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Serious Gaming For Learning The Intuitive, Non-Natural Control Of Prosthetic Hands

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SERIOUS GAMING FOR LEARNING THE INTUITIVE,
NON-NATURAL CONTROL OF PROSTHETIC HANDS

Morten Bak Kristoffersen

Serious gaming for learning the intuitive, non-natural control of prosthetic hands

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Serious gaming for learning the intuitive, non-natural control of prosthetic hands

PhD thesis

to obtain the degree of PhD at the
University of Groningen
on the authority of the
Rector Magnificus Prof. C. Wijmenga
and in accordance with
the decision by the College of Deans.

This thesis will be defended in public on

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by

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*Til min kæreste Ante
Vi skal for evigt samme vej*

Morten har et heftigt temperament og meget vred, hvis han ikke får sin vilje. Han er meget krævende og krævaftvisende.

Foreword

I was no ordinary child. Unlike most children, I hardly spoke in the first years of my life and I avoided eye contact when people wanted my attention. I appeared to be content playing for myself and exploring the world on my own. At age two, I was put through a plethora of tests, so the physicians could figure out what was wrong with me. First, they thought I was hard of hearing, so I had an audiometry test where I hardly reacted to any of their test sounds. As a result, I was given a hearing aid which I disliked so much so I hid it in a bush. Ultimately, they figured out that my hearing was fine, so I was put through a battery of psychological, cognitive, and physiological tests. My parents received a summary of the tests which were not written in layman terms, so our general practitioner translated terms such as lower extremities, somatotopic and neonatal period. According to the tests, I was not autistic, but I had psychotic tendencies and varying muscle tension in the legs¹. The recommendation was that instead of public school, I should be in a class for kids with developmental deficits. My parents did not like this idea at all and demanded that I attended the local public school just like my two older siblings. A struggle ensued with the school system. The school did not want the responsibility of having me and they were afraid that I would take too many resources from the teacher. My parents stood their ground, and a compromise was found where an extra teacher was hired part-time to assist.

A few years after I started school, the extra teacher was deemed unnecessary as I started to catch up with the other kids. However, despite my development the school did not believe in me, as my parents were told that I would not achieve the level required for gymnasium (secondary school).

And now you are about to read my PhD thesis.

With this foreword, I want to inspire you to not let the expectations of others dictate your life. To forge your own path and not let unwritten rules like the Scandinavian Law of Jante or the Dutch "doe normaal"-mentality hold you back.

Finally, I want to thank my parents for taking the struggles with the school when I was a child. If they had not done that, I would probably have ended up in a very different place today. Tak Mor og Far!

¹ The physician noted that this was probably related to my willingness to be examined.

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1

GENERAL INTRODUCTION

1.1 Introduction

The human hand is marvellous. It is sensitive enough to perform surgery with millimetre-precision and robust enough to stack ~20 kg hay bales the entire day during harvest season. Some even hypothesize, that the development of the brain was accelerated by the hand (Lundborg, 2014, Chapters 2–3). While it took evolution 3-400 million years to develop a human-like hand with an opposable thumb as seen in “Ardi”, it *only* took another ~4 million years for the brain to grow 4-5 times in volume. In particular, from homo habilis (“handy man”) to homo erectus the size of the brain might have increased by 50% in just a few hundred thousand years. It has been hypothesized that increased tool use (made possible with hands) was the catalyst for this explosive growth. (Antón et al., 2014; Lundborg, 2014)

The hand can therefore be considered an inherently human feature and the loss of the hand is the stuff of myths and legends. From Tyr the god of war in Norse mythology, who sacrificed his hand to bind the monstrous Fenris wolf (Sturluson, 1220, para. 33) to modern fables in popular science media which makes prosthetic limbs appear superior to human limbs (Sprenger, 2018; Yaniv & Sillman, 2015). Probably the most famous example is Luke Skywalker from Star Wars who loses his hand to Darth Vader, but who is given a new perfect replacement marking the start of the hero's journey. The DEKA arm (Resnik et al., 2014), one of the most advanced arm prosthetics funded by the US military, was given its commercial name after Luke Skywalker – The LUKE arm.

Unfortunately, the LUKE arm, or any other prosthetic hand, do not live up to the promise of a perfect replacement of the hand. Instead, they are all iterations towards a perfect replacement that has been on-going for more than two thousand years. The earliest record of a prosthetic hand dates back to the Romans (Zuo & Olson, 2014) and various one-off designs have been made since then. However, it was not before the 1860s that a body-powered system was introduced which was widely used. The body-powered system was attached with a harness and by using the contralateral (opposite) shoulder to pull on straps connected to a hook the user could open and close the hook. This system was refined after the 2nd world war with the introduction of a body-powered prosthesis based on the Bowden cable² system, which allowed for a sleeker harness and improved function (Zuo & Olson, 2014). Modern body-powered prosthetics are based on the same principles and are cheap and robust. However, some users experience shoulder complaints when using a body-powered prosthesis and the harness is considered cumbersome by some. Furthermore, most commercial body-powered prosthetic hands only pinches with a

1 Ardipithecus ramidus, our earliest ancestor

2 The cable used for modern bike brakes

quarter of the force generated by the user (Smit & Plettenburg, 2010) and are limited to one degree of freedom (DoF).

Externally powered prosthetic hands were developed alongside the body-powered hands throughout the 20th century. Most commonly, electricity provided by a battery is the power source which drives an electric engine inside the prosthesis. For example, in 1948 the first prosthetic hand based on electromyography was created, the so-called myoelectric prosthesis (Childress, 1985; Wirta et al., 1978). Electromyography (EMG) is the measurement of the myoelectric signal which is the electric potential generated when muscle cells are activated by the nervous system (muscle contraction). A myoelectric prosthesis functions by measuring the myoelectric signal at the surface of the skin. Conventionally, two electrodes are placed above a pair of agonist/antagonist muscles. In the case of a transradial (forearm) amputation, one electrode is normally placed on the wrist extensors and one is placed on the wrist flexors. When either muscle group contracts, a myoelectric signal is generated which is measured by the corresponding electrode making the prosthesis open or close. One muscle group generates the signal for opening the hand and the other generates the signal for closing. Compared to body-powered prosthetics, a myoelectric prosthesis does not require a harness, looks more life-like and some can be combined with a wrist rotation unit so the user can control two DoFs: open/close hand and hand rotation. However, many users experience that the control is not very robust and that sensory feedback is poor, and users of myoelectric prosthetic hands are dependent on vision to keep track of the hand (Bouwsema et al., 2012; Parr et al., 2018; Sobuh et al., 2014). See Figure 1 for an illustration of different types of upper-limb arm prosthetics.

While most myoelectric prosthesis users are still using a prosthesis that is not remarkably different from those that existed 30-40 years ago, there have been some developments in recent years that might benefit prosthesis users. Firstly, the multi-articulated myoelectric prosthesis hand that unlike conventional myoelectric prosthetics can actuate the digits independently. Independent digits allow the prosthesis to change its grip type so instead of being restricted to a cylindrical or lateral grip, it can also do a pinch grip and even specialised gestures such as pointing³. Multi-articulated prostheses are generally controlled using the same two electrodes used for single DoF/grip hands which means that only one DoF/grip can be operated at a time. To switch DoF/grip a trigger signal is used. Trigger signals are specific myoelectric signals that the user can learn to generate. When a trigger signal is detected, the prosthetic hand switches from one grip to another, so instead of opening and closing the hand in a cylindrical grip, the control

3 Some refer to different grips as different DoFs, but in this thesis I make a distinction between a DoF and different grips/postures. A prosthetic hand that can close in a cylindrical and lateral grip is by my definition a one DoF hand with two grips. A hand that can only close in one mode but has wrist rotation is a two DoF hand with one grip.

signals may open and close the hand in a lateral grip. Examples of trigger signals include co-contraction, which is when both control signals simultaneously reach a set threshold. Another example is a double pulse, which is when one control signal crosses a threshold twice in quick succession while the other control signal is below the threshold. Trigger signals are commonly applied when using multi-articulate hands, but it is generally agreed upon that triggers are unintuitive and slow (Franzke et al., 2019; Resnik et al., 2018; Simon et al., 2019). While some hands have more than 20 grips, most users only use a few (Simon et al., 2019; Spiers et al., 2017). Triggers are hard to execute, because people have poor control of their myoelectric signal and learning to execute them reliably and fast requires a lot of training (Franzke et al., 2019). A solution to this problem is to offload the burden of training from the user and move it to the prosthesis itself. This leads us to the second development in hand prosthetics in recent years; machine learning, also known as pattern recognition.

Figure 1. Illustration of different types of arm prosthetics and electrodes. Top row from left to right: Body-powered prosthesis, myoelectric prosthesis with one degree of freedom and multi-articulate myoelectric prosthesis. Bottom row left: Bipolar electrode with integrated filters and amplifier as commonly used for a prosthetic hand with one degree of freedom. Two electrodes are used: one is visible and the other electrode is placed on the opposing side of the arm. Bottom row right: Steel dome electrodes as commonly used for machine learning control. Two electrodes are used per channel and up to eight channels are commonly used, evenly spread around the stump. Steel dome electrodes allow for more flexible positioning but requires external amplification which is usually built into the socket.

Machine learning refers to any technique in which an algorithm is *trained* to make a prediction. Machine learning is used when searching online, when a smartphone corrects typos and is even used to trade on the stock markets. One of the simplest methods is linear regression in which you find a linear relationship between an independent variable and a dependent variable. As an example, if you have measurements of the height and weight of several people, linear regression can be used to create a model of the relationship between height and weight. By inputting the height into the model, it will give a prediction of the corresponding weight. The quality of the prediction depends on the amount and quality of the data. In principle, the exact same thing happens when using machine learning to control a myoelectric prosthetic hand. The idea is to use the myoelectric signal to predict the intent of the user. The assumption underlying this idea is that each intent of the user can be manifested as a distinct, repeatable myoelectric signal. See Figure 2.

Figure 2. The idea of machine learning myoelectric control is to predict the intent of the user based on the myoelectric signals. Example: the user intends to activate the point posture of the prosthesis so he generates the myoelectric signals for pointing. The machine learning algorithm analyses the myoelectric signals and sends the pointing command to the prosthetic hand. This idea is often referred to as “intuitive control” since the prosthesis follows the intention of the user and there is no need for unnatural trigger commands.

When using machine learning with a myoelectric prosthesis more than two electrodes are used. Commonly between four to eight. Using more electrodes means that there is more data to train the algorithm which leads to better predictions. To train the algorithm, the user must don the electrodes and perform a procedure known as a recording session. In the recording session, the user is prompted to perform the movements of the prosthetic hand, such as “open hand” or “wrist flexion”. There are in general two ways a person with upper limb absence can perform

these movements (Powell & Thakor, 2013; Roche et al., 2015). If the person has a phantom limb sensation, they can try to perform the movements with the phantom limb which usually makes the muscles in the stump contract. If the person does not have a phantom limb, they usually perform the movement with the unaffected hand and mimic the muscle contractions in the remnant limb. While following the prompted movements, the myoelectric signal is recorded and associated (labelled) with the corresponding movement. After the recording session, the myoelectric signal is processed, and features of the myoelectric signal are calculated. Examples of such features include the mean absolute value and the number of zero crossings. When the algorithm is trained, the algorithm would be able to predict the movement intent of the user based on the myoelectric signal. Ideally, this means that the user has intuitive control over the prosthesis and removes the need for unnatural trigger signals. See Figure 3 for an overview of the steps required for training the machine learning algorithm and using it to predict movement intent (online use).

