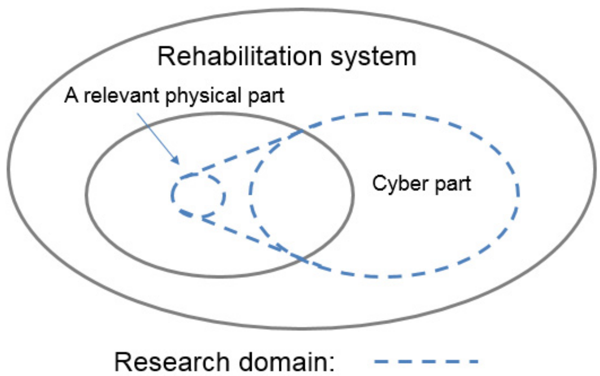

Figure.2 Research domain: cyber part with a minimal of physical part

intention of arriving at a manageable complexity and utility, the scope of research was defined so as to conduct extensive experimental studies and develop research means concerning the cyber part, and to provide only a minimal but proper physical part that allows the operationalization of the cyber part and makes it possible to test and validate its usability and utility in some practical cases. The functionality of the cyber part of the target system facilitates: (i) interaction with the patient, (ii) monitoring the patient's status, and (iii) reasoning about a personalized approach to enhancing the engagement of different patients. The highlight of the work is smart adaptation of the stimulation strategies according to run time obtained data.

3 Research vision, objectives, and hypotheses

Cyber-physical systems (CPSs) are confluences of knowledge and technologies of computing and informing, and knowledge and technologies of physical artifacts and engineered systems towards situated intelligent operation and servicing as actors in human and social contexts (Horváth et al., 2014). CPSs consist of a digital cyber-part and analog physical-part, which are supposed to work together towards a high-level functional and structural synergy (Horváth and Gerritsen, 2012). In addition, the components of CPSs are knowledge-intensive and able to handle: (i) built-in formal knowledge, (ii) the knowledge obtained by sensors, and (iii) the knowledge generated by reasoning and learning mechanisms. Though most of the CPSs grew out from the merge of distributed systems and embedded systems, which are typically model-based controlled, smart CPSs learns from and adapt themselves to varying situations based in their innate reasoning mechanisms.

Our research vision was that a cyber-physical stroke rehabilitation system can enhance the engagement of patients. It is assumed that CPSs developed for situated smart operations should have built in mechanisms for sensing, reasoning, learning, adaptation, and actuation and/or informing. In addition to the capability of self-adaptation, smart CPSs can serve as actors in human and social context. When applied in the field of rehabilitation, they may act as artificial multi-agents and penetrate into real life human and environmental processes associated with stroke rehabilitation. Due to these characteristics and affordances of CPSs, a cyber-physical augmentation solution has enormous potentials to be integrated with robotic rehabilitation system and to enhance patient engagement during rehabilitation exercises in this manner. Based on the above research vision, the main research objective addressed in this PhD research was to cope with cyber-physical augmentation of assistive robotics-based rehabilitation, and to study the effectiveness of a cyber-physical solution in enhancing the engagement in stroke rehabilitation. The overall objective was decomposed into three sub-objectives, driven by the following research questions:

- What are the influencing factors and the causalities with regards to patient engagement in the context of robot assisted rehabilitation?

- What are those limitations of the current engagement enhancing methods, which result in inefficiency in terms of providing engaging training during robot-assisted rehabilitation?
- How the system characteristics and the reasoning affordances of CPSs can enhance patient engagement during robot assisted rehabilitation?

Thus, the first sub-objective was to identify the factors that influence engagement as well as to study the engagement enhancement opportunities (methods) and their effects on engagement. In order to evaluate the different engagement enhancing methods, there was a need to identify indicators and measures towards s quantitative evaluation of engagement.

The second sub-objective aimed at identifying some of the major limitations of the current engagement enhancement approaches. Based on this knowledge, opportunities for cyber physical solutions could be identified and ideas could be formed about integrated robot-assisted rehabilitation engagement enhancement techniques.

The third sub-objective was to explore which characteristics and reasoning potentials of CPSs could be used for enhancing patient engagement during rehabilitation. Based on the identified opportunities, a first manifestation of the cyber part of the target CP-SRS has been conceptualized, implemented in a testable form, and functionally validated. The target cyber-physical stroke rehabilitation system exploits cyber-physical computing and demonstrates the benefits of a CPS solution in enhancing engagement.

Based on the objectives and the research questions, the research hypothesis is that the CP-SRS is able to enhance the patient engagement in robot assisted rehabilitation. This hypothesis is decomposed to three sub-hypotheses:

- There are reliable indicators to represent the engagement from the motor, perceptive, cognitive and emotional aspects.
- There are technologies that can reliably measure the level of engagement in these four aspects.
- There are cyber-physical computation-based engagement enhancing methods that can be applied to maintain and enhance the patient engagement.

4 Overall research approach

Due to the variety of objectives and contexts, a multi-methodological framing was applied to set up the research design. The whole of the PhD research project was divided into five interrelated research cycles (RCx) as it is shown in Figure 3. Each cycle had its own objective, context, and framing methodology. For this purpose, the methodological framing theory, proposed by Horváth (2013), has been applied.

In research cycle 1, the objective was to collect information about the current state of knowledge and art concerning engagement in rehabilitation. To achieve this, we aggregated

