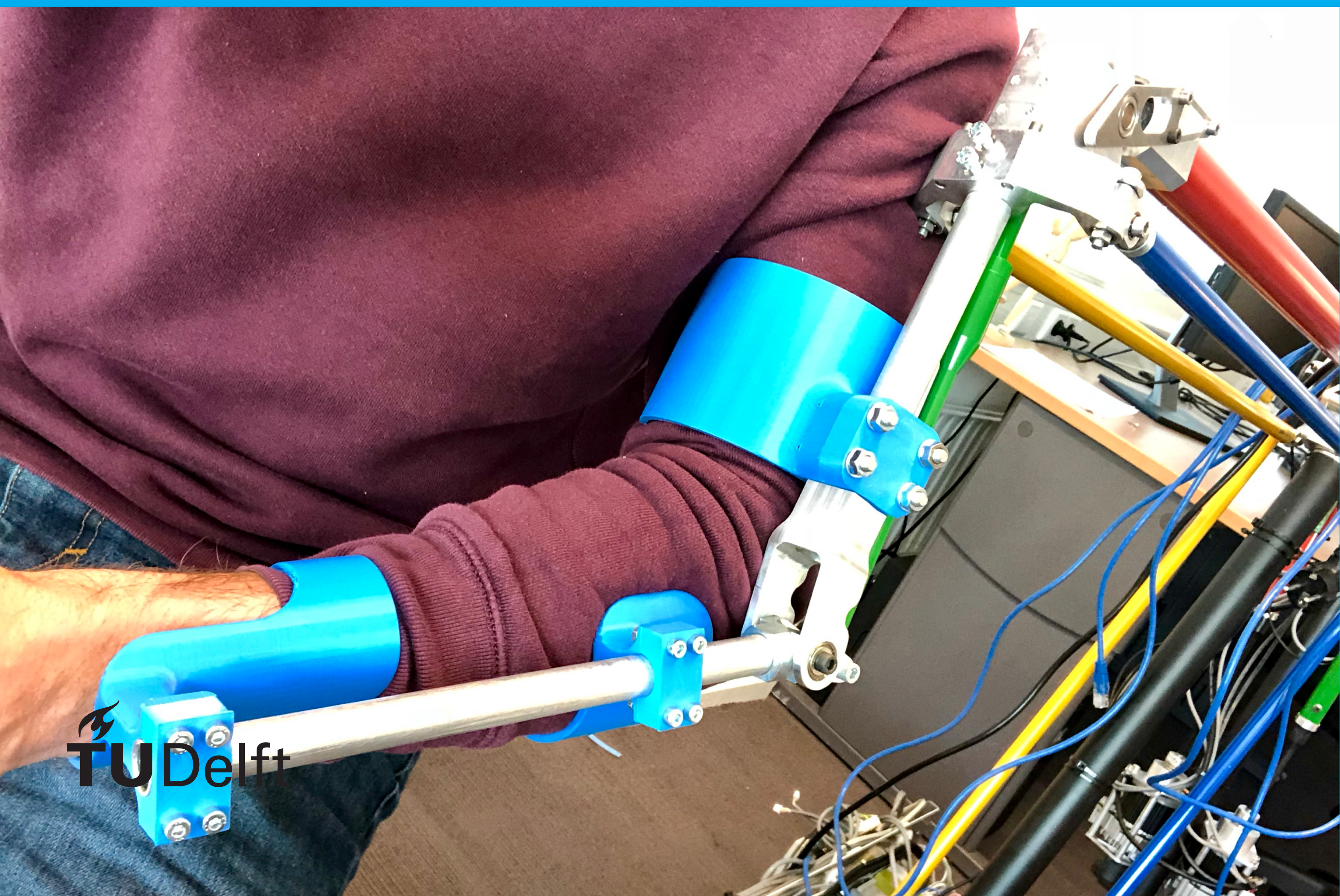
Technische Universiteit Delft

Improving Learning Performance in a Reaching Task by Real-time Adaptation of Augmented Error Feedback Rules

M. J. Elzinga



TU Delft

Improving Learning Performance in a Reaching Task by Real-time Adaptation of Augmented Error Feedback Rules

by

M. J. Elzinga

to obtain the degree of Master of Science
at the Delft University of Technology,
to be defended on Monday December 17, 2018 at 10:30 AM.

Student number:	4158539	
Project duration:	May 1, 2018 – December 17, 2018	
Thesis committee:	Dr. ir. A. C. Schouten	TU Delft, supervisor
	Dr. ir. W. Mugge	TU Delft, supervisor
	Dr. ir. P. Martens	Motekforce Link
	ir. J. W. Spronck	TU Delft

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

TU Delft

Acknowledgements

This work is the result of my graduation project and the final step to obtain the title Master of Science at Delft University of Technology. It is also the end of a great time in Delft. I want to thank everyone who made this possible.

Alfred and Winfred, thank you for not letting me choose between the two of you when you agreed to be my supervisors. We did not meet often, but when we did I always gained insight and a moral boost. Your feedback was key to keep this project going in the right direction and I appreciate your understanding of the circumstances at all times.

Motek Forcelink - especially Peter - for providing the opportunity to do an internship and graduation project. I appreciate the effort you put into making this possible even though the project was not entirely in line with the companies' road map. It was a great experience to work in the development department of such an inspiring company.

Nathan, I am very grateful for your help. With your patience and interest in my project we managed to make the software work after all, so I could do my experiment.

Thanks to everyone who has been an important part of my student years, regardless of studying: Lacanau, Mach, BT28/OD12.

Finally, I'd like to thank Taco, Marjolijn and Hester for all their support and wise counsel.

Preface

One of my biggest interests has always been in product development. When I started thinking about my thesis project I quickly knew I wanted to do this project at a company that develops medical devices. During my first MSc year, I attended a guest lecture by Motekforce Link and the name has stuck with me ever since. I am excited that I could do a graduation internship with them.

From an academic point of view, doing a development internship can introduce some difficulties. Commercial and scientific approaches are not always compatible and both had to be respected to satisfy requirements for a development intern and a MSc graduate simultaneously. I learnt that the device I was going to work on, the Armbot, did not yet have the training exercises (software) for which it was designed and built. From my literature review, I knew what types of assistive algorithms were used and I had some ideas about what would be suitable for the Armbot. The resulting plan was to design and implement a new training algorithm and validate the performance in an experiment.

Development of the Armbot was discontinued due to organizational decisions during my internship. I got the opportunity to stay and finish my thesis, but this meant nobody but me was involved in the project. Also, the people who used to work on the Armbot had left the company. It took a lot of time and effort to find out what I was dealing with, especially since I had no knowledge of the matter and nobody around was familiar with details about the Armbot. It was quite a struggle finding documentation, learning C++, setting up a cross-compile tool chain and finding and fixing bugs in the software. Although these circumstances might have had a negative impact on the project, I learned a lot. For me personally, this type of experience is at least as valuable as the final result and I take all that I learned with me in the start of my professional career.

Concluding my remarks on this eventful project, I think I did manage to achieve a fair balance between development and scientific value. There is still a lot to improve and although further development of the Armbot seems unlikely, I look forward to seeing all the other exciting product ideas from Motekforce Link come to life.

M. J. Elzinga
The Hague, December 2018

Contents

Acronyms

AAN	Assist As Needed
ADL	Activity of Daily Living
ANOVA	Analysis Of Variance
API	Application Programming Interface
DALY	Disability Adjusted Life Year
DOF	Degree Of Freedom
PAN	Punish As Needed
RMS	Root Mean Square
VR	Virtual Reality

Improving Learning Performance in a Reaching Task by Real-time Adaptation of Augmented Error Feedback Rules

Maurits Elzinga

Delft University of Technology
December 3, 2018

Abstract – Neurologically impaired patients can regain motor function by engaging in rehabilitation. Currently there is no conclusive evidence that robotic rehabilitation has better clinical results than conventional rehabilitation but robotic rehabilitation has the potential to increase efficiency and patient motivation, justifying improvement of rehabilitation robotics. A variety of approaches to design the interaction between a robotic trainer and the patient is used. For the purpose of improving rehabilitation robotics, a new adaptive algorithm is proposed. Assistive algorithms seem suitable for training impaired patients but prove difficult to validate with healthy subjects. For healthy subjects, error augmentation is shown to be more effective for learning. In an experiment, 13 healthy subjects performed a reaching task while strapped to an upper extremity exoskeleton. During this task they were subject to an adaptive augmented error feedback controller. Subjects were divided into three groups in which one of each, or both the following parameters of a force field were adapted: dead band width and divergent force field strength. Performance was measured as amount of deviation from a straight line between two targets. Adapting dead band width results in a better movement performance than adapting force field strength (p = 0.0069). Adapting force field strength in addition to adapting dead band width did not improve movement performance (p = 0.9960). It is concluded that an adaptive augmented error feedback mechanism can improve movement performance in a reaching task with healthy subjects.

1. Introduction

Neurological injuries such as stroke, traumatic brain injury and spinal cord injury often cause loss of motor function. Yearly, 6.3% of disability adjusted life years (DALY's) are caused by neurological injury [1] and the world-wide burden of stroke is increasing [16]. Examples of neurological injuries are stroke, spinal cord injury and traumatic brain injury, which can result in loss of the ability to perform activities of daily living (ADL's). 30-40% of patients suffering from neurological injuries are limited in or incapable of walking, even after rehabilitation [28]. Of patients that are heavily affected in the upper limb, only 18% regain full motor function [31]. For these patients rehabilitation can be beneficial to recover motor function by improving motor neuron output as well as muscle morphology [2], a combination referred to as motor plasticity. Rehabilitation is shown to be effective to improve motor plasticity [7] [36] when it is task-oriented, repetitive and of long duration [32] [24]. The need for repetitive and intensive training is expensive and labor-intensive for therapists, but robotic rehabilitation devices can be used to lift this burden. State of the art rehabilitation robots help patients during rehabilitation tasks by assisting them in their movements and providing visual, auditory and haptic feedback. There is currently no consensus about the clinical benefits of robotic rehabilitation over conventional rehabilitation [30] [27] [22]. However, robotic rehabilitation has the potential to surpass conventional therapy when it comes to efficiency and cost effectiveness while simultaneously making rehabilitation more pleasant and motivating for patients by using games in virtual reality (VR) [26] [9] [18] [37] [25]. This makes improving the design of rehabilitation robotics worth the effort.