Figure 3. Top row: The steps required for training a machine learning algorithm. Bottom row: The steps required for applying a machine learning algorithm for predicting movement intent. In the literature the trained algorithm is often referred to as a classifier.

As early as 1993 Hudgins and colleagues demonstrated offline classification accuracies with a mean of 85.5% for participants with upper limb absence using a neural network (Hudgins et al., 1993). Offline accuracy refers to the trained algorithms' capability to distinguish a recorded set of signals (i.e. the performance measurement after performing the steps in the top row of Figure 3). For the following 15-20 years research focused on improving the algorithms, the signal acquisition and signal processing to increase the offline accuracy. As computers became faster, focus shifted more towards online testing where the user is controlling a virtual prosthesis in real time which allowed for the calculation of the online accuracy. Online accuracy is a truer

measure of a user's control capability than offline accuracy and since it was discovered that the correlation between offline and online accuracy is weak (Ortiz-Catalan et al., 2015), offline accuracy is hardly reported anymore.

While online accuracy is a better measure of control capability than offline accuracy, it is still not a true measure of an individual's capability to use a prosthesis. This is mainly because that online accuracy is commonly measured using on-screen tests where the user is seated with the arm in a static position without wearing the prosthesis. To measure true prosthesis control capability, a physical prosthesis must be used in functional tasks (dynamical measurements). However, doing so is much more challenging than measuring online performance (static measurements), as the myoelectric signals are non-stationary when using a prosthesis for functional tasks. Simply moving the arm changes the myoelectric signal due to synergistic muscle activations and due to the weight of the prosthesis pulling on the muscles. Furthermore, moving the arm with a heavy⁴ prosthesis leads to sweating which changes the impedance of the skin-electrode interface leading to additional changes in the myoelectric signal. Such exertion will eventually lead to fatigue and the myoelectric signal of fatigued muscles differs from those of non-fatigued muscles (Kyranou et al., 2018). The combined effect often changes the myoelectric signal in such a way that the machine learning algorithm can no longer recognise it. This means that control becomes unreliable and the user lose their trust in the system. For a review of factors (also known as non-stationarities) affecting the myoelectric signals see the work of Kyranou and colleagues (Kyranou et al., 2018).

A considerable amount of research has gone into reducing the effect of the non-stationarity changes of the myoelectric signal. Efforts range from new algorithms to recording data in different limb positions. However, there is a lack of research to the human side of the machine learning myoelectric control equation. Maybe investigating the capabilities of the prosthesis user will reveal opportunities for countering the non-stationarity changes. What if the prosthesis user somehow could generate myoelectric signals of such a high *quality*, so that the effect of the non-stationarity changes will not lead to severe degradation of the control?

As mentioned earlier, the assumption of machine learning myoelectric control is that the intent of the user can be manifested as a distinct, repeatable myoelectric signal. I suggest that we investigate if we can improve the myoelectric signals of the user so that they will be distinct and repeatable.

⁴ Lightweight prosthetic hands weight roughly the same as their biological counterpart (~500 grams), but since the weight is carried by the socket compressing soft tissue most prosthesis users still consider prosthetic hands too heavy.

1.2 Motor learning and rehabilitation: learning to hit a moving target

The classic way to improve human motor performance is training. Training can make you a great singer, a blistering fast guitar player, or a hardcore gamer. Whether you train the control of your vocal cords or the precision of your wrist movements you engage in motor learning. Humans are incredible at motor learning and can learn to solve complex tasks if they have proper feedback and spend enough time learning it. Different theories of motor control and the processes related to motor learning exist. Broadly speaking, they can be divided in two groups: executive “top-down” theories and self-organisation “bottom-up” theories (Turvey, 1990, fig. 1). The executive theories commonly describe the existence of internal models in the brain. Internal models can be either forward models or inverse models. Forward models predicts the sensory feedback of an action and inverse models compute the required movements to perform a task (Huys et al., 2014; Sensinger & Dosen, 2020). If someone wants to pick up an empty opaque bottle, the brain will use an inverse model to calculate how to activate the muscles to move the joints as to pick up the bottle. The forward model predicts the sensation of picking up the bottle. However, if there is a mismatch in the prediction of the forward model and the sensation of picking up the bottle (e.g. the bottle turned out to be full) the motor program is updated to accommodate. Importantly, the same task can be achieved using different internal models. That is, if one were to pick up the bottle using two hands, a different internal model would be used than if the bottle were picked up with one hand. This means that internal models are independent of the task at hand. In the executive theories, motor learning is the creation of new internal models. Initially, the model might be sub-optimal or “noisy”, which refers to errors in the model. Through training, the model is refined and becomes more and more accurate and noise is reduced. Notably, variation in motor control is often considered as noise, as optimal control should lead to minimal variation (de Rugy et al., 2012; Sensinger & Dosen, 2020). For an overview of the computational theories (a subset of the executive theories) in the context of upper limb prosthetics I recommend the recent work of Sensinger and Dosen (Sensinger & Dosen, 2020).

In contrast, the self-organisation theories consider motor control as a self-organised complex system consisting of many parts with no top-level controller. There is thus no internal model in the brain. Instead, the motor system is described as action systems, which is the organisation of the body to accomplish a certain task. The action systems are task dependent. As an example, the action system for locomotion is the same whether one locomotes by walking, running, or crawling. What defines whether one walks, runs or crawls depends on the state of the system. The state of the system changes depending on the organism and the environment and can be described using the extensive literature on dynamical systems (Stepp & Turvey, 2017; van Emmerik et al., 2016; Warren, 2006). In terms of learning a new task, existing action systems

are used and are continuously adapted until a new action system emerges (i.e. the system changes to a new state). In contrast to the internal model theories, variability in motor control is considered to be natural and a part of an ever-evolving system.

Machine learning myoelectric control training is a special case of motor learning. Most motor learning requires controlling one's limbs to achieve a goal, but myoelectric control does not. Myoelectric control requires controlling the myoelectric signal, which is a by-product of controlling one's limbs. Since people cannot directly control their myoelectric signal, the only way to learn myoelectric control is to learn which muscle contractions lead to the desired myoelectric signal. From an internal model perspective, this can be described as creating a model which maps different muscle contractions to different myoelectric signals. This internal model would be used when recording signals to train the system and later on when wearing the prosthesis. From an action systems perspective this is not as straightforward as action systems are task dependent. This means that one action system would be needed when performing the task "record signals to train the system" and another would be used to use the prosthesis to pick up a glass (van Dijk et al., 2017). These two action systems might be able to converge to a state where the myoelectric signal that is generated is similar enough to the one which the algorithm was trained on. However, it might also be that the action systems are too different and that the generated signals differ too much for robust prosthesis use. If the self-organisation theories on motor control are correct, it might have high consequences for machine learning myoelectric control.

Training machine learning myoelectric control is usually done with a coach (Powell et al., 2014; Resnik et al., 2018; Roche et al., 2015; Simon et al., 2012). The coach helps the trainee to perform the muscle contractions in such a way, that they are distinct from each other and repeatable in terms of the generated myoelectric signal. The coach does this by looking at the patterns of the myoelectric signals to determine which patterns are overlapping (not distinct). After determining the overlapping patterns, the coach gives explicit instructions to the trainee on how the patterns can be separated by adapting the muscular contractions. This sort of explicit feedback is limited by the capabilities of the coach and implicit feedback, where the trainee can explore different solutions, is often preferred (E. Kal et al., 2018). However, providing implicit feedback at this stage of training is difficult, as the machine learning algorithm must be trained before feedback can be given. Furthermore, the explicit feedback given focuses on the trainee's body parts and not on the end goal (e.g. controlling the prosthesis), which is referred to as an internal focus of attention. An internal focus of attention is often regarded as inferior to having an external focus of attention where focus is on the outcome of the movement (Kal et al., 2013).

After the coaching, the signals are recorded again using the adapted muscular contractions and the coach analyses the patterns again. When there is no or minimal overlap, the trainee will try and control a virtual or table-mounted prosthetic hand to practice prosthesis control. If the trainee experiences problems controlling some of the movements of the virtual or table-mounted prosthesis, they receive further coaching followed by the recording of new signals and performance evaluation. Depending on the specific protocol, the physical prosthesis may be donned to evaluate functional prosthesis control. The loop consisting of recording, evaluating, and coaching is repeated until control is satisfactory.

While training as described above leads to improved control, it has some limitations:

1. Training is dependent on the coach, leading to limited training exposure.
2. Training is slow, as it can take several minutes from the moment feedback is given (coaching) to the moment when result of the feedback can be evaluated.
3. Training is based on declarative statements and therefore does not achieve possible benefits from implicit feedback.
4. Feedback leads to an internal focus of attention which is when training focuses on body parts.

User training for machine learning myoelectric control including these limitations has hardly been studied. The few studies on user training that exist are all based on coaching as described earlier (Kuiken, Miller, et al., 2016; Powell et al., 2014; Powell & Thakor, 2013; Resnik et al., 2018; Roche et al., 2015; Simon et al., 2012). Furthermore, the study of Bunderson & Kuiken investigates the differences in the myoelectric patterns between novices and experienced users (Bunderson & Kuiken, 2012), but does not train the users as such. Similarly, the study of He and colleagues investigates user adaptation over time and the effect it has on the myoelectric patterns, but they do not provide feedback (He et al., 2015).

An alternative to coaching which has gained popularity is the use of serious games. Serious games are (computer) games which are entertaining while teaching the player new skills that are applicable outside of the game. The benefits of serious games are that players are motivated to train more because training is entertaining and can be done from home without a coach. Furthermore, serious games can provide instantaneous implicit feedback that is adapted to the player. Lastly, players have an external focus of attention as they are immersed in the game and focus on the screen. The challenge of using serious games is to design them in such a way that playing the game leads to improved performance in the real world. This is commonly referred to as *transfer*. A few studies exist describing serious games to train players to use a conventional one DoF myoelectric prosthesis (van Dijk et al. 2016; Prahm et al. 2019; Prahm and

Vujaklija 2017; Tabor, Bateman, and Scheme 2018; Winslow, Ruble, and Huber 2018). Most of these studies focus on the motivational aspect of the games and indeed they appear to motivate the players. However, the studies do not assess if the players become better at using their prosthetic hand after playing. Instead, the assumption of these studies is that an increase in their outcome metrics (e.g. amplitude, isolation) directly correlates with prosthetic control. The only study which assessed if players became better at using a prosthesis is the study of van Dijk and colleagues (van Dijk et al., 2016b). The study of van Dijk demonstrated that a serious game could teach proper grasping behaviour to able-bodied participants using a prosthesis simulator. While the game of van Dijk might not be motivating (it was not assessed), I believe it is easier to make a game motivational than it is to make the skills learned in the game transfer to real-life. When designing a training scheme, it is important to demonstrate that the skill learned during training transfer to the skill that one is trying to improve. There is a consensus in the motor learning literature that transfer requires training to be task specific, which means that the goal of training should be similar to the goal of the task one is learning (Schmidt & Lee, 2005; van Dijk et al., 2016b). For many tasks this is not a problem. For example, most people learn to drive a car by driving a car together with an instructor. However, would it be possible to learn how to drive a car by driving a tractor or playing a serious driving game? Possibly, but a car driving test would be needed to evaluate if driving a tractor or playing a serious driving game leads to better driving. However, some studies evaluate the effect of training using measures that do not measure transfer (see examples in the previous paragraph). Examples of this are measures that are assumed to correlate with task performance, or especially for serious games, game scores. For the driving example, one could measure driving skill as how much the car deviates from the middle of the lane during driving, which might relate to but is not the same as driving skills required to deal with complex traffic situations with different drivers involved.