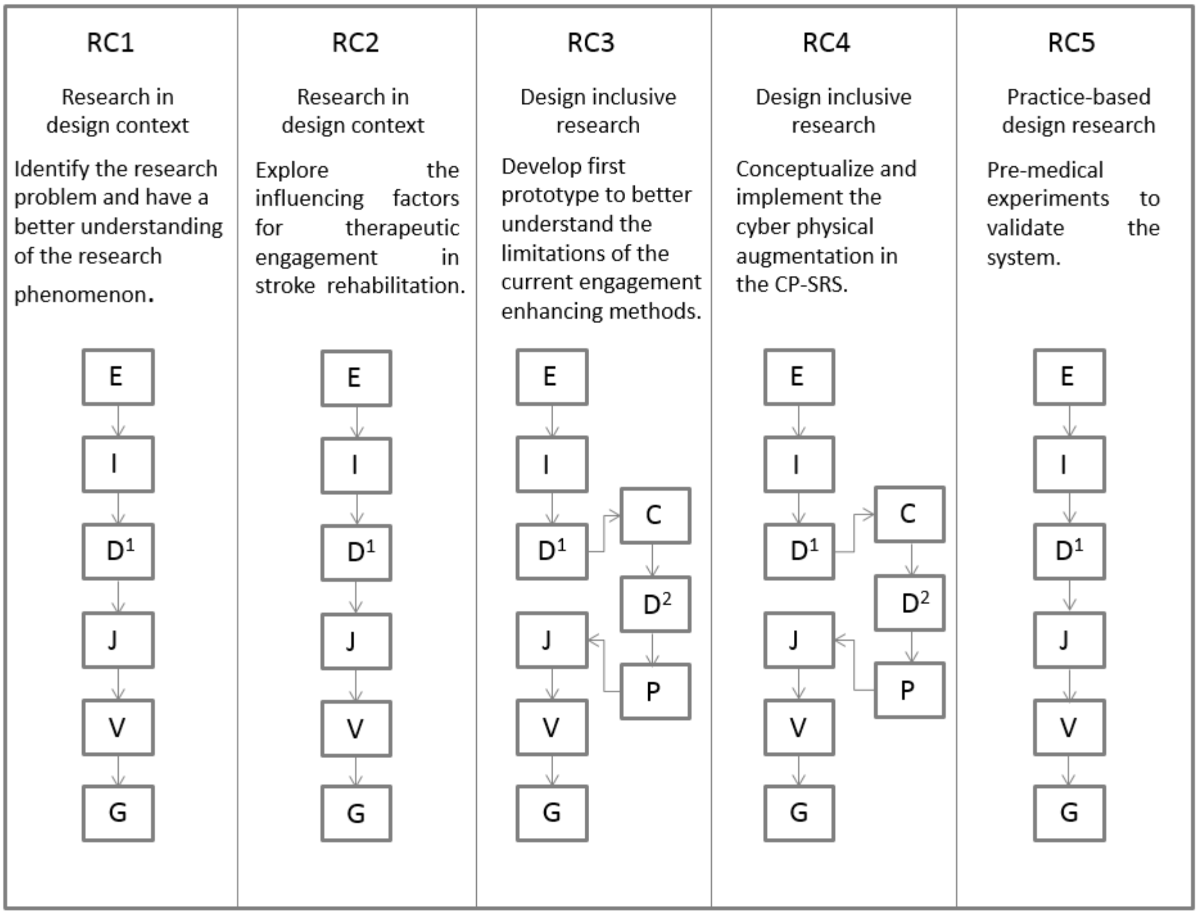

Figure.3 Methodological framing
(Meaning of the letters are: E: exploration, I: induction, D^1: deduction, J: justification, V: validation, G: generalization, C: conceptualization, D^2: detailing, P: prototyping)

knowledge about existing models of engagement, the various manifestations of engagement, the current state of engagement enhancement methods and tools, and the opportunities of influencing enhancement of stroke patients.

In research cycle 2, a prototype was developed in order to understand the limitations of the current engagement enhancing methods from a practical perspective. The prototype is an upper limb rehabilitation robot integrated with video games and used in the conducted experiment. The experiment concentrated on exploring the influence of complementing this robotic upper limb rehabilitation system with video games on the engagement of the participants. The findings were combined with the findings of the theoretical investigations in research cycle 1, and were used to create a robust knowledge platform for conceptualization of the whole and the smart reasoning mechanism of our cyber-physical stimulating rehabilitation system (CP-SRS) proposal.

In research cycle 3, the concept of the smart reasoning components of the CP-SRS was developed and concept feasibility testing has been carried out. CP-SRS includes multiple functional components, which have been defined and integrated. The learning and reasoning mechanisms were created. A computer simulation was conducted to study the feasibility of the smart learning mechanism (SLM) as part of the cyber physical augmentation.

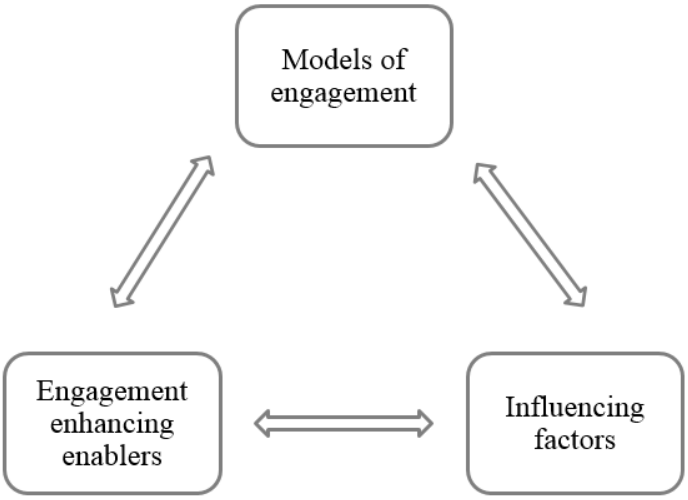

Figure.4 Reasoning model used in the survey

In research cycle 4, a tangible prototype of the concept was implemented. Experiments were conducted to test if the identified indicators for engagement can represent the actual level of engagement. In this pre-medical experiments, the goal was to characterize the range and accuracy of the engagement indicators by influencing the subjects into different engaged states. Different setups were created to mimic the situations in which the subject was in engaged, unengaged, or neutral engagement state. Our assumption was the measurement of the indicator could reflect subject's engaged state.

In research cycle 5, More pre-medical experiments were conducted to test the system from the perspective of two assumptions: (i) if the stimulation strategies can maintain and enhance the level of engagement, and (ii) if the effects of the stimulation strategies on the level of engagement can be captured by smart learning mechanism.

were used to create a robust knowledge platform for conceptualization of the whole of the proposed cyber-physical stimulating rehabilitation system (CP-SRS) and its smart reasoning mechanisms.

5 Review on therapeutic engagement and current limitations in engagement enhancing methods

In research cycle 1, a literature survey was conducted in order to collect information about the current state of knowledge and art concerning engagement in rehabilitation. In addition to focusing on definitional and conceptual issues, we intended to aggregate knowledge about existing models of engagement, the various manifestations of engagement, the current state of engagement enhancement methods and tools, and the opportunities of influencing enhancement of stroke patients. Together with the investigation of the current day practical limitations, which was presented and discussed in research cycle 2, this knowledge can be used to create a theoretical platform and conceptual framework for our support system development objectives.

Shown graphically in Figure 4, these perspectives were used to frame and provide a reasoning model over the knowledge domains of importance for our explorative survey. These knowledge domains are mutually connected and the interconnections have been considered at drawing our conclusions. The first domain of interest is engagement models that have been discussed in the literature in various contexts, such as engagement increase by gamification, enhancement of engagement in education, social and cognitive engagement, and engagement in therapeutic context. The variety of the models is large, ranging from theoretical through conceptual and procedural models to operation models. The second domain of interest is influencing factors, which play a role in therapeutic engagement in stroke rehabilitation and within which the human-related ones play an important role. Actually, we concentrated mainly on these human-related factors in our review. We observed that the overwhelming majority of engagement models were probably defined by considering a set of fundamental influencing factors. We imposed a classification on the derived set of influencing factors so as motor, perceptive, cognitive, and emotional. This created an interrelationship between the engagement models and the influencing factors. The third domain of interest is enablers of engagement enhancing. Various engagement enhancing systems have been developed considering the influential factors, (i) virtual reality-based environments/systems, (ii) personalized treatment systems, and (iii) cyber-physically supporting systems.

Based on our literature study we argue that gamification is still a proliferating approach in robot assisted stroke rehabilitation. But the literature study also demonstrated that the rapidly emerging and proliferating field of cyber-physically supporting rehabilitation systems provides opportunities for: (i) self-adaptive personalized treatment, (ii) monitoring and evaluation of engagement, (iii) creating synergy between real life cyber and physical processes. We concluded that most of the current personalized treatments consider the patient's motor capability or performance only. Nevertheless, perceptive, cognitive, and emotional factors also influence engagement – a fact implies that comprehensive personalization methods are needed in rehabilitation. Possible stimulation strategies for enhancing engagement were also identified in the aforementioned four aspects.