Many considerations, such as mechanical design [17] and control architecture, are important in the development and validation of robotic rehabilitation devices. These considerations are partially based on the nature and severity of patients' impairments, but also on theoretical approaches about motor learning and sensorimotor control. Especially for the control architecture and design of learning tasks, a multitude of computational approaches to motor learning are used [4] [19]. A lot of scientific research is done on adaptive controllers, which mimic the role of a therapist. An issue with the validation of robotic rehabilitation methods is that often healthy subject groups are used [11] [3] [20] [21]. Assessing the performance of a rehabilitation device on healthy subjects causes a conflict, because an impairment of some sort is designed for these healthy subjects and the device that is used to aid the subject is also used to impose that impairment.

An important question in robotic rehabilitation is how to design the interaction between the external trainer and the patient. A trainer can be a robot, therapist, or combination of both and has the task of observing a patients' movements, providing feedback to correct and improve these movements when necessary. At the same time a mechanism must be in place that minimizes the magnitude and frequency of the trainers' interventions. When voluntary movements are not encouraged, there is a risk that the patient starts relying on the trainer. This results in a sub-optimal movement strategy and thus sub-optimal recovery. A trainer should be able to monitor the performance of a subject and adapt its assistance accordingly to optimize motor learning. Optimizing trainer intervention forms the basis for development of adaptive training algorithms, widely referred to as Assist As Needed (AAN) [10] [14] [15] [13] [6].

Many forms of adaptiveness can be used and the optimal trade-off between practical application and theoretical correctness depends on factors such as training goal, mechanical design and computational cost. In theory, the optimal way of modeling adaptive controllers is to model them according to physiological processes in a human body [34] [38] [23] [39]. The rationale behind this approach is that if the robot learns in a similar way the human does but slightly slower, interventions are optimized to human performance. Modeling a robot after human learning processes can be done by combining optimization algorithms or neural networks with muscle models [12]. To create a reliable neural- or muscle model, physiological parameters of humans are required [5], which is a patient-specific and labor intensive procedure. An adaptive algorithm that does not require much tuning or a priori knowledge is desired.

In this project an adaptive algorithm is used with an upper extremity exoskeleton and healthy subjects performing a learning task. While AAN helps severely impaired patients, patients who have regained motor skills benefit less from such an assistive rehabilitation task. For healthy subjects assisting does not improve motor learning at all, but punishing does [33] [8], which is the reason for using an augmented error feedback mechanism. Besides testing the effect of an adaptive augmented error mechanism, various adaptation rules are used to gain understanding of what might be the optimal way to adapt such an algorithm to promote motor learning.

Performance is quantified as movement deviation from an optimal path. Augmenting the movement error is done by introducing a divergent force field when a subject deviates from the optimal trajectory, while free movement is allowed within a dead band zone. Two parameters were adapted: stiffness of the force fields' virtual spring and width of the dead band. Three subject groups conducted the experiment, one for each update parameter and one with both. The goal of analyzing movement performance was to determine if adapting the algorithm improved learning performance, and if so which of the adaptation rules had the best results.

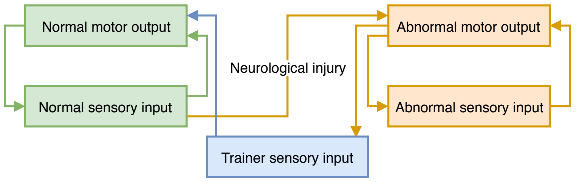


Figure 1: Sensorimotor control and the role of a trainer. When not neurologically impaired, normal sensory input results in normal motor output. Neurological injury increases the probability of normal sensory input resulting in abnormal motor output. A trainer introduces a new sensory state which can help correct abnormal motor output.

1.1. Background

Motor learning is the process of adapting movement strategies to an environment. This includes creating/strengthening neural pathways, altering joint impedance or optimizing movement strategy. When a subject is presented with a new scenario or a new environment, he/she needs to learn how to react to that environment. In a task-based training scenario, the environment acts on the subject in a way that simulates an ADL. In an assistive setting the environment might be programmed to help a subject reach a certain point when this subject is not capable of performing that movement. Making this environment adaptive can help optimize the intervention of the environment and movement performance of a subject. However, there is always a risk that an assistive environment results in sub-optimal motor learning. An explanation for this can be found when looking at sensorimotor control as an adaptive Markov model [34]. When a subject has a neurological injury, the probability that a neural command results in abnormal motor output is increased as a result of damage to the neurological pathways [34]. When a normal motor command results in an abnormal motor output, this will in turn cause an abnormal neural command. This loop of abnormal sensorimotor control can be broken by introducing a trainer. The role of a trainer is to recognize abnormal motor output and correct it, so a normal neural command is generated (Figure 1).

According to the Hebbian feedback control law [29] 'neurons that fire together wire together', meaning that the trainer will help a subject strengthen neural pathways by repeatedly making correct movements. However, at a certain moment this does not hold any longer. When a subject recognizes that the trainer will always assist, the subject starts relying on the trainer and the development of neurological pathways stops. To solve this problem, a trainer needs to be able to

Group	Participant	Age	Dominant arm	Sex
1	1	24	L	F
1	7	32	R	F
1	10	31	R	M
2	2	24	R	F
2	8	34	R	M
2	11	35	R	M
2	13	25	R	M
3	3	56	R	M
3	6	24	R	M
3	9	24	R	F
3	12	30	R	M

Table 1: Subject groups & details. Adaptation rules: Group 1 - dead band, Group 2 - stiffness, Group 3 - dead band and stiffness. Of 13 participants, 2 were excluded due to technical reasons.

recognize the performance of a subject and act accordingly. Because healthy subjects do not benefit from assistive environments, they should train with resistive or punishing environments [8] [33]. It has been shown that motor learning in healthy subjects can indeed be improved by amplifying errors [35]. Subjects learn that it takes less effort to slightly increase joint impedance than it takes effort to return to the dead band from a divergent force field.

2. Materials & Methods

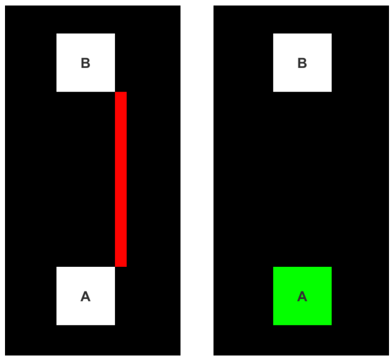
An experiment was conducted in which 13 healthy subjects were asked to move their left hand back and forth between two targets while connected to a robotic device. Deviation from a straight line between the two targets was measured and used to quantify the development of movement performance during the given task. Free movement was allowed within a dead band zone around the straight line between the two targets. Outside this dead band zone a divergent force field was present, acting in the direction perpendicular to the line between targets. Depending on the performance during the trials, the robotic algorithm could update the dead band width and/or the strength of the force field. Subjects were divided in three groups, as seen in Table 1. The goal of this experiment was to find out what effect adapting the algorithm had on the task performance, and see what kind of adaptation yielded the best results.

2.1. Experiment protocol

Participants were provided an information sheet (Appendix E) about the experiment and the background and provided their informed consent. Instructions were also given verbally after the participants read the information sheet, and a researcher helped the participant put on the cuffs of the robotic device. Each participant was asked to perform 225 trials, one trial being moving from target A to target B or vice versa. The first 20 trials were used to get familiar with the procedure and the algorithm was not updating during that time. After the test trials, subjects could continue until they reached trial 225. Catch trials were present on pre-defined trial numbers, during which the force field was turned off (stiffness set to zero) even if subjects moved outside the dead band. Subjects were randomly placed in one of the three groups (Table 1). Before each experiment, the robotic device was re-initialized and force sensors were calibrated. Measurements from the adaptive algorithm as well as from the force sensors were recorded at a sample frequency of 500 Hz.

2.2. Feedback

To know whether a target was reached, subjects were presented a game providing visual feedback on a screen in front of them (Figure 2). This game was running on an external computer and measurement information was retrieved in real-time from the robotic device via an application programming interface (API). More details about this game can be found in Appendix D. Two squares, representing target A and B, were shown on screen. If a target was reached it turned green. Also, when the subject would move outside of the dead band a red bar was shown on the corresponding side. A counter was used to indicate the end of the test period (first 20 trials) and the end of the experiment (225 trials).



(a) Force field (b) Target reached

Figure 2: Armbot game visual feedback during experiment. In 2a the subject is ouside of the dead band, in 2b the subject reached a target.

2.3. Robotic device

The experiment was done with an upper extremity exoskeleton called the Armbot (Figure 3). The Armbot has four actuated degrees of freedom (DOF's) and is designed as a lightweight rehabilitation robot that is easy to attach to and detach from a patient. The Armbot is an admittance-controlled device, using force sensor data to calculate position, velocity and acceleration of a virtual mass model. When modeled correctly, moving an arm while strapped in the Armbot feels transparent, as if there were no exoskeleton. To this mass model, virtual effects such as dampers or walls can be added in a haptic renderer. These haptic effects are used to design the feedback given in training excercises. In the experiment an adaptive augmented error feedback algorithm is implemented as a virtual spring.