Transfer is also relevant for training machine learning myoelectric control. The goal of training machine learning myoelectric control is for the user to improve their control of their prosthesis. However, most training focuses on training the generation of distinct and repeatable myoelectric signals. The result of training is often evaluated using an online test as described earlier where the user controls a virtual limb or matches prompted movement. However, while generating distinct and repeatable myoelectric signals is supposedly important for achieving good control of a prosthesis, having distinct and repeatable myoelectric signals is not the same as having good control over a prosthesis. I believe that training machine learning myoelectric control requires learning two distinct tasks (and achieve two transfers). First, the user must learn to generate distinct and repeatable myoelectric signals and transfer those to the recording session in order to record data that will lead to a well-trained machine learning algorithm (high offline accuracy). Secondly, the user must learn to generate myoelectric signals that is recognised by

the machine learning algorithm as the intended movement and transfer those to functional prosthesis use. See Figure 4.

Figure 4. Overview of transfer from training to performing a task. A) In most motor learning there is a direct transfer from the training activity to the task. B) In machine learning myoelectric control there are two training tasks and thus two transfers: from training activity A to the recording session and from Training B (which uses the output of the machine learning algorithm trained on data from the recording session) to functional use. The requirement of the trainee is that the myoelectric signals are kept constant (transferred) between activities even though the task constraints change.

In theory, the myoelectric signals required for functional use should be the same as for the recording session. However, considering how the machine learning algorithm maps the feature space, the non-stationarities and generating the signals while trying to accomplish a task with the prosthesis, is very different from generating the signals for the recording session. In practice, this means that the signals the user is trained to generate for the recording session, might not lead to good control of the prosthesis.

1.3 Context and outline of the thesis

This thesis was written as part of the European Union's Intuitive Natural Prosthesis UTilization (INPUT <http://www.input-h2020.eu/>) project. The goal of the INPUT project was to move a state of the art machine learning controlled three DoFs myoelectric prosthesis out of the lab and into the clinics. The prosthesis together with the machine learning algorithm used is described in detail in chapter 5 of this thesis. Considering the goal of the INPUT project and the current state of the art. The goal of this thesis is to investigate current training methods and develop new training methods based on serious games.

An important prerequisite for translating lab results to the clinic is that the methods used in the lab do not differ too much from the clinical reality. For research on upper limb prosthetics, this ideally means that research should be conducted on participants with upper limb absence and that the prosthetic hardware is robust enough to work in many unpredictable situations. However, due to the low number of people with upper limb absence it can be difficult to recruit enough participants to achieve significant results. This means that most studies recruit able-bodied participants in their stead. Methods that can bring the performance of able-bodied participants closer to the performance of participants are needed if the gap between lab and clinic is to be closed. Such methods could include prosthesis simulators, which allow able-bodied participants to don a prosthesis or interventions that make the muscle contractions of able-bodied participants more alike those of participants with upper limb absence.

The outline of the thesis is as follows:

Chapter 2 is an investigation into how the myoelectric signals of able-bodied participants can be made more alike the myoelectric signals of individuals with upper limb absence by using an orthosis.

Chapter 3 investigates the effect of different kinds of feedback (no external feedback, visual feedback or visual feedback with coaching) during machine learning myoelectric control training. To this day there are no strong correlations between qualities of the myoelectric signal and skill in machine learning myoelectric control. Such a correlation would help guide research to develop better training schemes.

Chapter 4 compares a serious games approach to machine learning myoelectric control training with the conventional approach with able-bodied participants.

Chapter 5 compares a serious games approach to machine learning myoelectric control training with the conventional approach with participants with upper limb absence. The study uses the state of the art machine learning controlled three DoFs myoelectric prosthesis developed by the INPUT project and training is evaluated using functional tasks.

Chapter 6 discusses the results of the work presented in this thesis and proposes steps to move the field of machine learning myoelectric control forward.

SHOULD HANDS BE RESTRICTED WHEN MEASURING
ABLE-BODIED PARTICIPANTS TO EVALUATE MACHINE
LEARNING CONTROLLED PROSTHETIC HANDS?

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Abstract

Objective: When evaluating methods for machine-learning controlled prosthetic hands, able-bodied participants are often recruited, for practical reasons, instead of participants with upper limb absence (ULA). However, able-bodied participants have been shown to often perform myoelectric control tasks better than participants with ULA. It has been suggested that this performance difference can be reduced by restricting the wrist and hand movements of able-bodied participants. However, the effect of such restrictions on the consistency and separability of the electromyogram's (EMG) features remains unknown. The present work investigates whether the EMG separability and consistency between unaffected and affected arms differ and whether they change after restricting the unaffected limb in persons with ULA. **Methods:** Both arms of participants with unilateral ULA were compared in two conditions: with the unaffected hand and wrist restricted or not. Furthermore, it was tested if the effect of arm and restriction is influenced by arm posture (arm down, arm in front, or arm up). **Results:** Fourteen participants (two women, age=53.4±4.05) with acquired transradial limb loss were recruited. We found that the unaffected limb generated more separated EMG than the affected limb. Furthermore, restricting the unaffected hand and wrist lowered the separability of the EMG when the arm was held down. **Conclusion:** Limb restriction is a viable method to make the EMG of able-bodied participants more similar to that of participants with ULA. **Significance:** Future research that evaluates methods for machine learning controlled hands in able-bodied participants should restrict the participants' hand and wrist.

2.1 Introduction

After enduring a hand loss, individuals experience a reduction in their action capabilities as the degrees of freedom of the hand become unavailable. Many actions that were once easily performed must be relearned during rehabilitation using alternative degrees of freedom. To reduce the strain on the remaining body structures, a prosthetic hand might be provided to regain some of the lost degrees of freedom. Prosthetic hands have until recently only offered one degree of freedom. However, myoelectric multi-articulated hands and machine-learning (ML) control systems have been recently introduced to the market offering multiple degrees of freedom. Such hands are controlled using electromyography (EMG) signals measured from the remnant limb using an array of electrodes. Features of the EMG signals are calculated and constitute a feature space in which a ML classifier is trained. Different regions of the feature space correspond to different movements. Whenever an EMG feature pattern is measured, as during normal use, the ML algorithm maps the pattern in the feature space and sends the corresponding control command to the prosthetic hand. For successful use of a ML-controlled hand, it is required that the EMG feature patterns from the same movement must be consistent and the EMG feature patterns from different movements must be separate in the EMG feature space (Bunderson & Kuiken, 2012; He et al., 2015; Powell et al., 2014; Resnik et al., 2018). Since people do not intuitively have good control over their EMG generation, these requirements are difficult to satisfy (Johnson et al., 2017; Martinez Valdes et al., 2018). Furthermore, EMG signals are non-stationary in real-life environments due to various factors such as limb posture and electrode shift during arm movements, and also due to sweat or fatigue, which cause EMG artefacts (see (Kyranou et al., 2018) for a review). Additionally, only a few minutes of data from selected fixed limb postures are normally used to train the classifier, which means that the classifier has to account for many other possible situations.

The requirements of the EMG feature patterns for ML control are especially a challenge for those with upper limb absence (ULA) due to the physiological and musculoskeletal effects, which are a consequence of their limb loss. These effects include the deterioration of the neurological link to the muscles in the stump as result of altered cortical areas corresponding to the missing limb (Chen et al., 2013; Flor et al., 1995; Wesselink et al., 2019). Additionally, when muscles are not being used, fatty degeneration will occur making the muscles weaker, which lowers the magnitude of the EMG (Lowery et al., 2002) and causes less separable EMG feature patterns. Furthermore, if the muscles are sutured to the bone (myodesis), only isometric contractions can be performed, which possibly results into less separable EMG feature patterns as muscle movement is limited. Moreover, altered proprioceptive feedback has been assumed to cause less consistent EMG feature patterns (Young et al., 2013). Finally, stump length, phantom limb

sensation and time since amputation all relate to control performance (Atzori et al., 2016).

Despite these differences, the extent to which limb loss in participants with ULA influences the EMG feature patterns is not well understood (Amsuss et al., 2014; He et al., 2015; Hudgins et al., 1993; X. Liu et al., 2009; Powell et al., 2014; E. J. Scheme et al., 2011, 2013; Wirta et al., 1978). Moreover, able-bodied participants are recruited more often than participants with ULA during research on ML prosthetics to overcome the small number of persons with ULA that can be found or are available. There is however growing evidence indicating that able-bodied participants perform considerably better in various metrics than those with ULA (Amsuss et al., 2014; Campbell et al., 2020; He et al., 2015; Li & Kuiken, 2009; X. Liu et al., 2009; Powell et al., 2014; E. J. Scheme et al., 2011, 2013), as well as being grouped into different clusters using hierarchical cluster analysis and principal component analysis than able-bodied participants (Campbell et al., 2020). Therefore, the validity of recruiting able-bodied participants as substitutes for participants with ULA is questionable. To overcome the above limitations it has been suggested that the effects of limb loss can be reproduced in able-bodied participants by restricting the movements of the hand and wrist using a brace or splint (Dyson et al., 2018; Fougner et al., 2014; Malesevic et al., 2020; Pistohl et al., 2013), thus making their EMG features more similar to those of people with ULA. The assumption behind this method is that a constrained hand and wrist would perform only isometric contractions, which should resemble the EMG contractions of a participant with ULA. However, this assumption has never been tested. In summary, the influence of ULA and of wrist-hand restriction on the characteristics of EMG feature patterns represent two unaddressed research assumptions at the basis of many experiments on ML prosthetic control. In this study we address these issues by investigating the influence of ULA on the EMG feature patterns by using the other (intact) limb of people with ULA as a control. We further assess the effects of hand restriction on the quality of EMG feature patterns. Individuals with unilateral ULA were measured while performing bilateral movements in two conditions: one with the unaffected hand-wrist unrestricted and one with the unaffected hand-wrist restricted. Additionally, these movements were measured in different arm postures, since ML classifiers are often trained on EMGs from different arm postures. However, the effect of posture on the EMG's separability and whether it changes between unaffected and affected arms is also not well understood.

To address the issues laid out above, several factors need to be investigated: limb, restriction, postures. Therefore, we performed an experiment with a full factorial design. This allows to investigate the main effects, but also the interactions between these factors. Within this factorial design this research concentrated on two objectives. First, we wanted to understand if the affected and unaffected arm differ in terms of EMG feature patterns consistency and separability. If they differ, this might provide insight to why able-bodied participants achieve

better ML control than participants with ULA. Secondly, we investigated if restricting unaffected hands and wrists makes the EMG feature patterns generated by this arm more similar to those generated by affected arms in terms of consistency and separability. If this is the case, it would support the hypothesis that restriction of the able hand makes the generated EMG more similar to the EMG generated by an affected limb.

We expected that the EMG feature pattern consistency and separability are lower in affected arms than in unaffected arms and that restricting the unaffected hand and wrist lowers the consistency and separability of the EMG feature pattern.

2.2 Materials and Methods

Participants

Participants were deemed eligible to take part in the study if they had an acquired unilateral limb-loss at the transradial level. The stump needed to have been properly healed with sufficient reduction of the stump oedema. Participants should have had at least a 2 cm wide region on the forearm without scars. Understanding the Dutch language was required to follow the study protocol. This study was approved by the local ethics committee (ECB/2017.01.30_2). Participants provided written informed consent before entering the study.

EMG Measuring

EMG was measured using sixteen active bi-polar electrodes (Otto Bock 13E200=50AC) where eight electrodes were attached to each of two elastic bands. The bands were fastened to the forearms of the participant. On the affected side, the band was fastened at the location where there was muscle activity with no scars present. Muscle activity was determined by palpating the forearm while the participant performed phantom movements. The other band was fastened at the corresponding location on the unaffected side. EMG was sampled at 1000 Hz and transmitted wirelessly to a laptop (Dell XPS 9550).