According to the literature review, there are three main limitations in the current engagement enhancing approaches, namely: (i) they typically consider only one form of engagement of the four identified forms (motor, perceptive, cognitive, and emotional), (ii) there is no reliable solution to engage the patients because current rehabilitation systems fail to deliver a fully personalized training, and (iii) no quantitative measurement of engagement is available in the current rehabilitation practice. Since CPSs offer the affordances of multi-sensor networking, generation of problem solving strategies, conducting situational learning, and synergistic coupling cyber and physical processes, they have the potential to improve the efficacy of rehabilitation based on personalized enhancement of engagement.

The main objective of research cycle 2 was to understand the limitations of current engagement enhancing methods in practice. To this end, an upper limb rehabilitation robot integrated with video games was designed and realized. Another goal was to understand which factors in the gamification method make the video game exercise engaging. Therefore, three exercises, namely: (i) video game exercise, (ii) tracking exercise, and (iii) traditional exercise were conducted, and the engagement states and levels of the participants during each exercise were compared. Combining the results of the survey of the current theoretical/methodological state of the art with the limitations found in the experimental investigation, we can conclude that:

- Gamification is not enough for maintaining engagement. When the subjects are becoming familiar with the exercise, their engagement decreases. Therefore, the stimulation strategies identified in research cycle 1 should be considered as interventions to maintain and enhance engagement during rehabilitation exercises.
- Personalized treatment is needed to engage the patients. The results of the experimental study also showed that different factors, such as increasing versatility of movements, providing continuous feedback, involving cognitive tasks, introducing competiveness or challenge in the training tasks, and introducing challenges in both motor and cognitive aspects, have different effects on different subjects. For each and every stroke patient, the parameters of the influential factors have to be tailored according to their interests and capabilities. Therefore, personalized stimulation strategies are needed to enhance engagement of the stroke patients during rehabilitation training exercises.
- A major limitation in this field is that there is no quantitative method to evaluate engagement. In this experiment, based on the relationship between engagement level and muscle activity, normalized EMG can be used as the indicator to represent engagement level of the muscle activities during rehabilitation exercise. This enables the rehabilitation system can monitor the status of the subjects and apply the interventions when the engagement level decreases.

6 The essence of the concept

In order to eliminate the limitations identified with regards to the current engagement enhancing methods, the overall functional requirements for the CP-SRS were defined as follows: (i) provide proper intervention were needed to maintain the engagement when the engagement level decreases, (ii) evaluate the engagement whenever is needed in order to determine when to apply the interventions, and (iii) provide adapted interventions for different patients. The CP-SRS was conceptualized according to these stated requirements.

Architecturally, the CP-SRS is composed of five subsystems, namely of: (i) an assistive robotic subsystem, (ii) a gamification subsystem, (iii) an engagement monitoring subsystem, (iv) a smart learning mechanism (SLM), and (v) an engagement enhancement subsystem (EES) (Figure 5). As its name implies, the assistive robotic subsystem supports the stroke patients during the execution of the physical exercises in the rehabilitation program in order to compensate for deficits in their motor function disability. The main function of the cyber-physical augmentation of the robotic system is to enhance the patient's engagement by introducing interventions during rehabilitation exercises. The gamification subsystem integrates video games with the training exercises and enables human-computer interaction. To determine the point in time of introducing the interventions, the engagement monitoring subsystem EMS monitors patient's engagement level.

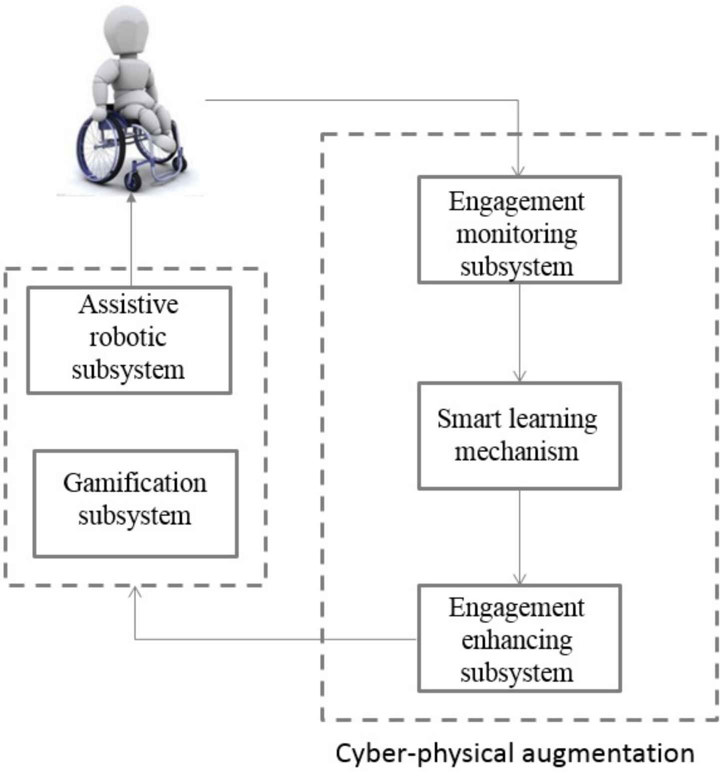

Figure.5 Cyber-physical stroke rehabilitation system

Basically, when the patient's engagement level decreases, the system introduces interventions. Through the interventions it is able to re-engage the patients and maintain a high level engagement of the patient. The interventions introduce stimulations in motor, perceptive, cognitive, and emotional aspects, depending on the actual state of the patient. Stimulation strategies are created as a combination of stimulations in multiple aspects. It is the task of the EES to apply the stimulation strategies by adjusting a bundle of parameters of the training exercises. There are several modes of stimulations in each aspect. Based on the knowledge it has learnt in the previous cases, the SLM is able to determine which stimulation strategy is the most relevant in a given case and situation, and to make suggestions on which stimulations to apply. In the next section, a detail description of the concept and prototype of the EMS, SLM, and EES system modules is presented.

7 Detail description of the concept

Considering the factors influencing therapeutic engagement, four types of engagement were defined and indicators for different types of engagement have been identified for the EMS

(Figure 6). According to these indicators, engagement can be measured by sensors by the EMS during rehabilitation exercises. Motor engagement (ME) is defined as a state in which the patient moves with active and effortful motion. It has been recognized that it can be quantified as the root mean square (RMS) of the EMG signal divided by the velocity of the movement.