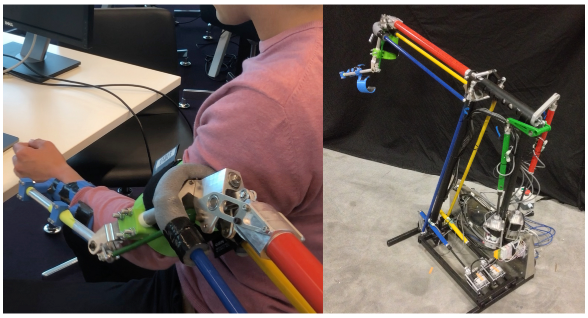


Figure 3: Armbot prototype #13. Four electrical motors drive the actuated DOF's via pushrods: elbow flexion (green), shoulder abduction (red), shoulder endo-/exorotation (blue and yellow), shoulder flexion (blue and yellow). The subject is strapped to the device with one cuff for the upper arm and two cuffs for the forearm. A BeagleBone Black running realtime Linux runs the control software.

2.4. Adaptive error augmentation

For the experiment, an adaptive augmented error feedback algorithm was implemented in the control loop of the admittance controlled mode of the Armbot. The functionality in this algorithm is twofold: augment movement error by introducing a force field and adapt the characteristics of this force field. Because of its nature the algorithm is called Punish As Needed (PAN), Figure 4 shows an overview of the control structure of the Armbot and the addition of the PAN algorithm. The current implementation can be found in Appendix A and other design considerations for the PAN algorithm can be found in Appendix C.

Force field

When moving outside of the dead band, a resistive force field is turned on. This force field is created by adding two virtual springs to the haptic renderer. One spring acts on the shoulder endo- and exorotation and the other on shoulder abduction. On the shoulder endo-/exorotation axis the spring pulls in the direction of the movement error, perpendicular to the optimal trajectory (augmenting shoulder endo- or exorotation). The shoulder abduction spring only pulls in the abduction direction. The task space was divided into the following zones (Figure 5):

1. Target zone (A or B)
2. Dead band
3. Resisting zone
4. Stabilizing zone

Subjects were asked to move back and forth between zones A and B. In these zones no force field was active. A straight line from A to B was the theoretical optimal movement trajectory in terms of resistance. Within the dead band, free movement is allowed, and no additional forces are imposed on the arm. In the resistive zone, a force field pushes the subject away from the optimal trajectory. For stability and safety, a stabilizing zone is included. This stabilizing zone is a force field in the opposite direction of the resistive zone which restricts further movements and prevents the subject from ending up in uncomfortable positions.

The zones were defined and measured in the motor space of two joint DOF's: shoulder rotation and shoulder flexion. Both DOF's were actuated by the same motors (blue and yellow rods in Figure 3) and motor space was defined as the linear displacement of the rods in [m], directly converted from motor encoder ticks. The displacement of these two motors was used to see if a target was reached, if the force field should be turned on or off and what the direction of the spring should be (Appendix A). The PAN function was called in the force control loop of the Armbot.

Adaptation rules

Dead band width (wDB) was decreased and spring stiffness (K) was increased when a subject did not move outside the dead band during one trial. To measure this, a movement error parameter was updated constantly during each trial. When moving inside the dead band the movement error remained zero. When moving outside the dead band the movement error was increased. After reaching a target the movement error was evaluated and when it was zero for the previous trial, an update of the force field parameters was done. The movement error parameter was set to zero again before each next trial. Depending on the subject group, spring stiffness, dead band width or both were updated. The adaptation rules for each group were the same: an incremental increase of the stiffness and an incremental decrease of the dead band width.

$$K = K + 2$$
$$wDB = wDB - 0.0001$$

Both increment values were determined by trial and error, with the requirement that the task should be easy in the beginning and become hard enough so that subjects would feel the effect of the force field towards the end of the experiment. Initial values were: K 10, wDB 0.02. Updating the force field parameters was done in the following way: upon entering a target zone, the total error was evaluated and if the error was larger than zero, parameters were updated.

2.5. Data Analysis

All measured data was separated per trial. For each trial the root mean square (RMS) of all samples was calculated. An exponential fit was applied to the averaged movement performance RMS per group. The parameters of these fits indicate average learning rates of the groups. The applied fit is

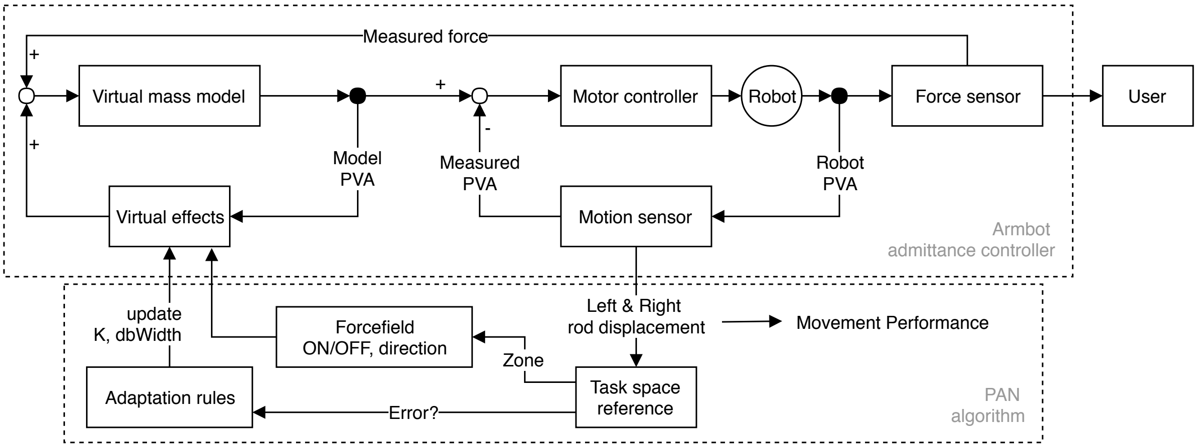


Figure 4: Armbot control structure with PAN algorithm. The main realtime control loop is an admittance controller that uses measured force to calculate model position, velocity and acceleration (PVA) to drive the robot. A position control loop uses measured PVA to compensate for play and friction. The PAN algorithm uses measured position of two rods to determine in which zone the subject is positioned. The zone and movement error determine if the virtual force field should be turned on or off, and if the parameters of virtual effects should be updated. Movement performance is always recorded as absolute difference between two rods.

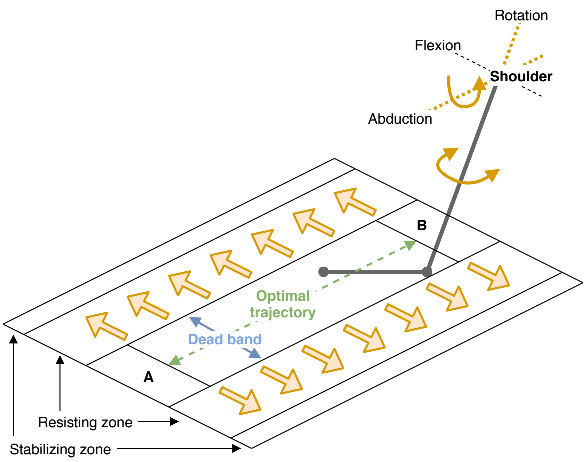


Figure 5: Task space zones and force field directions. Between two targets A and B the optimal trajectory is a straight line. The area around the optimal trajectory is a dead band in which haptic effects are turned off. Outside the dead band lays the error augmenting zone, with virtual springs acting on shoulder abduction and rotation. In the outer stabilizing zone springs on shoulder abduction and rotation prevent the user from reaching uncomfortable positions.

in the following form:

$$y_{fit} = ae^{-bx}$$

In which y_{fit} is the response, a is a multiplying factor, b is a decay rate and x is a time factor (trials).

To evaluate the statistical significance, a one-way ANOVA between groups was done. If group means were significantly different, a Tukey-Kramer post-hoc test was done. All data processing was done in MATLAB R2016b.

3. Results

3.1. Algorithm adaptation

Table 2 shows the total amount of force field activations after 225 trials for each participant. There is a significant difference between the amount of activations between groups, F(2,8) = 8.86, p = 0.0094. Group 1 has a significantly higher amount of activations than Group 2 (p = 0.0292) and Group 3 has significantly more activations than Group 2 (p = 0.0114). There is no significant difference between Groups 1 and 3 (p = 0.9250). The adaptation of algorithm parameters corresponds to the rates seen in Figure 6. The rate of force field activations between groups is not significantly different (between trial 25 and 75 p = 0.4236, between trial 75 and 125 p = 0.2141, between trial 125 and 175 p = 0.2097, between trial 175 and 225 p = 0.6809). The adaptation of dead band width and stiffness

Group 1	Group 2	Group 3
94	2	87
58	38	104
54	10	53
	17	55

Table 2: Total force field activations per participant for each group. In group 3 the force field was activated the most, followed by Group 1 and Group 2.

are shown for each individual participant in Figure 7. In trials where the forcefield is not activated (horizontal line in Figure 6), the parameters of the algorithm are updated. The difference in dead band adaptation is significant between groups (p = 2.25635 e-5). In Group 1 and 3 the dead band width changes significantly more than in Group 2 (p = 0.0000, p = 0.0001). Difference in dead band width adaptation between Group 1 and 3 is not significant (p = 0.8806). Group 2 has a significantly higher stiffness adaptation than Group 1 (p = 0.000) and Group 3 has a significantly higher stiffness adaptation than Group 2 (p = 0.0000).

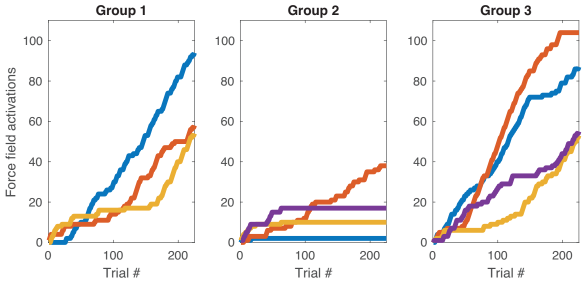


Figure 6: Cumulative amount of trials with errors. Each trial in which subjects moved outside the dead band one or more times is counted as a trial with an error. Each line represents one subject. The rate of force field activations is the amount of activations per 50 trials.