Conditions

The experiment consisted of two conditions during which the unaffected side was compared to the affected side. In the “Unrestricted” condition the unaffected hand and wrist were unrestricted. In the “Unaffected Hand Restricted” (UHR) condition the unaffected hand and wrist were restricted using a medical arm brace (Wrist Lacer, Medical Specialties, USA)) while holding a tennis ball and having the digits taped around the ball, so wrist, thumb and finger movements were restricted as much as possible, see Figure 1.

Figure 1. Restriction of the unaffected hand and wrist as used in the study. Left: participants wore a wrist brace while holding a tennis ball to restrict wrist movements. Right: The hand was subsequently taped in using skin tape while holding the tennis ball to restrict movement of the thumb and fingers. The band of electrodes is shown at the bottom of both pictures.

Procedure and Design

The participants sat on a chair with armrests in front of a laptop computer. The electrode bands were fastened to the forearms of the participant. The order of the conditions of the unaffected hand and wrist (restricted or not) were balanced across participants. The participant executed bilateral movements in three different arm postures. The movements were executed in different postures since EMG differs depending on the posture (Kyranou et al., 2018). The three postures were down, front or up, see Figure 2.

Figure 2. Overview of procedure, postures and movements used per condition. For each of the three postures the seven movements were executed three times for three seconds. Postures were randomized between participants and participants had a six second break between movements.

In the down posture the arms of the participant would hang down by their sides (shoulder flexion 0°, elbow flexion 0°, Figure 2A). In the front posture the participant would have their arms on the armrest of the chair, with the elbows flexed (shoulder flexion 0°, elbow flexion 90°, Figure 2B). In the up posture the participant would have their upper-arms parallel to the ground while their elbows were flexed so the forearms would be straight upwards (shoulder flexion 90°, elbow flexion 90°, Figure 2C). In the up posture, participants would put their arms down to rest them in the period between movements. The order of these postures was randomised.

Outcome Measures

Features of EMG commonly used in machine learning based control were calculated; the mean absolute value, slope sign changes, wavelength and zero crossings. Features were calculated from 200 ms time windows with an overlap of 50 ms.

EMG Feature Pattern Consistency

Pattern consistency was calculated as the distance between patterns from different repetitions of the same movement by using the Within-class Distance (WD_{total}) (Kristoffersen et al., 2019) formulated as:

$$WD_{total} = \frac{1}{7} \sum_{j=1}^7 \left(\sum_{k=1}^3 \frac{dist_{kj}^{rj} * dist_{rj}^{kj}}{dist_{kj}^{rj} + dist_{rj}^{kj}} \right) \quad (1)$$

Where $dist_{kj}^{rj}$ and $dist_{rj}^{kj}$ are half the Mahalanobis distances in feature space between repetitions r and k of movement j and between repetitions k and r of movement j respectively:

$$dist_{kj}^{rj} = \frac{1}{2} \sqrt{(\mu_{Trj} - \mu_{Tkj})^T * S_{rj}^{-1} * (\mu_{Trj} - \mu_{Tkj})} \quad (2)$$

$$dist_{rj}^{kj} = \frac{1}{2} \sqrt{(\mu_{Tkj} - \mu_{Trj})^T * S_{kj}^{-1} * (\mu_{Tkj} - \mu_{Trj})} \quad (3)$$

Where μ_{Trj} and μ_{Tkj} denote the feature vectors from repetition r and k respectively. S_{rj} and S_{kj} are the covariances of the training data from repetition r and k respectively. Smaller WD corresponds to more consistent EMG feature patterns. d and participants were allowed to rest between postures for as long as they needed.

In each of the three postures, the participant performed seven bilateral (phantom) movements, namely wrist flexion, wrist extension, pronation, supination, open hand, key grip and fine pinch, three times each for three seconds for a total of 63 movement executions for each condition (restricted or not). See Figure 2. To aid in the movement executions, the experimenter said the name of the movement and performed the movement with the participant. Additionally, on the laptop, a picture of the movement was shown together with a progress bar indicating

the remaining duration of the movement. Between repetitions the participant relaxed for three seconds. Between movements a six second break took place. All seven movements were executed in the same posture before moving on to the next posture. After a break, the participant followed the same procedure for the other condition. See Figure 2.

EMG Feature Pattern Separability

Pattern separability was calculated as the distance in feature space between patterns from different movements by using the Inter-class Distance Nearest Neighbour (IDNN_{total}) and Inter-class Distance All Neighbours (IDAN) (Kristoffersen et al., 2019). The difference between IDNN_{total} and IDAN is that IDNN_{total} measures the distance to the nearest neighbour in feature space, whereas IDAN measures the average distance to all other neighbours in the feature space. The IDNN_{total} and IDAN are formulated as:

$$IDNN_{total} = \frac{1}{7} \sum_{j=1}^7 \left(\min_{i=1, \dots, j-1, j+1, \dots, 7} \frac{dist_j^i * dist_i^j}{dist_j^i + dist_i^j} \right) \quad (4)$$

$$IDAN = \frac{1}{7} \sum_{j=1}^7 \left(\frac{dist_j^i * dist_i^j}{dist_j^i + dist_i^j} \right) \quad (5)$$

Where $dist_j^i$ and $dist_i^j$ represent half the Mahalanobis distances in feature space between movements i and j and between movements j and i of movement j respectively:

$$dist_j^i = \frac{1}{2} \sqrt{(\mu_{Ti} - \mu_{Tj})^T * S_i^{-1} * (\mu_{Ti} - \mu_{Tj})} \quad (6)$$

$$dist_i^j = \frac{1}{2} \sqrt{(\mu_{Tj} - \mu_{Ti})^T * S_j^{-1} * (\mu_{Tj} - \mu_{Ti})} \quad (7)$$

Where μ_{Ti} and μ_{Tj} denote the feature vectors from movement i and j, respectively. S_i and S_j are the covariances of the data from movement i and j, respectively. Larger IDNN_{total} and IDAN corresponds to more separate EMG feature patterns.

Data Analysis

For the analyses the metrics described in Outcome Measures were averaged over the seven movements and used as the dependent variables. All the dependent variables were tested for normality using separate Kolmogorov-Smirnov tests with Lilliefors correction. The dependent variables were analysed using a three-way repeated-measures ANOVA with arm (affected and non-affected), restriction (restricted and non-restricted) and arm posture (down, front and up) as within-subject factors. In the case of a 3-way interaction effect being present, the difference between restrictions was calculated and a two-way repeated measures ANOVA was performed with arm and arm posture as within-subject factors. This was done to reduce the number of

post-hoc tests required, minimising the risk of making a type-1 error.

Effect sizes were calculated using generalized eta-squared statistics (Bakeman, 2005). Post-hoc testing was done using t-test with Bonferroni correction. Results are reported using mean $\pm$ standard error of the mean (SEM). The level of significance was set at $\alpha < 0.05$.

2.3 Results

Fourteen participants joined the study (12/2 M/F, age=53.4 $\pm$ 4.05). See Table 1 for characteristics of the participants.

Table 1. Participants' characteristics.

ID	Sex	Age	Side of amputation	Loss of dominant hand	Time since loss (years)	Pros. type	Pros. use	Hours daily pros. use
1	F	43	Left	No	2.5	Cosmetic	Daily	5-12
2	M	74	Right	Yes	53	Myo	Daily	12+
3	F	50	Left	No	21	Myo	Daily	12+
4	M	26	Right	Yes	0.5	-	-	-
5	M	59	Right	Yes	25	Myo	Daily	12+
6	M	47	Left	No	3	Myo	Daily	5-12
7	M	30	Right	No	7	Myo	Daily	12+
8	M	45	Right	Yes	11	Myo	Daily	5-12
9	M	80	Left	Yes	29	Myo	Daily	2-5
10	M	67	Right	Yes	47	-	-	-
11	M	54	Right	No	26	Myo	Daily	12+
12	M	52	Left	No	32	-	-	-
13	M	59	Right	Yes	49	Myo	Daily	5-12
14	M	62	Left	No	47	Myo	Daily	12+

Abbreviations: M = male, F = female, ID = identification number, Myo = Myoelectric. Pros. = Prosthesis.

The subject with ID 11 was excluded from the data analysis since he was not able to perform pronation/supination nor wrist flexion/extension.

Analysis of EMG Feature Pattern Consistency and Separability

For WD, 6 of the 12 conditions were normal distributed. For the IDNN_{total} 11 of the 12 conditions were normal distributed. For IDAN 4 of the 12 conditions were normal distributed. Since ANOVAs are robust to violations of normality we proceeded with the analyses as planned.

The analysis on WD revealed no significant effects. The analysis on $IDNN_{total}$ revealed a significant main effect of arm on $IDNN_{total}$ ($F(1,12) = 7.613$; $p = .017$; $\eta^2_G = .047$), showing that the EMG feature patterns were less separated in the affected arm. We found two significant interaction effects: restriction & arm ($F(1,12) = 7.285$; $p = .019$; $\eta^2_G = .019$), that was mediated by posture, ($F(2,24) = 6.728$; $p = .005$; $\eta^2_G = .017$), see Figure 3.

Figure 3. Interaction effect of arm & restriction & posture on the Interclass Distance Nearest Neighbour ($IDNN_{total}$). Each bar denotes the $IDNN_{total}$ for one arm in one condition. The diamonds denotes the mean and the circle with a dot denotes the median. The green, red and blue bars denote the posture. The bottom and top edged denotes the 25th and 75th percentile respectively. + signs denote outliers. Abbreviations: UHR = Unaffected Hand Restricted.

To understand this three-way interaction, we calculated the difference in $IDNN_{total}$ between the unrestricted condition and the UHR condition and performed a new analysis on this difference. This post-hoc analysis revealed a significant main effect of arm ($F(1,12) = 7.182$; $p = .02$; $\eta^2_G = .06$) and arm & posture ($F(1,24) = 6.654$; $p = .005$; $\eta^2_G = .06$), see Figure 4. Post-hoc t-tests showed that

the UHR condition causes a significant decrease in $IDNN_{total}$ for the unaffected limb compared to the affected limb in the down posture ($t(12) = -3.911$; $p = .002$, $r = .76$) whereas no significant decrease was found for the front ($p = .066$, $r = .50$) and up ($p = .500$, $r = .19$) postures.

Figure 4. Effect of condition on Interclass Distance Nearest Neighbour (IDNN). The red line denotes the median and the black diamond the mean. The bottom and top edged denotes the 25th and 75th percentile respectively. + signs denote outliers. Data points from individual participants are plotted next to the boxes. The * and the bracket marks the two conditions that are statistically significant. Abbreviations: Unaff = Unaffected, Aff = Affected.

The analysis on IDAN revealed no significant effects.

2.4 Discussion

In this study the differences in EMG feature pattern consistency and separability were investigated between unaffected and affected arms in individuals with ULA in different arm postures while the unaffected hand and wrist was either restricted or not. The EMG feature pattern separability of the unaffected unrestricted arm appeared to be generally higher than in the other conditions (Figure 3, three leftmost bars). We conclude that the unaffected arm differs from the affected arm in terms of EMG feature patterns consistency and separability. However, the difference was smaller than what we anticipated considering the differences in ML control performance between able-bodied participants and participants with ULA (Amsuss et al., 2014; He et al., 2015; Li & Kuiken, 2009; X. Liu et al., 2009; Powell et al., 2014; E. J. Scheme et al., 2011, 2013), we discuss this later in the Discussion.