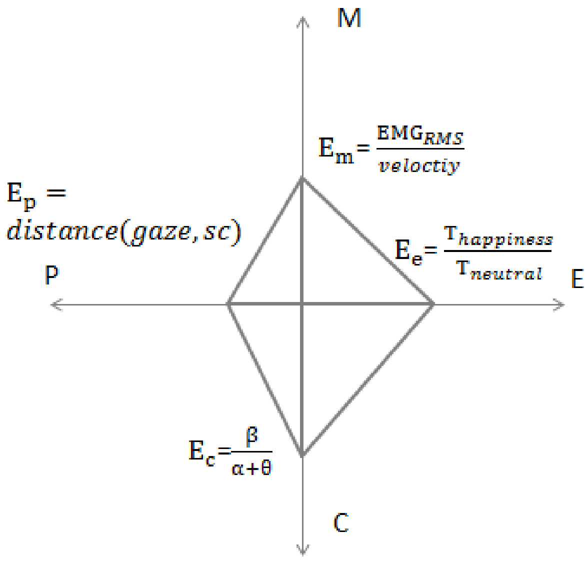

Figure.6 Engagement indicators

Perceptive engagement (PE) is defined as sensory concentration, such as visual, auditory and tactile. Visual engagement is evaluated as the distance between the position of patient's gaze and the position of the screen changes (sc), since the patient should concentrate on the display unit and interact with the video game. Cognitive engagement (CE) is considered as proportional with the level of concentration at performing cognitive tasks. Research has offered the formula shown in Figure 6 for determining indicator of cognitive engagement based on α, β and θ waves of brain signals that are highly correlated with the cognitive engagement of the patient (Pope, et al., 1995). Emotional engagement (EE) is defined as the degree of emotional involvement during the exercise. If the exercise can influence the patient's emotion, then it means that the patient is emotionally more engaged in the exercise. If the patient is emotionally engaged, the dominant emotion will change due to some different events in the game exercise. The indicator of the emotional engagement has been defined as the ratio between time duration when positive emotion is dominant and the time duration when negative emotion is dominant.

A smart learning mechanism (SLM) with a four stage workflow was conceptualized as illustrated by Figure 7. In the first stage, the system applies pre-programmed stimulation strategies, such as (i) change of the difficulty level of the motor tasks, (ii) change in the patient's sensory feedback, (iii) different cognitive tasks, or (iv) change in the competition or cooperation feature in the game exercises. The system monitors the engagement level of the patient and the SLM records the effect of applying the stimulation strategies in each aspect of engagement.

The data collected in the first stage are used to train the learning mechanism in the next stage. As shown in Figure 7, the inputs of the learning mechanism are the patient's profile/data and the changes of the level of engagement. The outputs of the learning mechanism differ in

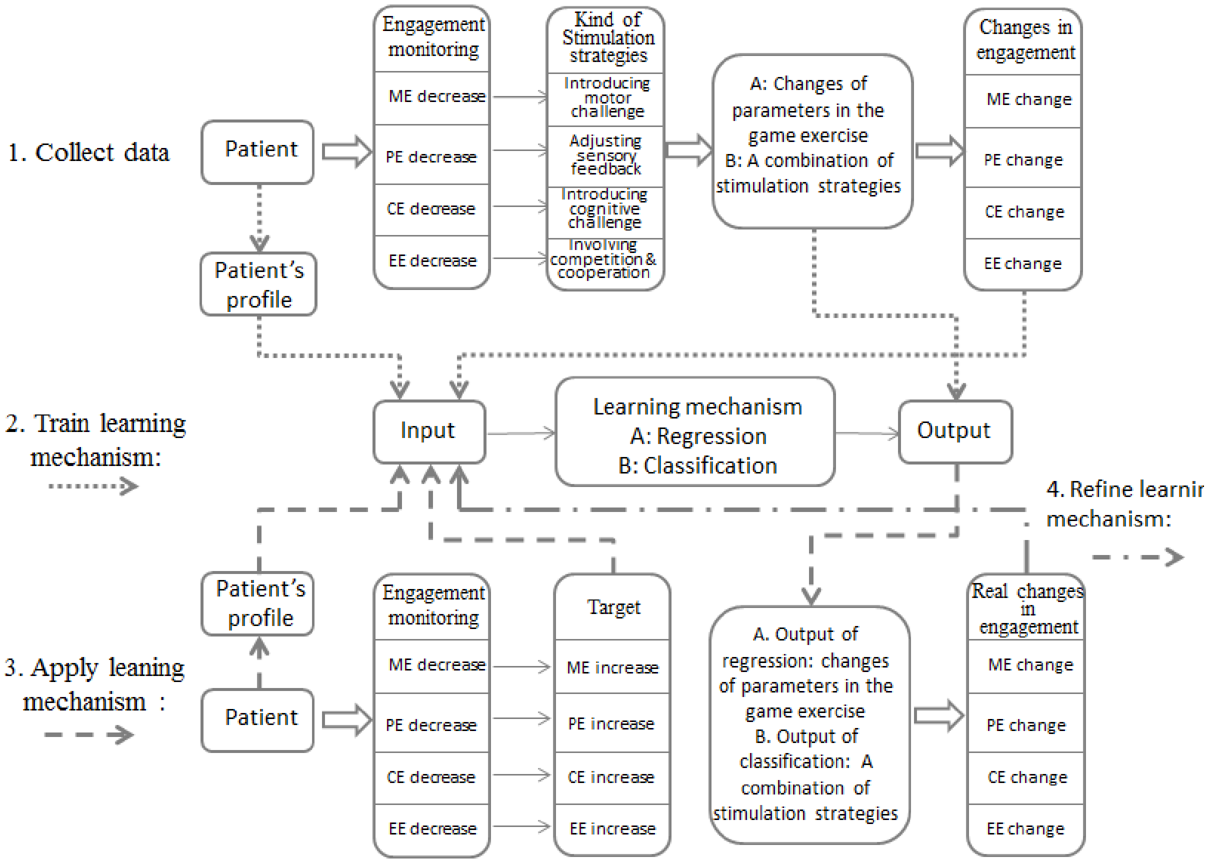

Figure.7 The reasoning scheme of SLM

regression mode and in classification mode. In regression mode, the outputs are the changes of the parameters. In classification mode, the outputs are a combination of stimulations. The patient profiles provide a kind of context information about the patients. The advantage of using patient profiles is that the learning mechanism can retrieve stimulation strategies, which have proven to be effective in the case of some previous patients, when another patient with similar profile uses the system. For a patient with the same patient's profile, the differences of the outputs generated by the learning mechanism are normally caused by the differences in the intended engagement levels.

In the third stage, the system applies the trained learning mechanism to recommend suitable combinations of stimulations based on the patient's profile and the intended change in engagement level. The intended engagement level is set by the system in line with the objective of enhancing the engagement in more than one aspect. In the fourth stage, the effects of the recommended stimulation strategies on the engagement level are recorded. These changes are used as additional input for refining the knowledge of the trained learning mechanism.

8 Implementation of a testable prototype

Figure 8 shows the prototype of the cyber-physical augmentation part of the CP-SRS. Its overall functioning was tested in a specific experimental set up. The rehabilitation therapy exercise was played with the computer mouse, which was integrated with the upper limb rehabilitation robot. The indicators for: (i) ME, (ii) PE, (iii) CE, and (iv) EE were monitored using: (i) MYO Armband with electromyographic sensors, (ii) Eyetribe eye tracking device, (iii) Emotiv Epoc headset (14 channel wireless EEG device), and (iv) a web camera, and Insight device, respectively. The data from these sensors were streamed to MATLAB via TCP/IP computer network transmission control protocol, where the engagement levels in the four aspects were interpreted.