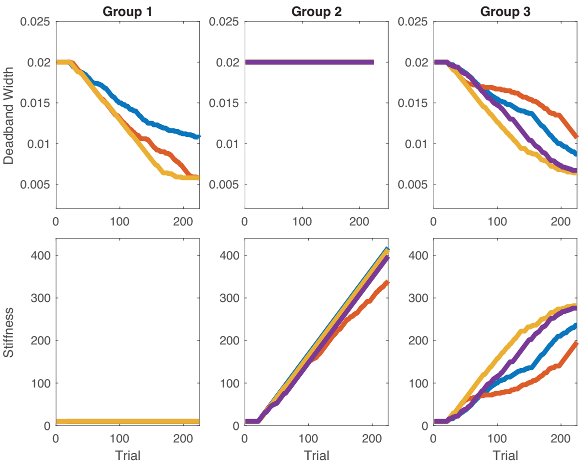


Figure 7: Adaptation of algorithm parameters per trial. Each line is one subject. In Group 1 only dead band width was updated, in Group 2 only stiffness of the virtual spring was updated and in Group 3 both dead band width and spring stiffness were updated.

3.2. Performance of subjects

The RMS of movement performance per group for the whole experiment is shown in Figure 8a (values per individual participant can be found in Appendix B). A lower value means a lower error, indicating better performance. There is a significant difference between the groups, F(2,615) = 14.7, p = 5.822e-7. Group 1 and 3 perform significantly better Group 2 (p = 0.000), but are not significantly different from each other (p = 0.9979). The same movement performance RMS data is shown for only the catch trials in Figure 8b. In these catch trials the movement performance between groups is also significantly different, F(2,93) = 6.63, p = 0.002. Group 1 is has a better performance than Group 2 (p = 0.0069), Group 2 has a better performance than Group 3 (p = 0.0054) but the difference between Group 1 and 3 is insignificant (p = 0.9960). When comparing the results of the whole experiment (Figure 8a) with results of only catch trials (Figure 8b), differences between

Group	a	b
1	0.0098	0.0020
1 catch	0.0081	0.0086
2	0.0098	9.1618e-4
2 catch	0.0095	0.0060
3	0.0119	0.0037
3 catch	0.0114	0.0327

Table 3: Parameters of exponential fit. Groups 3 has the highest decay rate, followed by Group 1 and then Group 2.

groups are similar: Groups 1 and 3 perform better than Group 2 but not different from one another.

In Figure 9 the average movement performance RMS of the first and last five catch trials is shown for each group. In Group 3 the performance improves the most (-0.0060), in Group 1 the movement performance increased less than in Group 3 (-0.0025) and in Group 2 movement performance increased the least (-0.0016). In Figure 10 the RMS of joint angles per trial are shown. Shoulder endo-/exorotation is significantly different for each group, F(2,2456) = 17.42, p = 3.08185 E-8. Group 1 has less shoulder endo-/exorotation than Group 2 (p = 0.0000), Group 3 has less shoulder endo-/exorotation than Group 2 (p = 0.0007) and Group 1 and 3 have similar shoulder endo-/exorotation (p = 0.0419). Difference in shoulder abduction between groups is not significant, F(2,2456) = 1.66, p = 1.1905. Shoulder flexion shows no significant difference between groups, F(2,2456) = 0.01, p = 0.9923. Elbow flexion is different between groups, F(2.2456) = 10.15, p = 4.08767E-5. Groups 2 and 3 have less elbow flexion than Group 1 but do not differ from one another (p = 0.2887). One participant in Group 2 discovered that elbow flexion was not necessary to complete the task and kept the elbow at a fixed angle. This data is not disregarded because the subject was technically successful in completing the trials.

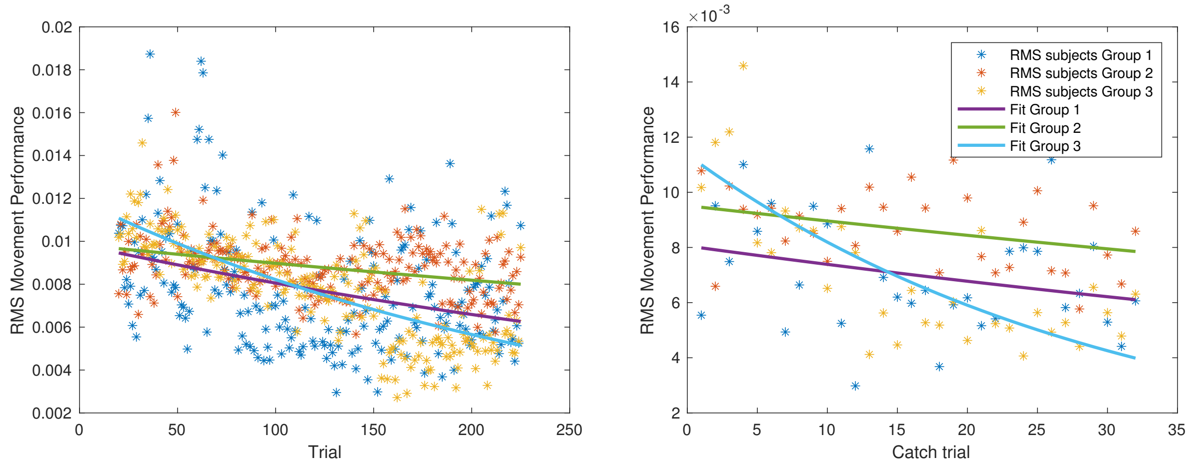
3.3. Learning rates

An exponential fit to the movement performance data is shown for each participant in Figure 8. Parameter values of each fit are presented in Table 3. The learning rates correspond to the differences in movement performance between the groups: Group 3 learning the fastest, followed by Group 1 and then Group 2.

4. Discussion

4.1. Difficulty & Adaptation

The task was most difficult for Group 1 and 3. This result is to be expected: the dead band keeps getting narrower until any subject would move outside it. This does not hold for adapting the stiffness. Once a subject is capable of performing the movement correctly, increased stiffness will never be noticed because a subject will not move outside the dead band. From the amount of force



(a) Movement performance RMS of all trials.

(b) Movement performance RMS of catch trials.

Figure 8: Movement performance RMS of each group. For each trial, the movement performance RMS is shown for each group (each color is a different group). Figure 8a: One dot represents the RMS of movement performance for one group. An exponential fit for each group is shown (solid lines). Figure 8b: Separated catch trials from figure 8a and performed identical exponential fit.

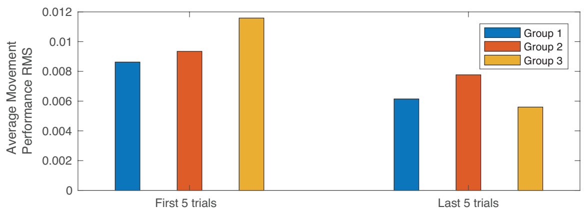


Figure 9: Movement performance average of first and average of last five catch trials. For each group, the average of the movement performance RMS over the first and the last five catch trials is shown.

field activations it can be concluded that the task gets harder when decreasing dead band width, but the task does not get harder when increasing only stiffness. Adding an increasing stiffness parameter when decreasing the dead band width parameter makes the task slightly harder, but the effect is not significant. From this it can be concluded that when subjects were punished, they were not punished enough because there was no extra incentive to increase their joint impedance over the time of the experiment.

The large differences in parameter adaptation between subjects within groups show that there is not one rule that fits everyone. Apart from the larger increments in algorithm parameter updates as mentioned before, a better approach is to adapt the rules based on a personal performance measure. Preferably using the measured error during a trial, instead of just a yes or no if there was an error during a trial. An error measurement could be used to calculate the magnitude of the next parameter adaptation. This method is presented in Appendix C. Furthermore, an exponential fit was used because the learning effect is expected to result in an exponential decay of movement error. Updating algorithm parameters in a linear way does not match this expectation, so an exponential decay factor might be included in the update rule. Another advantage of this approach would be that a longer experiment is not needed: in the beginning of the experiment large increments will be made, making the task challenging quickly. While skill is acquired, the increments decrease proportional to movement error.

Currently updating of both parameters is dependent on one measure: movement error. This means movement performance is defined by the ability to stay within the dead band and ability to return to the dead band from the force field simultaneously. For the purpose of this experiment that is a valid assumption, but in a real world application the meaning of movement performance should be re-evaluated. Is the training goal to improve joint impedance in a working area, or might the goal be to increase the range of this working area, or something else? Instead of deviation from a trajectory, range of motion or movement speed could be the error measure, or any other measurement of movement.

4.2. Movement Performance

Group 1 and 3 had similar movement performance, but performed better than Group 2. This is a result from the task being harder when dead band width is decreased. Increasing stiffness when the dead band is decreasing does not have a significant effect on task performance. This is not what would be expected. The subjects in Group 3 were punished as often as subjects in Group 1, but when they were punished they were punished harder because the stiffness was higher. This confirms the aforementioned conclusion that difficulty of the task was not high enough.