Restriction of the unaffected arm led to a significant decrease of EMG separability in the down posture. Moreover, for the front posture the post-hoc test revealed a p-value (.066) that was close to significance with a medium to large effect size ($r=.50$). This indicates that there probably is an effect of restriction in the front posture, especially given that with a sample size of 13 it is unlikely that significant effects can be detected with a moderate effect size. Taking the significant decrease of the down posture into account we consider this close to significant effect as a preliminary sign that restricting the unaffected arm could result in a moderate decrease in the separability of the EMG for most of the postures. The relevance of these findings lie in the conditions under which EMG feature patterns of able-bodied and of ULA participants can be made more alike for future EMG studies that employ able-bodied participants in place of participants with ULA. Such studies should now consider restricting the wrist and hand of their participants to make their EMG feature patterns and those of participants with ULA more alike. While able-bodied participants with restricted hand and wrist cannot serve as a substitution for recruiting participants with ULA, it will make the data collected more relevant when exploring new methods and during pilot testing.

Pattern Consistency

We did not find any effect of arm, restriction or posture on EMG pattern consistency. It should be noted that some studies on user training for ML devices have found that EMG pattern consistency improves with training (He et al., 2015; Powell et al., 2014). This means that EMG pattern consistency might still be an important parameter to consider even though it might not differ between able-bodied participants and participants with ULA. It could be that EMG pattern consistency is not affected by physiological factors.

Pattern Separability

Our finding suggests that participants with ULA generate less separable EMG feature patterns than able-bodied participants. This is in line with our expectations given the physiological and musculoskeletal effect of limb loss. That unaffected arms generate more separable EMG feature patterns might explain why able-bodied participants in general achieve better ML based EMG control compared to participants with ULA using their affected (Amsuss et al., 2014; He et al., 2015; Li & Kuiken, 2009; X. Liu et al., 2009; Powell et al., 2014; E. J. Scheme et al., 2011, 2013) or unaffected arm (Guanglin Li et al., 2010). However, the difference in EMG separability was smaller than what we anticipated. Literature suggests that training should focus on increasing the separability of the EMG patterns of participants with ULA (Kristoffersen et al., 2019; Powell et al., 2014). Future studies focusing on finding the optimal way of training EMG pattern separability should, based on the current findings, restrict the hand of able-bodied participants when experimentally exploring different training methods that maximally increase separability. However, when aiming for functional improvement with ML based EMG control it should be noted that separability is just one aspect to improve. That is, in other studies we found that the correlation between EMG pattern separability and performance is not linear suggesting that above a certain level of separability, higher separability does not appear to lead to better performance (A.W. Franzke et al., 2020; Kristoffersen et al., 2019). Furthermore, we only found a decrease in the $IDNN_{total}$ metric and not in the IDAN metric. It is unclear why the IDAN metric did not decrease in a similar fashion as the $IDNN_{total}$ metric. The relation between IDNN, IDAN and performance should be investigated in future research.

Effect of Posture

From previous research it is known that arm posture influences the EMG (Betthausen et al., 2018; A. Fougner et al., 2011; J. Liu et al., 2014), but it was not clear how it influenced EMG feature pattern consistency and separability. Interestingly, we found that the effects of arm and restriction on separability were not equal over the postures we measured. Most notably, in the postures where the hand is below the head the lowering effect of restriction on separability was most apparent. This specific effect of posture might be due to causes such as gravity compensation (limb stabilisation), skin-electrode interface changes, changes in the force-length relationship of the muscle, changes in musculotendon lever arm or changes in motor execution (A. Fougner et al., 2011). To preserve the effect of posture, we suggest, in line with other studies (Betthausen et al., 2018; A. Fougner et al., 2011; J. Liu et al., 2014), that in future research different arm postures should be used.

Bracing

Bracing of the hand and wrist in this study was done using a medical arm brace designed for comfortable long-term use and by taping the digits around a tennis ball. This method was chosen due to its simplicity and comfort. However, other studies used a glove attached to a board (Dyson et al., 2018; Pistohl et al., 2013) or have the hand grab a cylinder and encase the arm in stiff socket material (Fougner et al., 2014). The methods used in the other studies might have been more successful at enforcing isometric contractions, but were considered more complex. Furthermore, restricting the hand to a board would mean that the arm would be fixed in one posture. Moreover, our method was comfortable which is important since discomfort or pain can influence the contractions of the participants. The participants in our study did not express discomfort in wearing the brace and the other studies did not report if their participants found the bracing (un)comfortable. Therefore, it is unlikely that pain or discomfort caused the changes between the conditions.

To our surprise, there appears to be some change in the EMG of the affected arm whether the unaffected hand is restricted or not. This might be due to changes in bilateral motor control when the unaffected hand and wrist is restricted.

Limitations

A limitation of our study is that the participants did not wear their prosthesis while being measured, which might have led to different results as the weight of the prosthesis affects the EMG (Betthausen et al., 2018). This was unfortunately not possible since the prosthesis socket covered the forearm where we had to place the electrodes. Furthermore, we only measured participants with ULA at the transradial level, meaning that our results might not apply to participants with ULA at the transhumeral level. Additionally, the unaffected arm of an individual with ULA might differ from the arms of an able-bodied individual, which means the effects we observed might not apply to individuals with two intact arms. Lastly, our sample size was limited due to the challenges of recruiting participants with ULA and therefore our results should be confirmed in studies with larger sample sizes.

2.5 Conclusion

The separability of the EMG feature patterns was found to be lower in the affected arm than in the unaffected arm. Restriction of the able hand and wrist can be used to reduce the separability of the generated EMG patterns, but other parameters should be investigated before the restricted limb can be regarded as a good representative of the affected limb. Looking at

separability results, restriction might be useful when testing prosthetic algorithms or hardware on able-bodied individuals. However, restriction of the unaffected hand and wrist does not lower pattern separability when the hand is above the head and restriction has no effect on the consistency of EMG patterns. The consistency of EMG patterns was not found to differ between the affected and unaffected arms meaning that this metric might not differ between individuals with ULA and able-bodied individuals.

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THE EFFECT OF FEEDBACK DURING TRAINING SESSIONS
ON LEARNING PATTERN-RECOGNITION BASED
PROSTHESIS CONTROL

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Abstract

Human-machine interfaces have not yet advanced to enable intuitive control of multiple degrees of freedom as offered by modern myoelectric prosthetic hands. Pattern Recognition (PR) control has been proposed to make human-machine interfaces in myoelectric prosthetic hands more intuitive, but it requires the user to generate high-quality, i.e., consistent and separable, electromyogram (EMG) patterns. To generate such patterns, user training is required and has shown promising results. However, how different levels of feedback affect effectivity in training differently, has not been established yet. Furthermore, a correlation between qualities of the EMG patterns (the focus of training) and user performance has not been shown yet. In this study, 37 able-bodied participants (mean age 21 years, 19 males) were recruited and trained PR control over five days. Three levels of feedback were tested for their effectiveness: no external feedback, visual feedback and visual feedback with coaching. Training resulted in improved performance from pre- to post-test with no interaction effect of feedback. Feedback did however affect the quality of the EMG patterns where people who did not receive external feedback generated higher amplitude patterns. A weak correlation was found between a principal component, composed of EMG amplitude and pattern variability, and performance. Our results show that training is highly effective in improving PR control regardless of feedback and that none of the quality metrics correlate with performance. We discuss how different levels of feedback can be leveraged to improve PR control training.

3.1 Introduction

Myoelectric prosthetic hands have evolved from one degree of freedom (DoF) grippers to multi-articulated hands with multiple DoFs. However, the commercially available human-machine interface that should allow control of those multiple DoFs has not yet advanced to make the control process intuitive (Farina & Amsüss, 2016). In particular, the Direct Control (DC) scheme used by these hands only allows for control of one DoF at a time. Moreover, switching between DoFs is done sequentially using electromyography (EMG) trigger signals generated using unintuitive muscle contractions. Pattern-Recognition (PR) control has been proposed as an alternative, since the PR algorithm can learn to predict movement intent using EMG patterns generated from the corresponding (phantom) movement. This would allow for almost instantaneous switching between grips which could lead to faster, more fluent and more intuitive control (Betthausen et al., 2018; Hargrove et al., 2013; Nilsson et al., 2017a).

A prerequisite for good PR control is that EMG patterns have specific qualities. In the context of PR this means that EMG patterns are sufficiently distinct, not too variable and can be generated with high reliability (Bunderson & Kuiken, 2012; Maier et al., 2018; Powell et al., 2014). However, since the EMG patterns are measured at the surface of the skin, the quality of the EMG patterns is negatively affected by non-stationarity effects such as sweat and electrode shifts (Betthausen et al., 2018; Castellini et al., 2014). In addition, movement repetition variability can also negatively affect specific qualities of the EMG patterns so that they differ between repetitions, since humans cannot naturally generate EMG with such high precision (Johnson et al., 2017; Martinez Valdes et al., 2018). While non-stationarities can be reduced by improving algorithms' classification accuracy and reducing noise from data acquisition, the quality of the generated EMG patterns can only be improved by training the user.

Although user training for PR control has been studied previously (Powell et al., 2014; Simon et al., 2012), results are inconclusive as studies differ in methods, results and lack statistical power due to small sample sizes (Bunderson & Kuiken, 2012; He et al., 2015; Powell et al., 2014; Simon et al., 2012). All the aforementioned studies do however report significant improvements after training and most attribute the improvements to changes in a set of representative EMG features (Bunderson & Kuiken, 2012; He et al., 2015; Powell et al., 2014). This set spans a feature space and changes in said feature space have been hypothesized to correlate with performance improvements.

When analyzing the feature space, metrics such as the distance between EMG patterns of different movements (separability), the distance between EMG patterns belonging to the same

movement (consistency), and the size of the EMG patterns (variability) are used to assess the quality of the EMG patterns (Bunderson & Kuiken, 2012; He et al., 2015; Nilsson et al., 2017a; Powell et al., 2014). In studies on user training for PR control, EMG pattern quality improved, albeit in different ways. The level of feedback given during training differed among the studies which arguably played a role in those differences. The feedback ranged from no feedback (He et al., 2015), to visual feedback (Bunderson & Kuiken, 2012), to visual feedback with individualized coaching (Powell et al., 2014). It is currently unknown which aspects of EMG pattern quality are the most important for good prosthetic performance, as no clear correlation between any metrics derived from the feature space and PR control performance has been shown. To develop an effective training scheme for PR control it is important to know which aspects of EMG pattern quality to target and which level of feedback improves this most (Bunderson & Kuiken, 2012).

The main goal of this study is to determine the effect of the level of feedback on EMG pattern quality and how this influences PR control performance. The primary outcome variables used are the test scores (number of completed movements and online accuracy) measured after training, which describe PR control performance. The secondary outcome variables are a selection of metrics describing EMG pattern separability, consistency and variability, which overall describe EMG pattern quality. We hypothesize that (1) higher levels of feedback result in higher test scores and (2) that higher levels of feedback results in larger changes in quality of the EMG patterns and (3) that a strong correlation exists between the primary and secondary outcome variables.

3.2 Methods

Participants

Participants were eligible if they were able bodied with no physical limitations. The study took place in the laboratories of the Department of Human Movement Sciences at the University of Groningen, the Netherlands. Four junior researchers recruited the participants using their social networks and by advertising the study on student forums. Prior to participation all participants were informed about the experiment and signed a letter of informed consent. This study was approved by the local ethics committee (ECB/2017.01.12_1).

Materials

Participants were seated at a table with their non-dominant hand resting at the edge of that table and the elbow resting on the chairs' arm rest. Hand dominancy was determined using an adapted version of the Edinburgh inventory (Cohen, 2008; Oldfield, 1971).