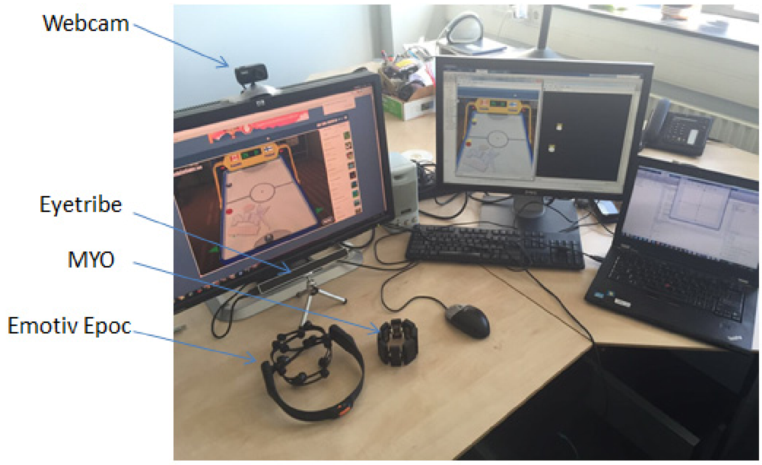

Figure.8 Prototype of the cyber physical augmentation

The architecture of this cyber-physical augmentation system is shown in Figure 9. It includes four layers of hardware, software, cyberware, and service components. The first layer includes commercialized hardware components capable to monitor the activities and physiological characteristics of patients. Because of the need for a two-strand parallel computation, two regular PC computers were used for the implementation of the prototype. One of them was used for visualization, and the other for monitoring. The MYO, Eyetribe, Emotiv Epoc devices, and the webcam were used to monitor the patient's (i) muscle activities, (ii) eye movement, (iii) brain activities, and (iv) facial expressions of emotion, respectively. The second layer, which includes third party software SDKs provided together with the hardware components, converts the measured signals into a time stamped data stream. The data are streamed from the Visual Studio and Processing to MATLAB via TCP/IP network. The software, implemented in MATLAB, processes the data and computes the actual engagement levels.

Based on the analysis of the current engagement level, the learning mechanism makes suggestions on the most suitable stimulation strategies to apply when the engagement is decreasing. The cyberware included in the cyber-physical augmentation subsystem consists of application software and database components. These handle (i) the engagement profile, (ii) the personal profile, (iii) the stimulation strategies, and (iv) contents learned by the learning mechanism. In the fourth layer, the recommendation mechanism of the CP-SRS can be found. It makes suggestions on the suitable stimulation strategies. This mechanism is integrated with the rehabilitation robot in order to apply various stimulation strategies by the means of adjusting the parameters in the robot assisted training. The typical adjustments are such as (i)

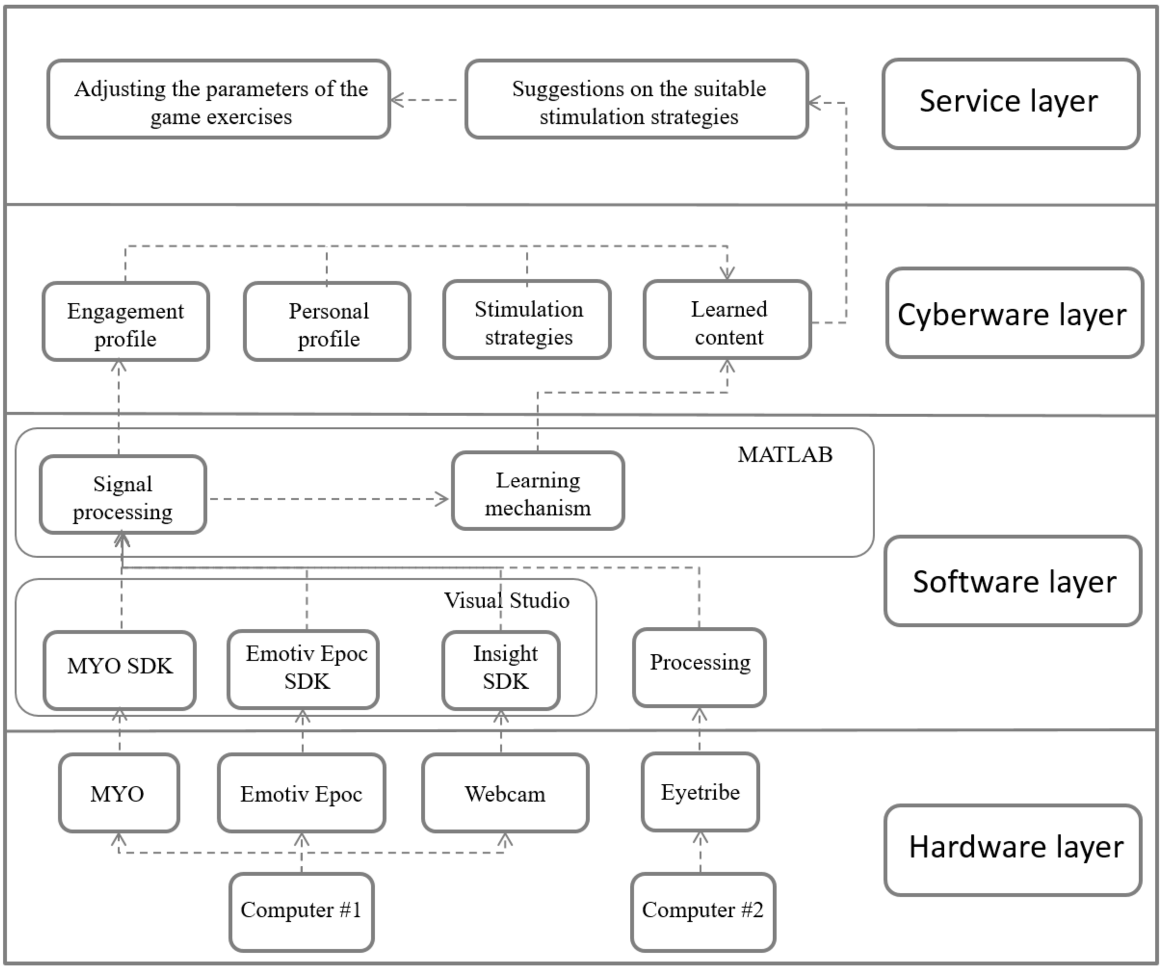

Figure.9 Architecture of the cyber-physical augmentation subsystem

the assisting force from the robotic arm, (ii) the threshold of the force sensor on the user interface, and (iii) the size of the moving space.

The overall operation flow of the system can be decomposed to four operation stages, called (i) preparatory, (ii) monitoring, (iii) stimulation suggestion, and (iv) stimulation application stages (Figure 10). In the preparatory stage, the physical therapist assists the patient to put on, start, and calibrate the devices, and to start the program to monitor the engagement status. In the next stage, the patient's engagement levels are monitored during the game exercises. In the third stage, the trained SLM suggests stimulations if the engagement level decreases. In the fourth stage, the stimulations are applied and the patient continues with the adjusted exercise. Additionally, when the stimulations have been applied, the effectiveness of the stimulation is evaluated and used to refine the contents learned by the SLM to make it more accurate.