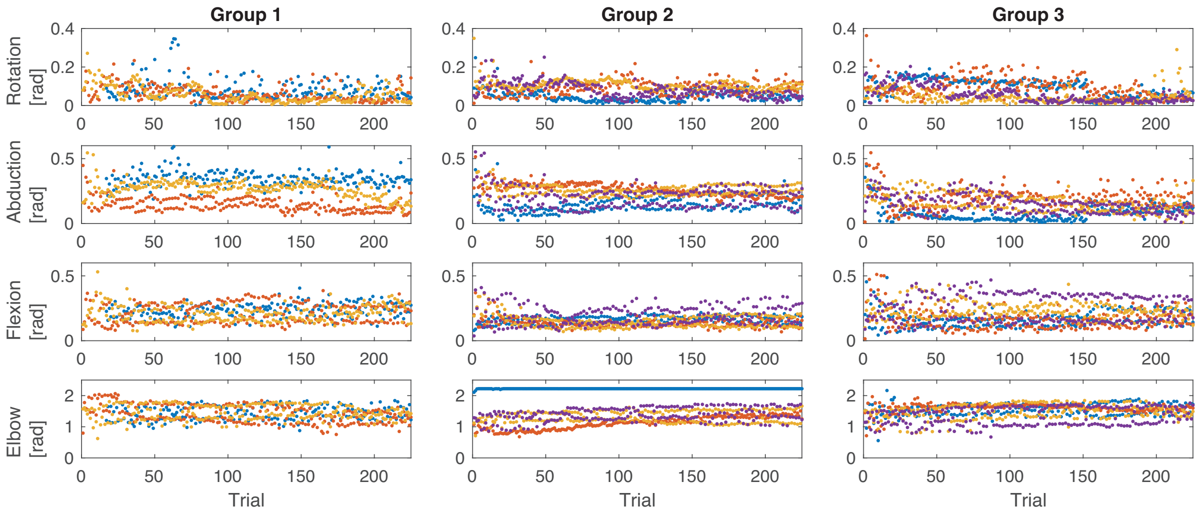


Figure 10: Human joint angles RMS per trial. For each group, the following joint angles are shown: shoulder endo-/exorotation ('rotation'), shoulder abduction ('abduction'), shoulder flexion ('flexion') and elbow flexion ('elbow'). In each group, one dot represents the RMS of a joint angle in radians for one trial, shown in a different color for each subject.

This particular training brings the performance of all subjects closer to each other, no matter what the adaptation rules are. Because this is a learning task, such an effect is to be expected regardless of updating the parameters. While the performance slightly increases in Group 1 and 3, the performance in Group 2 sometimes decreases (Appendix B). This is the opposite of what would be expected in a learning task. An explanation might be that subjects learned that there was some deviation allowed, and started to put less effort in moving in a perfectly straight line which results in a slightly worse movement performance. In this case narrowing the dead band would have kept the task more challenging.

4.3. Movement Strategy

The effects of training persisted during the catch trials, which indicates that subjects not only adapted their movement strategy during the presence of a force field but also afterwards. Movement strategy changed in order to better perform the task. Shoulder endo-/exorotation is directly related to the movement performance so the difference between groups is expected. Shoulder flexion is directly related to reaching the targets, so no difference between groups is expected. More shoulder abduction would be expected in groups where subjects were punished more often because the force field promoted shoulder abduction, but this effect is not seen which is another indicator that severity of the punishment was not sufficient. For a reaching movement, elbow flexion could be perceived to be necessary. However, because only shoulder flexion was used to determine if the endpoint was reached, elbow flexion was not required to complete the task. One subject in Group 2 discovered this and kept the elbow at a fixed angle during the whole experiment. Other than that there is no clear explanation for the significant difference between Groups 2 and 3, and 1.

The subject in Group 2 shows an important flaw in this experiment. The task is not implemented as a true virtual model of a point (corresponding to a subjects' hand) in Cartesian space, which is compared to the locations of the optimal trajectory, targets and dead band. Instead just two position measurements from motors are used to judge where the subjects' hand is located. This introduces the risk of learning a trick, instead of learning to truly move the hand in a straight line. Although learning a trick can still be considered learning a task, in this experiment it means that at least one DOF (elbow flexion) can be completely ignored. The resulting movement strategies and adapted joint impedances might be different because of this. In Appendix C an alternative approach to designing this experiment is proposed, which could overcome this problem.

4.4. Learning

Improved movement performance shows that subjects learned moving in a straighter line. However with only these results, it cannot be shown that subjects actually learn better when adapting the algorithms' parameters than when not adapting these parameters. It would be interesting to compare these experiments with an experiment in which the parameters are set to a difficult value from the start, to see if adapting the algorithm from an easy configuration is beneficial. An advantage of the method used in this experiment is that no subject-specific tuning is necessary. The parameters can be set so that the task is easy and every subject would eventually end up in a configuration that is hard, and at that point start learning.

4.5. Experiment Design

No live representation of the end point was presented to subjects in the visual interface. Subjects had to create some reference in their mind about where their hand was located relative to the target positions.

As shown in Figure 4, the virtual effects are based on measured PVA. This was done because of technical reasons, but it is not the ideal implementation. A more optimal way of modeling this would be to use the model PVA as input for the virtual effects.

The update rules were designed so that the task could only get harder. This was done based on the assumption that when subjects make a movement without moving outside the dead band, they are ready for a more difficult task. However, it might be the case that sometimes good movement performance is the result of luck and not skill.

Because of instability of the gravity compensation algorithm, causing unstable behavior of the system, gravity compensation has been turned off completely during the experiment. This could have caused an extra difficulty for subjects to move, because they had to do some gravity compensation that the Armbot was supposed to do for them. The resulting effect is that the force experienced by subjects was contaminated with gravitational effects, not purely the intended force field.

5. Conclusion

A functional adaptive error augmenting algorithm was built and implemented on the Armbot. With the adaptation rules used in this experiment, the following can be concluded:

- Decreasing dead band width made the task harder.
- Increasing force field strength did not make the task harder.
- Making the task harder improved learning performance.

There are some imperfections in the design of the algorithm and the experiment that need to be overcome. Despite of these issues, results of this experiment show that an adaptive augmented error algorithm can improve learning performance in a reaching task with healthy subjects.

5.1. Recommendations

The PAN algorithm can be improved by using model PVA data to calculate the actual end point (position of the hand) in Cartesian space. This results in a better performing algorithm because the force field strength can be dependent on the true model elongation of the spring: large movement errors will then be punished harder than smaller errors. Also, using Cartesian coordinates in the PAN algorithm has benefits for designing a better task space and visual references.

To improve the experiment, new update rules are recommended. A higher degree of error augmentation might lead to more improvement of performance, so using larger increments of parameter adaptation will be beneficial. Ideally, these increments are be based on an individual subject performance measure rather than fixed values as was done in this experiment. Additional improvements to the error augmentation would be to start with more difficult initial settings (lower dead band width and/or higher stiffness) or to let the parameters be incremented along an exponential decay.

Repeating the experiment with improved methods and knowledge from this experiment is necessary to reach a more determinate conclusion on the benefit of adaptive parameters over fixed parameters. If this new experiment under better conditions would point out that it is indeed possible to improve learning performance with an adaptive augmented error algorithm, the next step is to make a switch back to neurologically impaired patients and test the inverse of the paradigm presented here: an adaptive error reducing algorithm in which adaptation is based only on a subject performance measure. After validating basic assumptions in this experiment, many more improvements can be made to the therapy as a whole. Possible improvement include, but are not limited to: more different training tasks, VR environments and auditory feedback. Ultimately, the comparison with conventional therapy has to be made to decide for or against this robotic therapy.

Appendices

A

PAN algorithm

Presented here are outlines of the functions used in the PAN algorithm. The main function was Algorithm 2, which was placed inside the force loop in the Armbot real-time software. The task space design is based on values set by the user:

- `targetA`
- `targetB`
- dead band width `wDB`

Algorithm 1 Check target reached.

```
function TargetReached
    if Difference left and right rod < wDB then
        if Right & Left disp < target A then
            return true
        end if
        if Right & Left disp > target B then
            return true
        end if
        return false
    end if
    return false
end function
```

Algorithm 2 Activate virtual spring when not on target and outside dead band

```
function PunishAsNeeded
    ErrorCalculator
    if TargetReached == false then
        Spring = true
        if Difference left and right rod <= wDB then
            K = 0
        else if Difference left and right rod > wDB then
            K = K
            if RightRod > LeftRod then
                SpringLocation = -5
            else if LeftRod > RightRod then
                SpringLocation = 5
            end if
        end if
    else
        K = 0
    end if
    TrialUpdate
end function
```

Algorithm 3 Reset total error and call parameter update

```
function TrialUpdate
    if TargetReached then
        Reset Total error
        UpdateChallenge
    end if
end function
```

Algorithm 4 Movement error

```
function ErrorCalculator
    if Dead band == true then
        Movement error = 0
    else
        Movement error = Difference left and right rod - wDB
        Total error = Total error + Movement error
    end if
end function
```