A brace (Medical Specialties Wrist Lacer) was attached to the distal part of the non-dominant side, restricting the movements of the wrist and thumb. By restricting the wrist and thumb, participants produce isometric muscle contractions similar to those of a person with an upper-limb defect. (Fougner et al., 2014; Smith et al., 2016). We restricted the hand, to improve the transferability of our results to individuals with an upper limb defect.

Eight active bi-polar electrodes (Otto Bock 13E200=50AC) were attached equidistantly around the proximal side of the participants' non-dominant forearm. EMGs were sampled at 1 kHz and transmitted wirelessly to a laptop computer (Dell XPS 15 9550). Participants started training minutes after putting on the electrodes and noise was assessed before training by visual perusal of the EMG. Four time-domain features of the EMG (mean absolute value, waveform length, zero crossings and slope changes) were extracted from 128 ms windows with 32 ms overlap (Amsuess et al., 2015). The features were classified into one of 8 classes (7 movements + rest) using a Linear Discriminant Analysis (LDA) classifier and mapped to a movement and velocity.

Procedure

The experiment was conducted over five days, and consisted of daily sessions. EMG production during each session was limited to 30 minutes to avoid fatigue. On day 1 a pre-test was conducted followed by a 20-minute user training session. On days 2-4 the participants followed a 30-minute user training session. On day 5 the participants followed a 20-minute user training session and subsequently performed the post-test. Pre- and post-test lasted ~10 minutes. By changing the order between test and training on days 1 and 5, training time was maximized. Training, as well as the pre- and post-tests, consisted mainly of system training and Motion test procedures. Total session time was between 45 and 60 minutes.

Pre-test and Post-test.

The pre-test and post-test were identical and consisted of two parts: System training and Motion test (Kuiken et al., 2009).

System training

In PR control, system training is the procedure in which the user supplies training data to construct the feature space on which the PR algorithm is trained. In the current experiment system training was done with seven movements: supination, pronation, wrist flexion, wrist extension, hand open, key grip and fine pinch. Each of the seven movements was executed four times for three seconds: once at 100% maximum voluntary contraction (MVC), which was only used to calibrate the height of the visual cue on the screen (see Figure 1). Participants had to follow this cue when they performed subsequently the movement at 30%, 60% and 90% MVC

respectively (Amsuess et al., 2015). Each movement was demonstrated by the experimenter before and during system training. The movement executions at 30%, 60% and 90% MVC were used to train the classifier.

Figure. 1. Screen feedback given during system training in the pre- and post-test. A: Visual cue, the height of the moving red dot was determined by averaging the root mean square of the EMG over all electrodes. The participant was asked to match the height so that the red dot followed the blue trapezoid shape. B: picture of the requested movement. MVC=Maximal Voluntary Contraction

Figure. 2. Screen feedback given during the Motion test in the pre- and post-test. Left: Picture of the requested movement. The green bar (1) denotes the requested EMG amplitude and the smaller green bar with the handles (2) denotes the margin that the EMG amplitude from (1) should be within. Right: Picture of the predicted movement. The green (3) bar denotes the measured EMG amplitude. The red circle denotes the remaining time

(in this instance, almost half the time has passed, as shown by the semi-circle). When the movement was matched, a green circle started to form next to the red circle. The green circle was full when the movement was successfully completed.

Motion test

In the Motion test participants performed the same movements as in the system training, but now the PR algorithm was used to classify the movement performed by the participant. This was done using the feature space constructed with the data from the system training. In the Motion test, participants performed 21 movement trials; all movements from the system training at 30% ($\pm 15\%$), 60% ($\pm 20\%$) and 90% ($\pm 30\%$) MVC respectively, presented in random order. While performing the movement, participants saw an image of the requested movement, the predicted movement and a timer on a screen, as shown in Figure 2. A movement trial was considered successful if the participant could perform the requested movement in such a way that the PR algorithm classified it for a minimum of two seconds within a three second timeout at the requested MVC level. The Motion test is comparable to the test and training used in the study of Bunderson & Kuiken (Bunderson & Kuiken, 2012).

Training program

Identical to the pre- and post-test the user training sessions consisted of the system training and the Motion test, albeit with different feedback depending on the group to which the participant was assigned: no feedback, visual feedback, and visual+coaching feedback (see Experimental groups). System training and Motion test were chosen for training since proper execution of both is necessary to achieve good prosthesis control. Both were conducted as training, twice on day 1 and 5 (after and before pre-test and post-test, respectively) and thrice on days 2-4. Participants were assigned to a specific group based on the inclusion date, with 1/3 of consecutive participants in each group.

Experimental groups

All the groups received feedback about their performance in the pre-test and in the post-test; after the Motion test the number of correct movements and the online accuracy (See Performance metrics) were shown on the screen.

The groups differed with respect to the level of feedback they received during training, as described below.

No feedback [NF]

The NF group followed the training program, but without visual screen feedback. This meant they did not receive any feedback on how to perform the movements nor any feedback on their performance during training. More specifically, they did not see the content presented in Figures 1 and 2 during the user training sessions but only during the pre- and post-test. Participants in this group did not receive any visual feedback and relied on the cues provided by

the experimenter, who performed the movements and told the participants when to start and stop executing the movements.

Visual feedback [VF]

The VF group followed the training program while receiving visual screen feedback (see Figures 1 and 2) as in the pre-test and post-test.

Visual+Coaching feedback [VCF]

The VCF group received the same visual feedback as the VF group while in addition they received coaching from the experimenter after each Motion test. The coaching was based on different metrics (see Metrics) of EMG pattern consistency, separability and variability. Before coaching, the experimenter reviewed a plot for each metric. To train consistency, the experimenter would instruct the participant to focus on the execution of the movement with the worst reproducibility (highest within-class distance). To train separability, the experimenter would instruct the participant to adapt the least separable pair of movements so as to make them more separate in terms of EMG patterns, following the general principle used by Powell and Thakor (Powell & Thakor, 2013), see Figure 3. The experimenter also used a spider plot showing the root mean square of the EMG patterns to explain to the participant how the movement adaptations would affect the patterns and make them more separable, see Figure 3 (Roche et al., 2015). To reduce variability, if the movement with the highest variability was also in the pair of the least separable movements, the experimenter would instruct the participant to focus on the execution of the movement with the highest variability (highest mean semi-principal axis) to make it less variable.

Figure. 3 Example of movement adaptation and feedback given to VCF group. A: fine pinch grip with the non-essential fingers flexed. B: fine pinch grip with the non-essential fingers extended. Right: Example of spider plot with EMG patterns from three movements plotted. The spider plot shows the root mean square of the EMG pattern for each channel and serves as a simplified representation of the feature space with each movement (EMG pattern) represented by one colored shape. Overlap can be visually perused and the

experimenter can guide the participant to minimize it. Variations A and B of fine pinch are represented by the blue and the green shape respectively. For clarity we added a red dotted shape, representing an example EMG pattern that has considerable overlap with variation B of fine pinch. To show an example of an extreme case, the red shape was fabricated and is not based on EMG of a real grip. In this case, the experimenter would ask the participant to execute the fine pinch such as in variation A, to find the variation that causes the least overlap with the EMG pattern represented by the red dotted shape.

Metrics

Performance metrics

In the Motion test two feedback metrics were computed, number of completed movements and online accuracy. These two feedback metrics were the primary outcome variables.

Number of completed movements

The number of completed movements was the total number of successful movement trials (maximum 21).

Online accuracy

The online accuracy denoted the percentage of time participants conducted the movement in such a way that the classifier could correctly predict it independently of whether the movement trial was successful or not. The participant could always see the current prediction as depicted on Figure 2.

EMG pattern quality metrics

To determine the specific EMG pattern qualities related to PR control several metrics describing EMG pattern consistency, separability and variability were computed. These metrics were the secondary outcome variables.

Metric of EMG pattern consistency

Within-class Distance (WD)

The WD is a consistency metric of EMG patterns over repetitions of the same movement.

$$WD_j = \sum_{k=1}^3 \frac{dist_{kj}^{rj} * dist_{rj}^{kj}}{dist_{kj}^{rj} + dist_{rj}^{kj}} \quad (1)$$

Where $dist_{kj}^{rj}$ and $dist_{rj}^{kj}$ are half the Mahalanobis distances in feature space between the EMG patterns of repetitions r and k of movement j and between repetitions k and r of movement j respectively:

$$dist_{kj}^{rj} = \frac{1}{2} \sqrt{(\mu_{Trj} - \mu_{Tkj})^T * S_{Trj}^{-1} * (\mu_{Trj} - \mu_{Tkj})} \quad (2)$$

$$dist_{rj}^{kj} = \frac{1}{2} \sqrt{(\mu_{Tkj} - \mu_{Trj})^T * S_{Tkj}^{-1} * (\mu_{Tkj} - \mu_{Trj})} \quad (3)$$

Where μ_{Trj} and μ_{Tkj} denote the feature vectors containing the four features calculated from the system training data from repetition r and k respectively. S_{Trj} and S_{Tkj} are the covariances of the training data from repetition r and k respectively. When computing the total WD for a participant and not just one movement, we took the mean WD over all movements

$$WD_{total} = \frac{1}{7} \sum_{j=1}^7 \left(\sum_{k=1}^3 \frac{dist_{kj}^{rj} * dist_{rj}^{kj}}{dist_{kj}^{rj} + dist_{rj}^{kj}} \right) \quad (4)$$

Metrics of EMG pattern separability

Inter-class Distance Nearest Neighbor (IDNN)

The IDNN is based on the Separability Index (SI) of Bunderson & Kuiken (Bunderson & Kuiken, 2012) and is a separability metric of EMG patterns over different movements. We defined IDNN as

$$IDNN_i = \min_{i=1, \dots, j-1, j+1, \dots, 7} \frac{dist_j^i * dist_i^j}{dist_j^i + dist_i^j} \quad (5)$$

Where $dist_j^i$ and $dist_i^j$ is half the Mahalanobis distance in feature space between movements i and j and between movements j and i of movement j respectively

$$dist_j^i = \frac{1}{2} \sqrt{(\mu_{Ti} - \mu_{Tj})^T * S_{Ti}^{-1} * (\mu_{Ti} - \mu_{Tj})} \quad (6)$$

$$dist_i^j = \frac{1}{2} \sqrt{(\mu_{Tj} - \mu_{Ti})^T * S_{Tj}^{-1} * (\mu_{Tj} - \mu_{Ti})} \quad (7)$$

Where μ_{Ti} and μ_{Tj} denote the feature vectors containing the four features calculated from the training data from movement i and j, respectively. S_{Ti} and S_{Tj} are the covariance of the training data from movement i and j, respectively. This distance metric is the same as the one for WD (see equations 2 and 3) except that instead of measuring distances between clusters from the same movement the distance is measured between clusters of different movements. The IDNN differs from the SI in that the Mahalanobis distance between clusters are measured in both directions instead of only one, meaning that the covariance of both clusters is considered. The SI differs depending on which cluster is measured from ($dist_j^i \neq dist_i^j$) (Nilsson et al., 2017b; Roduit et al., 2006) whereas the IDNN between two clusters are always the same. When computing the total IDNN for a participant and not just one movement, we took the mean IDNN over all movements

$$IDNN_{total} = \frac{1}{7} \sum_{j=1}^7 \left(\min_{i=1, \dots, j-1, j+1, \dots, 7} \frac{dist_j^i * dist_i^j}{dist_j^i + dist_i^j} \right) \quad (8)$$

Inter-class Distance all Neighbors (IDAN)

The IDAN metric is similar to IDNN, with the difference that instead of measuring the distance to the nearest neighbor only, distances to all neighbors are calculated. Using the same notation as for IDNN (equation 5-8), we defined IDAN as

$$IDAN = \frac{1}{7} \sum_{j=1}^7 \left(\frac{dist_j^i * dist_i^j}{dist_j^i + dist_i^j} \right) \quad (9)$$

Most Separable Dimension (MSD)

The MSD metric is similar to IDNN, with the difference that instead of measuring the distance using the entire feature vector (i.e. all 32 dimensions) only the dimension in which the separability to the other movements is largest is used to determine the nearest neighbor. Using the same notation as for IDNN (equations 5-8), we defined MSD as

$$MSD = \frac{1}{7} \sum_{m=1}^7 \max_{d=1, \dots, 32} \left(\min_{i=1, \dots, j-1, j+1, \dots, 7} \frac{dist_j^i * dist_i^j}{dist_j^i + dist_i^j} \right) \quad (10)$$

Where the feature vectors of $dist(\mu_{ti})$ and μ_{tj} in equation 6-7) are calculated for each of the 32 dimensions ($d=1, \dots, 32$) and the dimension where the distance is the largest (max) is then used to calculate MSD.