9 Validation of the prototypes part of the system

To validate the research hypotheses, pre-medical experiments were conducted. First, Experiment II was conducted to individually test modules of monitoring motor, perceptive, cognitive and emotional engagement, and to validate if the EMS can determine the actual engagement of the participant. Experiment III aimed at validating the cyber-physical augmentation part of the CP-SRS from two aspects: (i) effectiveness of the stimulations in enhancing the engagement of the participants, and (ii) learning capabilities and limitations of the SLM subsystem concerning its ability to capture the relationship between the changes in the engagement and the applied stimulation strategies. In these experiments, within subject design was used because the measurements are very much dependent on the different participants.

(1) Validation of engagement indicators

Different experimental setups were created to mimic the situations in which the subject was in (i) engaged, (ii) unengaged, and (iii) neutral state. In the experiment conducted to validate the motor engagement indicator, the set ups were different. For instance, in the set up related to the engaged state, the participant was required to move his hand with an accuracy requirement. In the set up related to the neural state, the task was to move without any accuracy requirement. Finally, in the set up related to the unengaged state, the participant did not make any voluntary movement, but was driven by the experimenter to move passively. These setups were managed according to the implications of the definition of engagement in

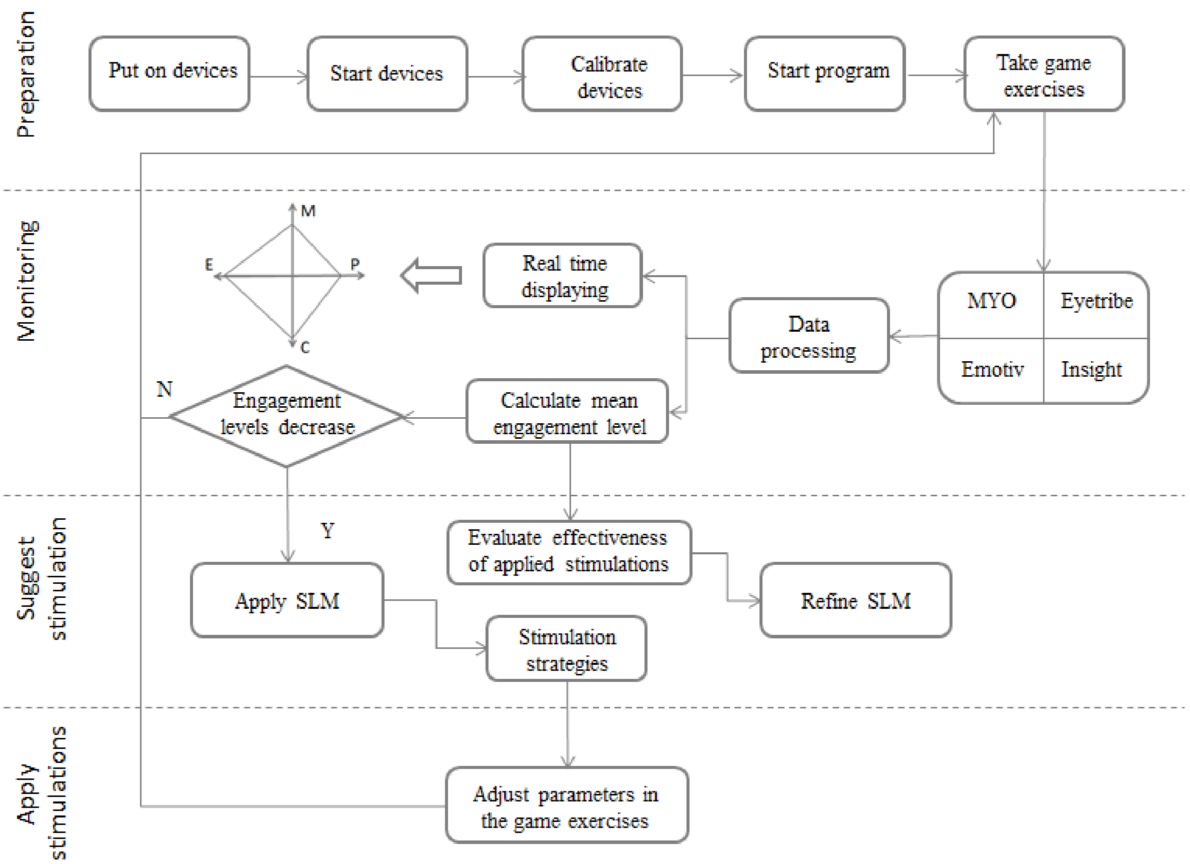

Figure.10 The four operational stages included in the operation flow

perceptive, cognitive, and emotional aspects. Various non-impaired participants were recruited to do the exercises in each setup. The results have shown that there were significant differences in the measured indicators of the motor, perceptive, and cognitive aspects comparing the results of the different experimental set ups. We can argue that the objective of the experiments i.e. testing if the proposed indicators can properly reflect changes in the engagement in different set ups, was achieved. This means that the proposed indicators can be used to represent the engagement of the participants during rehabilitation exercises, and that the implemented EMS could capture the actual (momentarily) engagement of the participants.

(2) Validation of the stimulation strategies

In Experiment III, the engagement of the participants was measured and compared before and after applying different stimulations. The stimulations were applied both individually and in combinations during practicing with two game exercises, which were orientated towards motor exercise and cognitive exercise, respectively. Within subject ANOVAs suggested that: (i) the tested strategies of motor stimulation, cognitive stimulation, and emotional stimulation were validated to be effective (i.e. they sufficiently increased the engagement in the motor, cognitive, and emotional aspect, respectively), (ii) SSs that involved coupled cognitive stimulation and emotional stimulation were able to increase the cognitive and emotional engagement concurrently, (iii) the tested stimulation strategies had similar effects on cognitive engagement and emotional engagement in both game exercises, and (iv) the participants tended to express positive emotions concerning the changes of the game exercise according to the effects of the stimulation strategies on the emotional engagement.

(3) Validation of the SLM

The data from Experiment III were used to test the training of the two reasoning mechanisms of the SLM, that are: (i) the neural network (NN), and (ii) the Naive Bayes (NB). The accuracy of the suggestions made by the NN-based and NB-based reasoning mechanisms of the SLM based on the test data set was 88.9% and 77.8%, respectively. In our application context, the NN-based SLM was more suitable for the purpose of learning the effects of and recommending personalized stimulation strategies, than the NB-based SLM. The results concerning the accuracy of recommendations entail that the reasoning mechanisms can better capture the changes caused by the stimulation strategies if the data show some patterns. Independent of the inputs, the NN-based SLM may recommend multiple alternative stimulation strategies that may cause the same effect on the change of engagement. In general, this would be considered as a misclassification made by the neural network. However, in our application context, this could be interpreted as an appropriate recommendation if the concerned stimulation strategy indeed achieves the goal of increasing the specific aspects of engagement. As a conclusion we argue that the NN-based reasoning mechanism considered in our prototype subsystem is a robust solution for the tasks.

10 Constraints on the research conduct

Since the focus of this research was on the cyber part of the whole system, we have not fully integrated the implemented system with the upper limb rehabilitation robot. Consequently, there was no clinical testing planned with stroke patients. However, the completed research was sufficient to show that the developed cyber-physical augmentation system can be used effectively in enhancing the engagement of healthy subjects during game exercises. In addition, the self-adaptive mechanism of the system is able to adjust stimulations strategies to different user profiles. It is expected that these mechanisms will have similar efficacy when applied in the case of stroke patients. Although one may argue that the indicators of the engagement of the stroke patients may be different, it has been shown that the system is capable to calibrate itself to capture the engagement profile of patients and to learn the effects of various stimulations on their engagement. Therefore, we are confident that this system can be utilized in the case of actual stroke rehabilitation and it will be proven in the follow up research work.