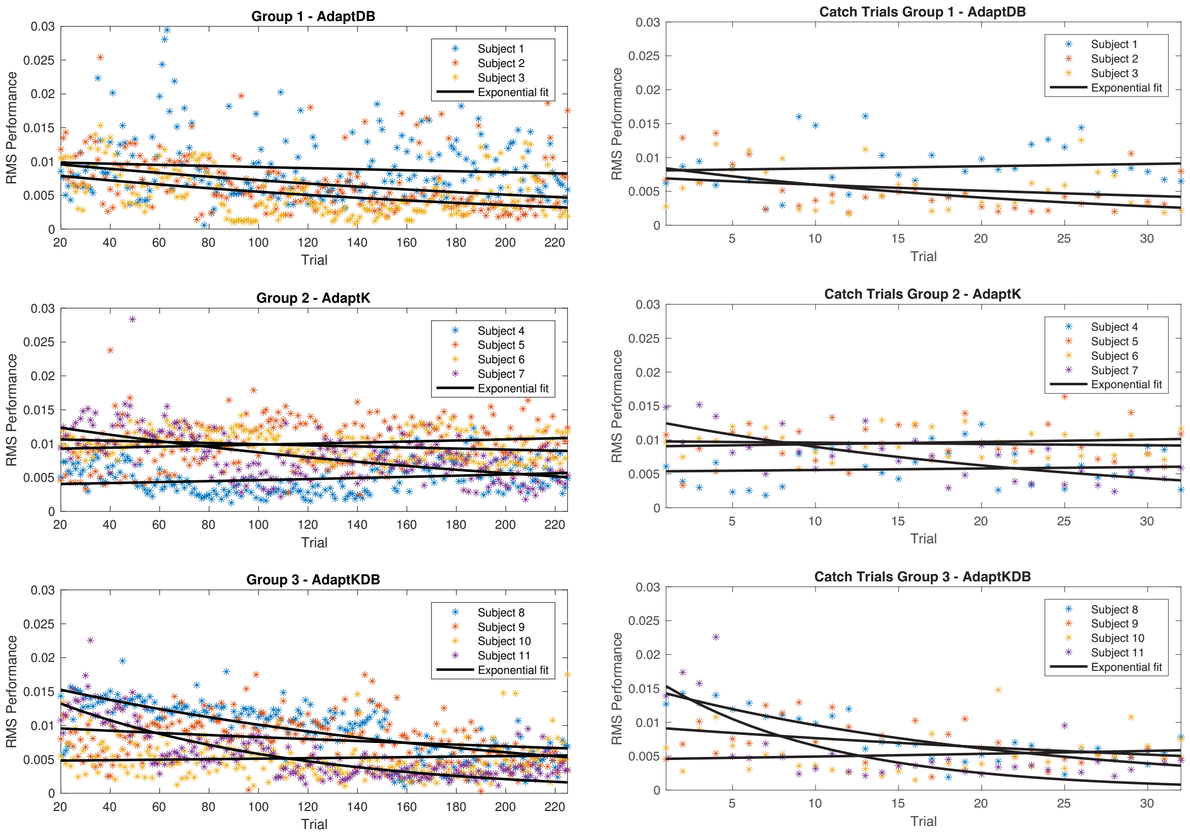
Algorithm 5 Parameter update

```
function UpdateChallenge
    if Total error == 0 then
        K = K + 2
        wDB = wDB - 0.0001
    end if
end function
```

B

Additional data

Movement Performance



(a) **Movement performance RMS of all trials.**

(b) **Movement performance RMS of catch trials.**

Figure B.1: **Movement performance RMS.** Figure B.1a: for each subject, the RMS of movement performance per trial is shown. A logarithmic fit for each subject is shown (solid lines). There is a significant difference between the groups ($p = 1.5602$ E-10). Group 1 and 3 significantly differ from Group 2 ($p = 0.000$), Group 1 and 3 are not significantly different ($p = 0.9740$). Figure B.1b: Separated trials from figure B.1a and performed identical exponential fit. Movement performance between groups is significantly different, $F(2,349) = 10.05$, $p = 5.71528$ E-05. Group 1 has a different outcome than Group 2 ($p = 0.006$), Group 2 has a different outcome than Group 3 ($p = 0.002$). The difference between Group 1 and 3 is insignificant ($p = 0.9989$).

C

Design of augmented error movement task

In the current implementation of the task and PAN algorithm, many concessions have been made for technical reasons. Here the originally intended algorithm design is presented. For a universally usable PAN algorithm we want to create a model of the Cartesian representation of the following elements:

- Subject/robot end effector (hand position)
- Task
  - Optimal trajectory
  - Targets
  - Dead band
  - Force field
  - Stabilizing zone

The implementation used in the experiment served the purpose of a straight reaching task reasonably well. However when there is a desire to design more complicated tasks with for example curved trajectories, that method will be practically unusable. The method proposed here can easily be applied to any desired trajectory, of course respecting physical constraints of the robot and human.

End effector position

The arm consists of two members: an upper arm and forearm (Figure C.1), the forearm length might be extended to include the hand. A vector representing each member is defined by the length of that member multiplied by the unit vector of that member. The upper arm and lower arm vector can be added to one another, resulting in an endpoint vector spanning from the shoulder to the end effector, or hand ($\vec{EP}$).

$$\vec{UA} = l_{ua}\hat{ua}$$
$$\vec{FA} = l_{fa}\hat{fa}$$
$$\vec{EP} = \vec{UA} + \vec{FA}$$

This end effector vector $\vec{EP}$ can be used to calculate the end effector position $pAct$ in cartesian space in relation to the shoulder joint, by multiplying $\vec{EP}$ with the unit vector of the x- y- or z-axis.

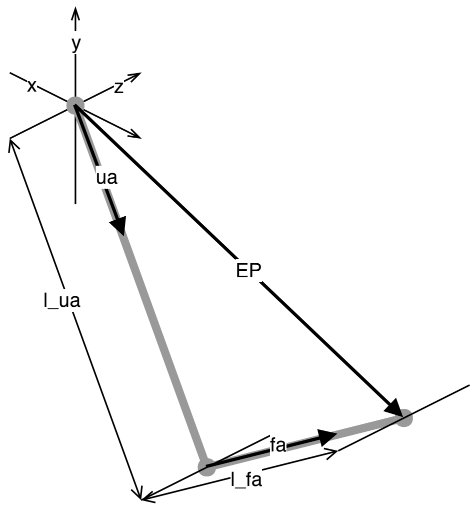


Figure C.1: **Composing end effector vector.** Upper arm starts in the shoulder along unit vector $\hat{ua}$ with length l_{ua}, forearm starts in the elbow along unit vector $\hat{fa}$ with length l_{fa}.

$$EP_x = \vec{EP}\hat{x}$$
$$EP_y = \vec{EP}\hat{y}$$
$$EP_z = \vec{EP}\hat{z}$$

Position related to task space

The end-effector coordinates can be used as reference to the locations related to the task. Force field zones will be designed as a cylindrical tunnel around the optimal trajectory, expressed as radius of that cylinder. The actual position $pAct$ is used to calculate $rAct$, the minimized Euclidean distance between the closest point on the optimal trajectory and the end effector position.

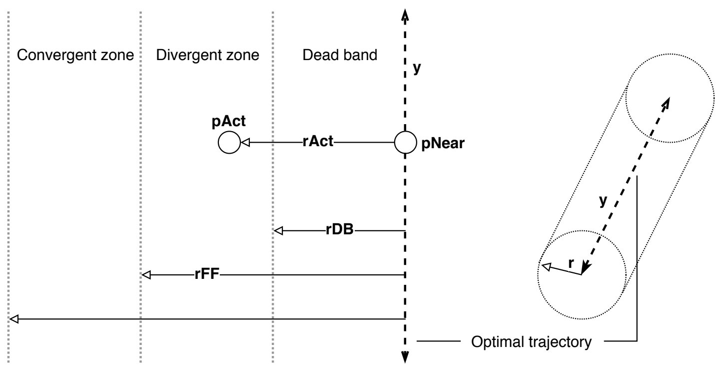


Figure C.2: **Actual position and zones as radius of cylinder.** An optimal movement trajectory y is the center of a cylinder. Force field zones are defined as circles around that center point.rDB is dead band radius, rFF is divergent zone radius and rSZ is stabilizing zone radius.

$$rAct = \min\|pAct - pNear\|^2$$
$$rAct = \min\sqrt{(EP_x - pNear_x)^2 + (EP_y - pNear_y)^2 + (EP_z - pNear_z)^2}$$

$rAct$ can then be used to easily calculate the end effect position in relation to the task space. Values for rDB, rFF and rSZ will be defined beforehand, and can be adapted based on the movement error. When subtracting the actual position from the zone in which the end effector is positioned, an error value results which can be used as input for the spring elongation.

$$elongation = \begin{cases} rAct - rDB & \text{for} \quad rDB < rAct < rFF \\ -rFF - rAct & \text{for} \quad rAct > rFF \\ 0 & \text{otherwise} \end{cases}$$

Force field design

The divergent force field should be along the vector $rAct$ and pointing outward. Because this force is not imposed on the end effector, is has to be devided over the shoulder and elbow joint. In other words, the direction of $rAct$ should be translated into a rotation of shoulder and elbow joint causing a movement of the end effector further along $rAct$.

Movement performance

It is desired to have an error metric that can be used to quantify the performance of subjects during the experiment. The optimal trajectory is assumed to represent the best movement, so deviation from this path is counted as error. An important difference with a measure such as spring elongation is that this error is also counted when inside the dead band. This is done because the performance always needs to be monitored. Movement performance MP is defined by the area between the end effector path and the optimal trajectory, calculated by taking the derivative of $rAct$ from the start to end of the trial.

$$MP = \int_0^t |rAct(t)||\dot{y}(t)|dt$$

Additional comments

Currently gravity compensation is implemented in the Armbot, but does not have a stable performance. Likely this is due to a mechanical axis offset in the shoulder joint: the abduction and rotations axis cross each other, but the flexion axis does not cross this junction. This causes the system to overcompensate the gravitational force and makes the gravity compensation unusable. For this reason gravity compensation has been turned off completely during the experiment.

D

Armbot Game

To provide feedback to subjects a small game was built in Unity. The main functionality was to show if a subject had reached a target or had moved outside the dead band. In the PAN algorithm, four `boolean` flags were included. These were:

- `targetA`
- `targetB`
- `ffLeft`
- `ffRight`

Each of them could be retrieved by sending a command to the API, receiving a string '1' or '0' back. This information was then used to trigger the various colors for targets and left or right dead band.

Game with end effector

As mentioned in the discussion, it is desired to have the end effector position displayed to give subjects a more useful feedback. When designing the task as presented in Appendix C, the Cartesian coordinates can easily be used to create a visual representation on screen. A

E

Experiment documents

PARTICIPANT INFORMATION SHEET

For a study investigating the behaviour of a robotic controller in an upper limb exoskeleton, by means of a reaching task.