Metric of EMG pattern variability

Mean Semi-principal Axis (MSA)

The MSA is unaltered from the formulation given by Bunderson & Kuiken (Bunderson & Kuiken, 2012) except that for feedback we only calculated the MSA for a single movement as opposed to the average of all movements as done by Bunderson & Kuiken. The MSA is a metric for how variable a movement of a participant is and is formulated as

$$MSA_k = \left(\prod_{k=1}^{16} a_k \right)^{\frac{1}{16}} \quad (11)$$

Where a_k is the geometric mean of the semi-principal axes of the hyperellipsoids. When computing the total MSA for a participant and not just one movement, we took the mean MSA over all movements

$$MSA_{total} = \frac{1}{7} \sum_{j=1}^7 \left(\left(\prod_{k=1}^{16} a_{jk} \right)^{\frac{1}{16}} \right) \quad (12)$$

Metric of EMG pattern amplitude

Mean Absolute Value (MAV)

The MAV metric was used to determine the EMG amplitude as EMG amplitude correlates with force. This metric was used in conjunction with the other metrics to determine if a change was

the result of increasing force or of change in dimensionality

$$MAV = \frac{1}{7} \sum_{m=1}^7 |EMG_m| \quad (13)$$

Where EMG_m is the EMG of movement m of the training data.

Data analysis

Several of the metrics used in the analyses were the same as those used to compute feedback to the participants in the VCF group (WD, IDNN, MSA). For the analyses the metrics were averaged over all movements as was described in section EMG pattern quality metrics. All dependent variables were tested for normality in separate Kolmogorov-Smirnov tests.

To establish the effect of feedback on movement performance and EMG pattern quality, training outcome results and EMG patterns from the pre- and post-test were analyzed in separate ANOVAs. These analyses were conducted using two-way repeated-measures ANOVAs with test outcome (pre-test vs post-test) as the within-subjects factor and group (feedback level) as the between-subjects factor, using each of the primary and secondary outcome variables as the dependent variable in separate ANOVAs. Effect sizes were calculated using generalized eta-squared statistics (Bakeman, 2005). Post-hoc testing was done using T-test with Bonferroni correction.

A Principal Component Analysis (PCA) (J. E. Jackson, 1991) was additionally conducted to determine if any principal components (PCs) derived from the secondary outcome variables were correlated with any of the primary outcome variables. The PCA was performed on the percentage of change from pre- to post-test for each participant (37 observations) with variables represented by one of the EMG metrics described above (6 metrics). Used in this manner, PCA can reveal if a combination of metrics can explain the effect of feedback on training. The PCs thus obtained, which are as many as the metrics, represent the normalized linear combination of the metrics that explain a percentage of the variance in the percentage of change. This is done so that the first PC has the largest variance, the second PC has the second-largest variance and so on. The loading vectors represent the directions of variability of the data in the variable space, with the first loading vector as the direction along which the data vary the most and so on. We analyzed the set of PCs that together explained 90% of the variance. The PCs between groups were compared using ANOVAs with group as between subject factor using the PCs as dependent variables. Post-hoc testing was done using the T-test with Bonferroni correction.

To determine if there was a correlation between pattern change and training outcome, we calculated Pearson's correlation coefficient between the primary and secondary outcome

variables. Pearson's correlation coefficient was also calculated between the primary outcome variables and the PCs. Results are reported using mean $\pm$ standard error of the mean. The PCA analysis was conducted using Matlab R2016a and all other analysis was conducted using IBM SPSS Statistics version 23.

3.3 Results

Thirty-seven participants were included in the experiment ($N=37$, female=18; mean age 21.6 ± 2.1 years). There were 13 participants assigned to the NF group, 12 to the VF group and 12 to the VCF group.

The Kolmogorov-Smirnov tests showed that all dependent variables followed a normal distribution.

Effect of test and feedback on primary outcome variables

The analysis on online accuracy revealed a significant effect of test ($F(1,34) = 48.41$; $p < .0001$; $\eta^2_c = .0009$) with an increase between pre- and post-test ($64\% \pm 2.3\%$; $85\% \pm 1.6\%$, Figure 4a). The analysis on the number of completed movements also revealed a significant effect of test ($F(1,34) = 175.121$; $p < .001$; $\eta^2_c = .66$) with an increase between pre- and post-test ($3.56 \pm .29$; $10.18 \pm .47$, Figure 4b)¹. In both analyses none of the effects involving the three feedback groups were significant.

Figure. 4 Boxplots showing (A) online accuracy (B) number of completed movements and (C) Interclass

¹ To assess if the increase in the primary outcome variables was due to training or was the result of a random effect, we performed a repeated measures ANOVA on the results from the intermediate Motion tests (first Motion test after pre-test, last Motion test on days 1-4 and the last Motion test before the post-test) as within-subject factor and Feedback group as between-subject factor. The ANOVA showed only a significant main effect ($p < .0001$) of the tests, thus we concluded that the effect is due to training.

Distance Nearest Neighbor (IDNN) from pre- to post-test. The red crosses denote the mean and the red line in each plot is the median. Outliers, marked with plus signs, are defined as points that lie outside 1.5 the interquartile range. Individual data points are marked with black crosses.

Effect of test and feedback on secondary outcome variables

Metric of EMG pattern consistency

No significant effects were found for WD.

Metrics of EMG pattern separability

IDNN showed a significant effect of test ($F(1,34) = 8.326$; $p = .007$; $\eta^2_c = .05$) with an increase from pre- to post-test ($7.6 \pm .27$; $8.37 \pm .29$, Figure 4c). None of the other effects were significant. No significant effects were found for IDAN and MSD.

Metric of EMG pattern variability

MSA revealed a significant effect of test ($F(1,34) = 12.174$; $p = .001$; $\eta^2_c = .064$) with an increase between pre-test and post-test ($56,764 \pm 3,521$; $67,297 \pm 3,333$). This effect of test interacted with that of group ($F(2,34) = 7.53$; $p = .002$; $\eta^2_c = .078$). Post-hoc analysis using Bonferroni correction revealed that participants in group NF increased MSA between pre-test and post-test ($p < .0001$) while participants in groups VF and VCF did not change ($p = .584$ and $.199$ respectively), see Figure 5.

Figure 5. Mean Semi-principal Axis for all groups from pre- to post-test. Error bars shows the standard deviation.

Metric of EMG pattern amplitude

MAV revealed a significant effect of test ($F(1,34) = 9.983$; $p = .003$; $\eta^2_c = .06$) with an increase between pre-test and post-test ($1,101 \pm 70$; $1,306 \pm 70$). This effect of test interacted with that of group ($F(2,34) = 7.842$; $p = .002$; $\eta^2_c = .09$). Post-hoc analysis using Bonferroni correction revealed that participants in group NF increased MAV between pre-test and post-test ($p < .0001$) while participants in groups VF and VCF did not change ($p = .486$ and $.372$ respectively), see Figure 6.

Figure 6. Mean Absolute Value for all groups from pre- to post-test. Error bars shows the standard deviation.

Three PCs were analyzed explaining 61%, 23% and 8% of the variance, respectively. The composition of the first two PCs can be seen in Figure 7.

The composition of the third PC is mainly explained by WD (0.93) and MSD (-0.28). The ANOVAs revealed that there was a significant effect of feedback group for PC1 ($F(2,34) = 5.863$; $p = .006$; $\eta^2_c = .13$). Post hoc tests revealed that participants in group NF had significantly larger values of PC1 than participants in group VF ($F(23)$; $p < .001$), but did not differ from VCF, see Figure 8.

Figure 7. Biplot of the first two principal components and loading vectors of the PCA. Each point represents the score of the first two principal components for one participant in a given group (NF/VF/CF). The lines represent the first two principal component loading vectors. Abbreviations: IDNN (Interclass Distance Nearest Neighbor), IDAN (Interclass Distance All Neighbors), WD (Within-class Distance), MSA (Mean Semi-principal Axis), MAV (Mean Absolute Value), MSD (Most Separable Dimension).

Figure. 8. Boxplot showing Principal Component 1 (PC1) from pre- to post-test. The red crosses denote the mean and the red line in each plot is the median. Outliers, marked with plus signs, are defined as points that lie outside 1.5 the interquartile range. Individual data points are marked with black crosses.

No significant effects were found for PC2 and PC3.

Correlation between pattern change and training outcome

The analysis revealed that there was no significant correlation between any primary and any secondary outcome variables. However, a correlation was found between online accuracy and PC1 ($\rho = .36$, $p = .028$). No significant correlation was found between the primary outcome variables and PC2 or 3.

3.4 Discussion

To the best of our knowledge, this is the first study that compared different levels of feedback during user training in PR control over several days to determine the effect of feedback on

control performance and EMG pattern quality. The results showed that user training improved PR control performance, independent of the level of feedback received during training. Training led to significant increases in performance (Figure 4a and 4b) that exceeds the ~10% error differences between different classifiers (Hargrove et al., 2007; Ortiz-Catalan et al., 2013). Training thus seems to have a larger impact on PR control than the choice of the classifier. For improving PR control, it might therefore be very beneficial to further investigate user training and its effect on classifier performance. In addition, we found that providing no external feedback during training led to higher amplitudes and more variability of the EMG patterns than training with feedback. Furthermore, a correlation was found between online accuracy and a principal component (PC1), primarily reflecting the amplitude and variance of the EMG patterns, derived from the feature space.

Training PR control is possible without coaching

Our results demonstrated that user training for PR control led to significant improvements in performance even without visual feedback on the screen or individualized coaching. It might thus be possible to develop effective training schemes for the home environment, where therapist coaching is difficult to organize, in which higher training exposure is easily possible. This is important from a clinical standpoint, since insufficient training has been linked to high prosthesis abandonment rates (Biddiss & Chau, 2007; McCarthy et al., 1998).

Our results are different from what we hypothesized and what would be expected from literature, where the study of Powell et al. [6] trains with high-feedback VCF and shows larger improvement after training than other studies training with less feedback (Bunderson & Kuiken, 2012; He et al., 2015). However, participants in the study by Powell et al. had an upper-limb defect, in contrast to the other studies (Bunderson & Kuiken, 2012; He et al., 2015) in which able-bodied persons participated. Consequently, the persons with limb defects had the lowest pre-test scores and thus more room for improvement. However, a more comprehensive understanding of how differences in training effects between able-bodied and those with an upper-limb defect are mediated by feedback levels requires a direct comparison of those groups in an experiment. Such a comparison is currently not available in the literature and is something we aim to address in a future study.