11 Conclusions, propositions and future work

Due to the characteristics and affordances of cyber-physical systems, cyber-physical augmentations can be integrated with robot assisted rehabilitation systems in order to enhance the engagement of patients during rehabilitation exercises. Based on the identified limitations in the current engagement enhancing methods, functionalities and architectural elements of the cyber-physical augmentation subsystem were identified, namely: (i) multi-sensor network, which can monitor patient's status, (ii) real time information processing, which can process and interpret the real time signals and generate engagement models, (iii) adaptive and personalized reasoning, which can provide adaptive stimulations for different patients, and (iv) automated problem solving and situational learning capability, which can automatically solve the problems based on learning. These functionalities and system components have been conceptualized and implemented in the CP-SRS at a testable prototype level.

The implemented engagement monitoring subsystem of the CP-SRS can monitor the patient's engagement level in the motor, perceptive, cognitive, and emotional aspects using MYO Armband, the Eyetribe, the Emotiv EPOC headset, and the Insight device, respectively. Having realized the prototype of the EMS subsystem, we developed and conducted a series of experiments to validate the functionality of this implementation. In the experiments, different setups were used to mimic the engaged, normal, and unengaged situations. The results showed that the proposed indicators for evaluation motor, perceptive, cognitive, and emotional engagement were correct and able to distinguish different engaged statuses.

Another experiment was conducted in order to validate the functionality of the stimulation strategies and learning mechanism. In the experimentation, different stimulation strategies were applied and the changes in the engagement levels were recorded. The analyses of the data demonstrated the effectiveness of several stimulation strategies in enhancing engagement, and more importantly, the learning mechanism was able to learn the relationship between the applied stimulation strategies and changes in the engagement level. This means that the learning mechanism is able to support a self-adaptive and personalized solution for different patients based on analyzing the data obtained in the monitoring and stimulation processes.

Based on the work and the results, we were able to derive the following propositions:

Proposition 1: *It has been found that the ratio of the root mean square of the measured EMG signal and the velocity of motion of the human limb is a reliable indicator of motor (function) engagement.* Δ

Proposition 2: *The indicators introduced for measuring the motor, perceptive, cognitive, and emotional engagement should be considered together to determine an optimal stimulation strategy and should be interrelated in order to form a distinct measure.* Δ

Proposition 3: *Though the motor, perceptive, cognitive, and emotional engagement indicators provide a robust basis for developing stimulation strategies, there is also a need for considering the personal profile of the patient.* Δ

Proposition 4: *Neural network-based smart learning mechanism is able to learn the effects of the different stimulations strategies on different persons and to propose personalized enhancement.* Δ

Proposition 5: *Self-adaptive and personalized training in rehabilitation achieved by continuous monitoring and smart learning can significantly increase the efficacy of stroke rehabilitation.* Δ

Proposition 6: *The identified engagement indicators can be useful not only for enhancing engagement, but also to understand the limitations of the current engagement enhancing methods.* Δ

Proposition 7: *A cyber-physical system oriented solution can successfully penetrate into the rehabilitation processes, which cannot be controlled otherwise.* Δ

Proposition 8: *Although the methodology developed for monitoring and enhancing engagement is dedicated for rehabilitation, this approach can be used in other fields as well, such as sports, driving, and education.* Δ

Self-publications based on the results of this PhD research:

1) Li, C., Rusák, Z., Horváth, I., Ji, L., & Hou, Y. (2014). Current status of robotic stroke rehabilitation and opportunities for a cyber-physically assisted upper limb stroke rehabilitation. Proceedings of TMCE 2014, May 19-23, Budapest, Hungary, 899-914.

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5) Li, C., Rusák, Z., Horváth, I., Kooijman, A., & Ji, L. Implementation and validation of engagement monitoring subsystem in an engagement enhancing rehabilitation system (Accepted for publication on IEEE Transactions on Neural System & Rehabilitation Engineering)

6) Li, C., Rusák, Z., Horváth, I., & Ji, L. Validation of the reasoning of an entry-level cyber-physical stroke rehabilitation system equipped with engagement enhancing capabilities (Under review at Engineering Applications of Artificial Intelligence)

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SAMENVATTING

CYBER-FYSISCHE OPLOSSING VOOR EEN REVALIDATIESYSTEEM OM DE TOEWIJDING VAN DE PATIËNT TE BEVORDEREN

Beroerte (cerebrovasculair accident, CVA) blijft een van de meest voorkomende oorzaken van beperkingen bij volwassenen. Wie een beroerte overleeft heeft vaak te kampen met verscheidene gebreken die de motorische, perceptuele en cognitieve vaardigheden verminderen. Halfzijdige verlamming veroorzaakt door een beroerte legt een zware last op patiënten en hun familie - vooral als een van de bovenste ledematen getroffen is, daar het gebrek aan bewegingscontrole over de arm een ongunstige invloed heeft op functionele onafhankelijkheid en de algemene dagelijkse levensverrichtingen. Op activiteit gerichte revalidatie kan helpen om de motoriek van de arm te herstellen. Dit is mogelijk dankzij hersenplasticiteit, d.w.z. veranderingen in zenuwbanen en synapsen die optreden als gevolg van veranderingen in gedrag, omgeving, neurale processen, denkprocessen en emoties.

Om fysiotherapeuten te ondersteunen in het consequent en reproduceerbaar trainen van beroertepatiënten zijn ongeveer 30 jaar geleden gerobotiseerde revalidatiesystemen ingevoerd. Hoewel zulke systemen veelbelovend blijken in het ondersteunen van specifieke revalidatieoefeningen (bijv. looptherapie) zijn ze maar beperkt inzetbaar voor armtherapie, waarbij taakgerichte handelingen moeten worden geoefend. Voor patiënten die met de huidige robotvoorzieningen revalideren bestaat vooral geen betrouwbare oplossing om te voorkomen dat alledaagse oefeningen verworden tot routine, of zelfs als vervelend worden ervaren. Dit proefschrift is gemotiveerd door de wens om een systeem te ontwikkelen dat de toewijding van beroertepatiënten bij robotondersteunde revalidatietraining moet bevorderen.

Het hier gerapporteerde onderzoek beoogde te verkennen *hoe cyber-physical computing bij de huidige robotondersteunde revalidatiesystemen de toewijding van de patiënt kan bevorderen*. Principes van cyber-fysische augmentatie maken het bij robotondersteunde revalidatie mogelijk om binnen te dringen in de fysiologische processen van patiënten om zo hun toewijding vast te houden en te vergroten. Het hoofddoel van dit promotieonderzoek was cyber-fysische augmentatie toe te passen op robotondersteunde revalidatie, en te onderzoeken hoe effectief een cyber-fysische oplossing bijdraagt aan het bevorderen van de toewijding van de patiënt.