Date 18-10-2018, Version 2.0

Dear Madam/Sir,

You have been asked to participate in a study during which the performance of a controller for a rehabilitation robotics exoskeleton is investigated by performing a reaching task with this exoskeleton. This information sheet provides some detailed information about the study. For questions, please get in touch with any of the researchers mentioned at the end of this information sheet,

Study background

When learning a motor task, the way an environment acts on a human determines how fast and how well the human learns this task. For healthy individuals, an environment that punishes incorrect movements has been shown to result in better learning results. A robotic exoskeleton is a form of an environment that can be used to impose forces on a human. In this study, we want to determine whether adapting this environment (the exoskeleton) results in an improved learning rate. To do this, we control an exoskeleton in such a way that it punishes you by pushing you away when you make mistakes during a movement task. The better you get in doing this task, the harder it will become because the exoskeleton will leave a decreasing amount of room for errors.

Study goal

The goal of this study is to investigate whether the robotic controller behaves (adapts to the human performance) as it should, and if this behaviour has a positive effect on the learning of a reaching task.

What does participating involve?

During this study, you are asked to make a movement with your arm between two points, while connected to an exoskeleton with your arm. Your upper and lower arm will be connected to this exoskeleton, and in front of you a screen will show two points representing the target positions (to which you are asked to move). You will start with your hand between the two targets and will move your hand back and forth between the two, in as straight a line as possible. The targets will turn green when you reach them. You will be asked to repeat this movements for several times. During the study, a force field can be turned on at random moments. When this force field is on, the exoskeleton will push your arm away to the side when you make movement errors. This sideways movement will be limited so that your arm will not end up in an uncomfortable position. If your arm is pushed away, you are encouraged to push it back in order to complete the task.

The study takes place in the headquarters of Motekforce Link, based in Amsterdam.

Risks

Risks associated with the study are minimal. Slight discomfort can occur as a result of being strapped in the arm cuffs. The force field can get strong when performing the task well, so making an error after many successful trials will be punished by a hard push away. An emergency button is present at all times, enabling us to stop the robot immediately.

Participation is voluntary!

Your participation in the study is voluntary. If you agree on participating in the study, you have the right to withdraw at any time (also during the study). There is no need to have a legitimate reason to do so. In case you agree to participant in the study you will be provided an informed consent form for you to sign.

Confidentiality
We will treat your personal details and data confidentially. People not authorised to access your details will not have the opportunity to do so. When the results of the study get published, it is impossible to trace this back to you.

Summary
Participating in this study is voluntary. You are free to decide whether or not you wish to participate. Summarized, when you decide to participate:

- You are willing to participate in research during which you will perform a reaching task, while connected to a robotic exoskeleton;
- You agree with the use of your data for purposes of the study;
- You understand we cannot provide individual study results.

Thanks in advance for your possible participation in the study,

Maurits Elzinga, researcher
m.j.elzinga@gmail.com
0613856006

Participant Personal Information

Date 20-07-2018

This information is confidential and will not be made available to third parties.

Personal information

Participant number	:			
Age	:			
Gender	:	M	/	F
Height	:			
Weight	:			
Dominant arm	:	Right	/	Left

Start experiment :
End experiment :
Total experiment time :

Consent Form for Armbot reaching task

Please tick the appropriate boxes	Yes	No
Taking part in the study		
I have read and understood the study information dated 18/10/2018, or it has been read to me. I have been able to ask questions about the study and my questions have been answered to my satisfaction.	□	□
I consent voluntarily to be a participant in this study and understand that I can refuse to answer questions and I can withdraw from the study at any time, without having to give a reason.	□	□
I understand that taking part in the study involves being strapped in an exoskeleton with one arm, and repeatedly making reaching movements between two points.	□	□
Risks associated with participating in the study		
I understand that taking part in the study involves the following potential risks: slight physical discomfort as a result of being strapped in the arm cuffs or the force field.	□	□
Future use and reuse of the information by others		
I give permission for the movement recording data that I provide to be archived in Motekforcelink M-drive so it can be used for future research and learning.	□	□

Signatures

______________________ ______________________ ________

Name of participant Signature Date

I have accurately read out the information sheet to the potential participant and, to the best of my ability, ensured that the participant understands to what they are freely consenting.

Maurits Elzinga ___________________ ________

Signature Date

Study contact details for further information:

Maurits Elzinga

m.j.elzinga@gmail.com

0613856006

Delft University of Technology
ETHICS REVIEW CHECKLIST FOR HUMAN RESEARCH
(Version 10.10.2017)

This checklist should be completed for every research study that involves human participants and should be submitted before potential participants are approached to take part in your research study.

In this checklist we will ask for additional information if need be. Please attach this as an Annex to the application.

Please upload the documents (go to [this page](#) for instructions).

Thank you and please check our [website](#) for guidelines, forms, best practices, meeting dates of the HREC, etc.

I. Basic Data

Project title	**Armbot adaptive controller**
Name(s) of researcher(s)	**Maurits Elzinga**
Research period (planning)	**August – September 2018**
E-mail contact person	**m.j.elzinga@gmail.com**
Faculty/Dept.	**Biomedical Engineering**
Position researcher(s):[1]	**MSs student**
Name of supervisor (if applicable):	**Alfred Schouten, Winfred Mugge**
Role of supervisor (if applicable):	**MSs thesis project supervisor**

II. A) Summary Research

The goal of this research project is to validate the controller of a robotic exoskeleton, designed for upper limb rehabilitation. Two main questions to be answered are 1. Is the controller able to help a subject complete a reaching task 2. Will the subject perform the task better after using the robotic device for some time. The robotic device has been developed at Motekforce Link, and the software to control the prototype will be new. Approximately 5-10 healthy subjects will be asked to carry out movements (shown on a screen in front of them) while connected to the exoskeleton for a duration of approximately 30 minutes. The exoskeleton will impose a force field which can be felt by the subjects.

B) Risk assessment

During the experiment, there might be a possibility that the device does not respond the way it should. This can result in an unwanted movement of the exoskeleton. As a failsafe, an emergency push button is always with hand to turn off the motors.

[1] For example: student, PhD, post-doc

III. Checklist

Question	Yes	No
1. Does the study involve participants who are particularly vulnerable or unable to give informed consent? (e.g., children, people with learning difficulties, patients, people receiving counselling, people living in care or nursing homes, people recruited through self-help groups).		x
2. Are the participants, outside the context of the research, in a dependent or subordinate position to the investigator (such as own children or own students)?[2]		x
3. Will it be necessary for participants to take part in the study without their knowledge and consent at the time? (e.g., covert observation of people in non-public places).		x
4. Will the study involve actively deceiving the participants? (e.g., will participants be deliberately falsely informed, will information be withheld from them or will they be misled in such a way that they are likely to object or show unease when debriefed about the study).		x
5. Personal data • Will the study involve discussion or collection of personal data? (e.g., BSN number, location, sexual activity, drug use, mental health). Please check the HREC website for definitions.		x
If yes': Did the data steward approve your data management plan? (Electronic Consent)		
6. Will drugs, placebos, or other substances (e.g., drinks, foods, food or drink constituents, dietary supplements) be administered to the study participants?		x
7. Will blood or tissue samples be obtained from participants?		x
8. Is pain or more than mild discomfort likely to result from the study?		x
9. Does the study risk causing psychological stress or anxiety or other harm or negative consequences beyond that normally encountered by the participants in their life outside research?		x
10. Will financial inducement (other than reasonable expenses and compensation for time) be offered to participants?		x
Important: if you answered 'yes' to any of the questions mentioned above, please submit a full application to HREC (see: website for forms or examples).		
11. Will the experiment collect and store videos, pictures, or other identifiable data of human subjects?[3]		x

[2] **Important note concerning questions 1 and 2.** Some intended studies involve research subjects who are particularly vulnerable or unable to give informed consent .Research involving participants who are in a dependent or unequal relationship with the researcher or research supervisor (e.g., the researcher's or research supervisor's students or staff) may also be regarded as a vulnerable group . If your study involves such participants, it is essential that you safeguard against possible adverse consequences of this situation (e.g., allowing a student's failure to complete their participation to your satisfaction to affect your evaluation of their coursework). This can be achieved by ensuring that participants remain anonymous to the individuals concerned (e.g., you do not seek names of students taking part in your study). If such safeguards are in place, or the research does not involve other potentially vulnerable groups or individuals unable to give informed consent, it is appropriate to check the NO box for questions 1 and 2. Please describe corresponding safeguards in the summary field.

[3] Note: you have to ensure that collected data is safeguarded physically and will not be accessible to anyone outside the study. Furthermore, the data has to be de-identified if possible and has to be destroyed after a

Question	Yes	No
If "yes", please fill in Annex 1 and make you sure you follow all requirements of the applicable data protection legislation. In addition, please provide proof by sending us a copy of the informed consent form.		
12. Will the experiment involve the use of devices that are not 'CE' certified? *Only, if 'yes': continue with the following questions:*	x	
➢ Was the device built in-house?		x
➢ Was it inspected by a safety expert at TU Delft? (*Please provide device report, see: HREC website*)		x
➢ If it was not built in house and not CE-certified, was it inspected by some other, qualified authority in safety and approved? *(Please provide records of the inspection).*		x
13. Has or will this research be submitted to a research ethics committee other than this one? (*if so, please provide details and a copy of the approval or submission).*		x

IV. Enclosures (tick if applicable)

- ○ Full proposal (if 'yes' to any of the questions 1 until 10)
- ○ Informed consent form (if 'yes' to question 11)
- ○ Device report (if 'yes' to question 12)
- ○ Approval other HREC-committee (if 'yes' to question 13)
- ○ Any other information which might be relevant for decision making by HREC
- ○ Data management plan approved by a data steward (if yes to question 5B)

V. Signature(s

Signature(s) of researcher(s)
Date:

Signature research supervisor (if applicable)
Date:

scientifically appropriate period of time. Also ask explicitly for consent if anonymised data will be published as open data.