Vanwege de verscheidenheid aan doelstellingen en contexten is voor een multi-methodologische opzet van het onderzoeksontwerp gekozen. Het hele promotietraject werd daartoe onderverdeeld in vijf onderling gerelateerde onderzoekscycli.

Doel van de eerste onderzoekscyclus was het verzamelen van informatie en kennis omtrent bestaande modellen die toewijding beschrijven, de verschillende manieren waarop toewijding zich kan manifesteren, de huidige stand van methoden en tools om toewijding te bevorderen, en mogelijkheden om de toewijding bij beroertepatiënten te beïnvloeden. Er werd geconstateerd dat er gebrek aan kennis is over de factoren die toewijding bij therapie bepalen, en over het beoordelen van de toewijding.

In de tweede onderzoekscyclus werd een prototype ontwikkeld van een armrevalidatierobot, die werd gebruikt in een experiment dat vanuit een praktisch oogpunt inzicht moest bieden in de beperkingen van de huidige methoden voor het bevorderen van toewijding. Het experiment richtte zich op verkenning van de factoren die toewijding bij robotondersteunde armrevalidatie beïnvloeden. De bevindingen van onderzoekscycli 1 en 2 duidden erop dat er het ontwikkelen van een cyber-fysisch stimulerend revalidatiesysteem *(cyber-physical stimulating rehabilitation system, CP-SRS)* dat motorische, perceptuele en cognitieve patiënttoewijding kan monitoren, nieuwe mogelijkheden biedt om de toewijding van patiënten te bevorderen, bepaalde aspecten van die toewijding te versterken door stimulatiestategieën toe te passen, en het effect van stimulatiestrategieën op de patiënt vast te stellen.

Uitgaand van de beperkingen vastgesteld bij de huidige methoden om toewijding te bevorderen, werden in de derde onderzoekscyclus de methoden, functionaliteiten en elementen voor de architectuur van het deelsysteem voor cyber-fysische-augmentatie bepaald, te weten: (i) een multisensornetwerk dat de toewijdingstoestand van de patiënt kan monitoren, (ii) informatieverwerking die de signalen real-time kan afhandelen en interpreteren en tevens modellen kan genereren die de toewijding beschrijven, (iii) adaptieve logica die kan voorzien in patiëntspecifieke adaptieve stimulaties, en (iv) geautomatiseerde probleemoplossing gebaseerd op situationeel zelflerend vermogen. Er is een concept ontwikkeld voor slimme logicacomponenten waarvan de haalbaarheid getoetst is. Verder is computersimulatie uitgevoerd om de haalbaarheid te toetsen van het slimme leermechanisme (SLM) als onderdeel van de cyber-fysische augmentatie. De resultaten lieten zien dat SLM gebaseerd op zowel neurale netwerktechnologie en SLM gebaseerd op naïeve Bayes-classificatie beide in staat zijn het verband te leren leggen tussen de gesimuleerde stimulaties en de veranderingen in de mate van toewijding.

In de vierde onderzoekscyclus werden de vastgestelde functionaliteiten en systeem-componenten geconceptualiseerd en geïmplementeerd in het CP-SRS tot op het niveau van testbaar prototype. Na realisatie van een prototype van het toewijdingsmonitoringsysteem *(engagement monitoring subsystem, EMS)* is er een reeks experimenten opgezet om de functionaliteit van deze implementatie te valideren. Het doel van deze nog niet in medische context uitgevoerde experimenten was het bereik en de nauwkeurigheid van de toewijdingsindicatoren te karakteriseren door proefpersonen in verschillende toewijdingstoestanden te brengen. Verschillende opstellingen werden opgezet om situaties na te bootsen waarin de proefpersonen in een toestand van resp. verveeld, neutraal en toegewijd terechtkwamen. Aangenomen werd dat in de toegewijde toestand de meetwaarden voor de indicatoren voor motorieke en cognitieve toewijding hoger zouden zijn en die voor perceptuele toewijding lager, in vergelijking met de neutrale en de verveelde toestand. De resultaten toonden aan dat de voorgestelde indicatoren om de motorische, perceptuele en cognitieve toewijding te toetsen correct waren, en het onderscheiden van verschillende maten van toewijding mogelijk te maken.

In de vijfde onderzoekscyclus werd nog een experiment uitgevoerd om de functionaliteit van de stimulatiestrategieën en het zelflerende mechanisme te valideren. In het experiment werden verschillende stimulatiestrategieën, zoals het opleggen van een motorische uitdaging, het aanpassen van sensorische feedback, het opleggen van een cognitieve uitdaging, en het inbrengen van een competitie-element toegepast, en de veranderingen in de mate van toewijding werden vastgelegd. De resultaten toonden het effect van stimulatiestrategieën bij het bevorderen van specifieke aspecten van toewijding. Bovendien werd aangetoond dat het slimme zelflerende mechanisme in staat was het verband te leren leggen tussen de toegepaste stimulatiestrategieën en de veranderingen in mate van toewijding. Deze bevindingen bewijzen dat het zelflerend mechanisme kan helpen een zelf-adaptieve en geïndividualiseerde oplossing te bieden voor patiënten met verschillende capaciteiten en interesses op basis van analyse van de data verkregen in het monitorings- en stimulatieproces.

Op basis van dit werk en de resultaten konden de volgende stellingen worden afgeleid:

Proposition 1. *De verhouding tussen het kwadratisch gemiddelde van het gemeten EMG-signaal en de bewegingssnelheid van de menselijke ledemaat vormt een betrouwbare indicator voor motorische toewijding.*

Proposition 2. *De voor het meten van motorische, perceptuele, cognitieve en emotionele toewijding ingevoerde indicatoren moeten tezamen worden beschouwd om een optimale stimulatiestrategie vast te stellen, en ze moeten wederzijds met elkaar in verband worden gebracht om een afzonderlijke meetwaarde te vormen.*

Proposition 3. *Hoewel de indicatoren voor motorische, perceptuele, cognitieve en emotionele toewijding een solide basis vormen voor het ontwikkelen van stimulatiestrategieën, is het ook nodig om het persoonlijke profiel van de patiënt te beschouwen.*

Proposition 4. *Het slimme zelflerende mechanisme gebaseerd op neurale netwerken kan zich de effecten van de verschillende stimulatiestrategieën op verschillende personen aanleren, en geïndividualiseerde verbeteringsvoorstellen doen.*

Proposition 5. *Zelf-adaptieve en geïndividualiseerde training bij revalidatie door middel van continu monitoren en slimme zelflerendheid kunnen in significante mate de effectiviteit van revalidatie na beroerte verhogen.*

Proposition 6. *De vastgestelde indicatoren voor de mate van toewijding kunnen niet alleen nuttig zijn om toewijding te bevorderen, maar ook om de beperkingen van de huidige methoden voor verbetering van toewijding te begrijpen*

Proposition 7. *Een cyber-fysisch-systeemgerichte oplossing kan succesvol doordringen in revalidatieprocessen die op geen andere manier kunnen worden beheerst.*

Proposition 8. *Hoewel de methodologie ontwikkeld om toewijding te monitoren en te verbeteren toegespitst is op revalidatie kan deze aanpak ook worden gebruikt in andere gebieden zoals sport, autorijden en onderwijs*