Bibliography

[1] Neurological Disorders Report. http://www.who.int/mental_health/neurology/neurological_disorders_report_web.pdf. [Online; accessed 27-December-2017].

[2] Per Aagaard. Training-induced changes in neural function. *Exercise and sport sciences reviews*, 31(2):61–67, 2003.

[3] Atif Alamri, Mohamad Eid, Rosa Iglesias, Shervin Shirmohammadi, and A El Saddik. Haptic virtual rehabilitation exercises for poststroke diagnosis. *IEEE transactions on instrumentation and measurement*, 57(9):1876–1884, 2008.

[4] Khairul Anam and Adel Ali Al-Jumaily. Active exoskeleton control systems: State of the art. *Procedia Engineering*, 41:988–994, 2012.

[5] Sivakumar Balasubramanian and Jiping He. Adaptive control of a wearable exoskeleton for upper-extremity neurorehabilitation. *Applied Bionics and Biomechanics*, 9(1):99–115, 2012.

[6] Sai K Banala, Suni K Agrawal, and John P Scholz. Active leg exoskeleton (alex) for gait rehabilitation of motor-impaired patients. In *Rehabilitation Robotics, 2007. ICORR 2007. IEEE 10th International Conference on*, pages 401–407. IEEE, 2007.

[7] Rita K Bode and Allen W Heinemann. Course of functional improvement after stroke, spinal cord injury, and traumatic brain injury. *Archives of physical medicine and rehabilitation*, 83(1):100–106, 2002.

[8] Etienne Burdet, Rieko Osu, David W Franklin, Theodore E Milner, and Mitsuo Kawato. The central nervous system stabilizes unstable dynamics by learning optimal impedance. *Nature*, 414(6862):446, 2001.

[9] James William Burke, MDJ McNeill, Darryl K Charles, Philip J Morrow, Jacqui H Crosbie, and Suzanne M McDonough. Optimising engagement for stroke rehabilitation using serious games. *The Visual Computer*, 25(12):1085, 2009.

[10] Lance L Cai, Andy J Fong, Chad K Otoshi, Yongqiang Liang, Joel W Burdick, Roland R Roy, and V Reggie Edgerton. Implications of assist-as-needed robotic step training after a complete spinal cord injury on intrinsic strategies of motor learning. *Journal of Neuroscience*, 26(41):10564–10568, 2006.

[11] Craig Carignan, Jonathan Tang, and Stephen Roderick. Development of an exoskeleton haptic interface for virtual task training. In *Intelligent Robots and Systems, 2009. IROS 2009. IEEE/RSJ International Conference on*, pages 3697–3702. IEEE, 2009.

[12] Ettore E Cavallaro, Jacob Rosen, Joel C Perry, and Stephen Burns. Real-time myoprocessors for a neural controlled powered exoskeleton arm. *IEEE Transactions on Biomedical Engineering*, 53(11):2387–2396, 2006.

[13] Alexander Duschau-Wicke, Andrea Caprez, and Robert Riener. Patient-cooperative control increases active participation of individuals with sci during robot-aided gait training. *Journal of neuroengineering and rehabilitation*, 7(1):43, 2010.

[14] Jeremy L Emken, James E Bobrow, and David J Reinkensmeyer. Robotic movement training as an optimization problem: designing a controller that assists only as needed. In *Rehabilitation Robotics, 2005. ICORR 2005. 9th International Conference on*, pages 307–312. IEEE, 2005.

[15] Jeremy L Emken, Raul Benitez, and David J Reinkensmeyer. Human-robot cooperative movement training: learning a novel sensory motor transformation during walking with robotic assistance-as-needed. *Journal of NeuroEngineering and Rehabilitation*, 4(1):8, 2007.

[16] Valery L Feigin, Rita V Krishnamurthi, Priya Parmar, Bo Norrving, George A Mensah, Derrick A Bennett, Suzanne Barker-Collo, Andrew E Moran, Ralph L Sacco, Thomas Truelsen, et al. Update on the global burden of ischemic and hemorrhagic stroke in 1990-2013: the gbd 2013 study. *Neuroepidemiology*, 45(3):161–176, 2015.

[17] Abhishek Gupta and Marcia K O'Malley. Design of a haptic arm exoskeleton for training and rehabilitation. *IEEE/ASME Transactions on mechatronics*, 11(3):280–289, 2006.

[18] Maureen K Holden. Virtual environments for motor rehabilitation. *Cyberpsychology & behavior*, 8(3):187–211, 2005.

[19] Vincent S Huang and John W Krakauer. Robotic neurorehabilitation: a computational motor learning perspective. *Journal of neuroengineering and rehabilitation*, 6(1):5, 2009.

[20] Shahid Hussain, Prashant K Jamwal, Mergen H Ghayesh, and Sheng Q Xie. Assist-as-needed control of an intrinsically compliant robotic gait training orthosis. *IEEE Transactions on Industrial Electronics*, 64(2):1675–1685, 2017.

[21] Urs Keller, Georg Rauter, and Robert Riener. Assist-as-needed path control for the pascal rehabilitation robot. In *Rehabilitation Robotics (ICORR), 2013 IEEE International Conference on*, pages 1–7. IEEE, 2013.

[22] Verena Klamroth-Marganska, Javier Blanco, Katrin Campen, Armin Curt, Volker Dietz, Thierry Ettlin, Morena Felder, Bernd Fellinghauer, Marco Guidali, Anja Kollmar, et al. Three-dimensional, task-specific robot therapy of the arm after stroke: a multicentre, parallel-group randomised trial. *The Lancet Neurology*, 13(2):159–166, 2014.

[23] Konrad P Körding and Daniel M Wolpert. Bayesian integration in sensorimotor learning. *Nature*, 427(6971):244–247, 2004.

[24] Gert Kwakkel, Robert C Wagenaar, Tim W Koelman, Gustaaf J Lankhorst, and Johan C Koetsier. Effects of intensity of rehabilitation after stroke. *Stroke*, 28(8):1550–1556, 1997.

[25] Gwyn N Lewis and Juliet A Rosie. Virtual reality games for movement rehabilitation in neurological conditions: how do we meet the needs and expectations of the users? *Disability and rehabilitation*, 34(22):1880–1886, 2012.

[26] Gwyn N Lewis, Claire Woods, Juliet A Rosie, and Kathryn M Mcpherson. Virtual reality games for rehabilitation of people with stroke: perspectives from the users. *Disability and Rehabilitation: Assistive Technology*, 6(5):453–463, 2011.

[27] Ho Shing Lo and Sheng Quan Xie. Exoskeleton robots for upper-limb rehabilitation: State of the art and future prospects. *Medical engineering & physics*, 34(3):261–268, 2012.

[28] Dennis R Louie and Janice J Eng. Powered robotic exoskeletons in post-stroke rehabilitation of gait: a scoping review. *Journal of neuroengineering and rehabilitation*, 13(1): 53, 2016.

[29] Siegrid Lowel and Wolf Singer. Selection of intrinsic horizontal connections in the visual cortex by correlated neuronal activity. *Science*, 255(5041):209, 1992.

[30] Paweł Maciejasz, Jörg Eschweiler, Kurt Gerlach-Hahn, Arne Jansen-Troy, and Steffen Leonhardt. A survey on robotic devices for upper limb rehabilitation. *Journal of neuroengineering and rehabilitation*, 11(1):3, 2014.

[31] Hirofumi Nakayama, Henrik Stig Jørgensen, Hans Otto Raaschou, and Tom Skyhøj Olsen. Recovery of upper extremity function in stroke patients: the copenhagen stroke study. *Archives of physical medicine and rehabilitation*, 75(4):394–398, 1994.

[32] Tobias Nef, Matjaz Mihelj, Gabriela Kiefer, Christina Perndl, Roland Muller, and Robert Riener. Armin-exoskeleton for arm therapy in stroke patients. In *Rehabilitation Robotics, 2007. ICORR 2007. IEEE 10th International Conference on*, pages 68–74. IEEE, 2007.

[33] Graziella Quattrocchi, Richard Greenwood, John C Rothwell, Joseph M Galea, and Sven Bestmann. Reward and punishment enhance motor adaptation in stroke. *J Neurol Neurosurg Psychiatry*, 88(9):730–736, 2017.

[34] DJ Reinkensmeyer. How to retrain movement after neurologic injury: a computational rationale for incorporating robot (or therapist) assistance. In *Engineering in Medicine and Biology Society, 2003. Proceedings of the 25th Annual International Conference of the IEEE*, volume 2, pages 1479–1482. IEEE, 2003.

[35] Simon Rüdt, Marco Moos, Solange Seppey, Robert Riener, and Laura Marchal-Crespo. Towards more efficient robotic gait training: a novel controller to modulate movement errors. In *Biomedical Robotics and Biomechatronics (BioRob), 2016 6th IEEE International Conference on*, pages 876–881. IEEE, 2016.

[36] Thomas Sinkjær and Dejan B Popovic. Trends in the rehabilitation of hemiplegic subjects. *Journal of Automatic control*, 15:1–10, 2005.

[37] Heidi Sveistrup, Joan McComas, Marianne Thornton, Shawn Marshall, Hillel Finestone, Anna McCormick, Kevin Babulic, and Alain Mayhew. Experimental studies of virtual reality-delivered compared to conventional exercise programs for rehabilitation. *CyberPsychology & Behavior*, 6(3):245–249, 2003.

[38] Chung Tin and Chi-Sang Poon. Internal models in sensorimotor integration: perspectives from adaptive control theory. *Journal of Neural Engineering*, 2(3):S147, 2005.

[39] Daniel L Young and C-S Poon. A hebbian feedback covariance learning paradigm for self-tuning optimal control. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, 31(2):173–186, 2001.