Feedback affects the quality of EMG patterns

We hypothesized that higher levels of feedback would lead to larger changes in the quality of the EMG, but it appears that this relation is not straightforward. The results show that training with no feedback increases EMG amplitudes (MAV) and pattern variability (MSA) compared to higher levels of feedback. Our results differ from those of He et al. (He et al., 2015) as we found no

significant changes in pattern consistency (WD). This might be the result of the different pattern consistency metrics used or the longer training duration in the study by He et al. (10 days vs. 5 days in our study). Unlike the study of He et al., we additionally found a significant change in pattern separability. This effect that was nearly significant in the study of Bunderson & Kuiken (Bunderson & Kuiken, 2012), who reported that experienced participants had significantly higher pattern separability compared to trained novices. Our study confirms that training leads to higher pattern separability. It appears that different levels of feedback have different effects on the quality of the EMG patterns.

Correlation between outcome metrics

We did not find a correlation between the primary and secondary outcome metrics. However, a compound metric derived from the secondary outcome metrics, namely principal component 1, was weakly correlated with online accuracy. While a compound metric, such as principal component 1, might be used to improve training programs, it is unlikely that the PCA space can be made generalizable enough to facilitate training for all PR control trainees.

Without a metric that correlates with performance it is difficult to facilitate training beyond trial and error. This is highly problematic since it is a requirement for designing an effective training scheme for PR control (Bunderson & Kuiken, 2012). We also find it problematic for the widespread adoption of PR control that a strong relationship has not yet been established. This might also explain why all studies we know of comparing PR control with conventional direct control have been unable to clearly show that PR is superior to direct control (Kuiken, Miller, et al., 2016; Mastinu et al., 2018; Resnik et al., 2018; Vujaklija et al., 2017) with the exception of one study performed on participants who had undergone targeted muscle re-innervation surgery (Hargrove et al., 2017). Additional studies on user training for PR control should be conducted using different feedback metrics to find a correlation that can be used to facilitate training beyond trial and error.

The absence of a correlation between the primary and secondary outcome metrics does not mean that the primary and secondary outcome metrics are not related. Separability (Interclass Distance Nearest Neighbor, IDNN) and performance both increased significantly, but did not correlate with one another. This might indicate that certain metrics are not related to better performance beyond a specific value. For example, if patterns do not overlap, better separability may not lead to better performance. If a tool could be developed that can identify when EMG patterns are separable enough it would mean that the trainee would know when to shift focus from separating patterns to improving other aspects such as repeatability.

Participants improve using the feedback that is available

It appears that all participants increased the separability of their EMG patterns (IDNN) from pre- to post-test using the feedback that was available to them. Participants in group NF appear to have done so by increasing the amplitude of their EMG. A suggestion that might explain why participants in the NF group generated EMG patterns with higher amplitudes than those in the other groups stems from the literature on motor learning (K. R. Lohse et al., 2010; Marchant et al., 2011; Vance et al., 2004; Wulf & Lewthwaite, 2010). It has been reported that having an internal focus (i.e. focus on one's movements, or one's muscle activity) as opposed to an external focus (i.e. focus on the results of one's movements) can lead to higher EMG amplitudes when learning motor skills. Participants in the NF group could only have used an internal focus since they did not have any external feedback (i.e. they could not see the result of their movements) and had to rely on the intrinsic feedback given by their muscles. The increase in EMG amplitude when training using an internal focus has been shown in activities ranging from bicep curls to dart throwing (K. R. Lohse et al., 2010; Marchant et al., 2011; Vance et al., 2004; Wulf & Lewthwaite, 2010). Interestingly, the presumed side effect of no feedback, which is using an internal focus, is the knowledge that increasing EMG amplitudes could be beneficial when learning PR based prosthesis control. While this was presumably the effect of participants in group NF having an internal focus, it could also be achieved by strength training. Strength training might thus be an overlooked path to improve PR control performance. While our results in this regard are inconclusive, we suggest that future research considers muscle strength, or a derivative thereof such as stump diameter, when assessing user PR control skill. If muscle strength does lead to better PR control, it could be a valuable tool in clinical rehabilitation.

Although the EMG patterns of group VF and VCF did not increase in amplitude as group NF, some trends can still be observed. EMG patterns of group VF were the only ones that did not trend towards an increase in amplitude following training (see Figure 6) and as a result the variability (MSA) of the EMG patterns was also low. This can be interpreted as that participants in group VF made their patterns less variable and became proficient in reproducing them. EMG patterns of group VCF varied a lot between participants considering the spread in Figure 7. This might be interpreted as that participants in the VCF group used different aspects of the feedback to improve. These findings show that feedback can be successfully given at different levels facilitating different kinds of training. A question for future research is if different levels of feedback can be combined to improve training. As an example, training could start with coaching in the clinic to introduce the concepts of PR control and give initial feedback on how to adapt movements to generate distinct patterns. When the user is at home, training could continue with visual feedback, to decrease pattern variability, and with no feedback to increase EMG amplitudes to make patterns more distinct. In this way, the specifics of each type of

feedback are optimally exploited in rehabilitation practice. A first step towards such a training scheme would be to validate the results of this work in a population with an upper-limb defect. If these effects have been established, other aspects of training can be further scrutinized in future research, such as optimal intensity of training and variability in training.

Limitations

Our study has some limitations, most prominently that participants were able-bodied and the results cannot be directly applied to those with an upper-limb defect. In research on PR algorithms similar performance differences have been found in participants with or without an upper limb defect (E. Scheme & Englehart, 2011) (e.g. the algorithm giving the best performance for able-bodied individuals also gave the best performance for those with an upper limb defect), but this has not been established for user training. Another limitation is that the outcome task, the Motion Test, does not measure prosthetic use, but only controllability of the classifier output. Lastly, the test and training platform were the same which means participants might have improved during testing. We believe this did not have an effect on the results, as all participants performed the same tests and all training was conducted between the two tests.

3.5 Conclusion

The present study demonstrated that user training is a highly effective way to improve PR control, independent of the level of the feedback given during training. Training led to higher EMG pattern separability independent of feedback and to higher EMG amplitude when training with no feedback. However, we found no correlation between qualities of the EMG and performance, indicating that the mechanisms behind improvement in user performance are not straightforward. Future research should investigate the effect of training on individuals with upper limb defects with a focus on functional prosthetic performance.

Such research could be important to develop effective training schemes that do not rely on trial and error. Furthermore, a metric which correlates the quality of EMG patterns with user performance would be an important step to improve training.

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SERIOUS GAMING TO GENERATE SEPARATED AND
CONSISTENT EMG PATTERNS IN PATTERN-RECOGNITION
PROSTHESIS CONTROL

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Abstract

Pattern-Recognition (PR) control of upper-limb prosthetics has shown inconsistent results outside lab settings, which might be due to the inadequacy of users' electromyogram (EMG) patterns. To improve the separability and consistency of their EMG, users can receive training. Conventional training uses an internal focus of attention as prosthesis users focus on the muscle contractions of their (phantom) hand together with explicit learning processes facilitated by a coach guiding the user. In this study we investigated if an alternative training paradigm using an external focus of attention exploiting implicit learning processes based on serious gaming without a coach could lead to more separable and consistent EMG. Able-bodied participants (N=25; mean age 22 years, 13 females) were recruited and followed conventional or game training for five days. In conventional training, participants performed the Motion Test thrice daily and received coaching on how to adapt their muscle contractions. In game training, participants controlled an avatar using a direct mapping from electrode to avatar direction. The participants utilized implicit learning processes, by exploring which muscle contractions made the avatar go in which directions. Performance in both groups was evaluated by using the Motion Test in a pre/post-test design. Training resulted in improved performance, with no differences between training paradigms. Participants who followed game training showed 51% more separated EMG patterns. EMG pattern consistency did not change over training. It was concluded that Serious game training using an external focus of attention and implicit learning can be considered as a viable alternative to conventional training.

4.1 Introduction

Myoelectric prosthetic hands with multiple degrees of freedom (DoFs) are commercially available. Controlling several DoFs by Direct Control, as commonly done in clinical practice, has however been proved problematic (Biddiss & Chau, 2007) due to the unintuitive nature of the control commands that are used to switch between DoFs. Pattern Recognition (PR) control has been suggested as an alternative and more intuitive way to control multiple DoFs. PR control is based on a direct mapping between electromyography (EMG) patterns generated while performing muscle contractions (e.g. phantom movements) and the corresponding prosthetic DoFs. In controlled laboratory environments PR control has shown great promise, however evidence shows that outside the lab PR control is hardly faster or more intuitive than conventional Direct Control (Kuiken, Miller, et al., 2016; Mastinu et al., 2018; Resnik et al., 2018; Vujaklija et al., 2017). Research showed that PR lacked robustness primarily due to the misclassifications of intent based on EMG patterns (Mastinu et al., 2018; Resnik et al., 2018). The misclassifications occur because of either external disturbances to the EMG (e.g. electrode lift-off, sweat) or because the EMG patterns of the user was not of a sufficient quality. To avoid misclassifications, the EMG patterns need to meet two quality criteria: separability and consistency (Bunderson & Kuiken, 2012; Nilsson et al., 2017a; Powell et al., 2014). Separability is fulfilled if EMG patterns from different muscle contractions are located in areas in feature space that do not overlap. Consistency requires that EMG patterns from repetitions of the same muscle contractions should overlap in feature space.

To ensure separability and consistency of EMG patterns, user training has been suggested. Conventional user training as presented in the literature often consists of three major phases: exploration, evaluation and education. Before the exploration phase, the naïve system training is performed which will enable the control needed for the exploration phase. The exploration phase then allows the trainee to get some initial feeling for what the effect of muscle contractions is, through computer-generated or table mounted prosthesis using explorative activities such as bilateral mirroring without any specific goals (T. Kuiken et al., 2016; Powell et al., 2014; Resnik et al., 2018; Roche et al., 2015; Simon et al., 2012). The evaluation phase consists of computer-based tests such as the Motion Test (Kuiken et al., 2009) or the Target Achievement Control Test (Simon et al., 2011). In these tests, the trainee must match a prompted prosthetic mode (e.g. prosthetic open hand) or prosthetic posture. Metrics such as completion rate and time are measured and presented to the trainee as feedback. In the education phase the trainee receives coaching by a researcher or a therapist and in some instances is told about the importance of EMG pattern separability and consistency (Powell et al., 2014; Resnik et al., 2018; Roche et al., 2015). The coach gives feedback on which EMG patterns were overlapping and/or inconsistent

and on how muscular contractions should be adapted to ensure separability and consistency. A core component of conventional training is that the adaptation of the muscular contractions are given in terms of phantom movements. Furthermore, the adaptations often involve the use of “non-essential” parts of a (phantom) movement, e.g. while in a regular pinch the little finger is flexed it might now be extended to improve separability or consistency (Powell et al., 2014; Resnik et al., 2018; Roche et al., 2015). The coaching is based on the EMG patterns, which are sometimes shown to the trainee, but always under the guidance of the coach. After coaching, the classifier will be retrained and the trainee will go through the three phases again. The phases are repeated until the trainee reaches the desired level of control.

Conventional training has been promising, but has not yet led to robust control outside the lab (Kuiken et al., 2016; Resnik et al., 2018; Vujaklija et al., 2017). This might partially be due to the effectiveness of the training in the education phase. The feedback provided in this phase induces an internal focus of attention, as the coaching focuses on muscular contractions and phantom movements and not on the actuation of the prosthesis resulting from said contractions/movements i.e. external focus of attention. An internal focus of attention has been shown to lead to worse performance (lower accuracy, lower speed) in a variety of motor tasks and to less automatized execution of tasks i.e. higher cognitive and neuromuscular effort (Vance et al., 2004; Wulf & Lewthwaite, 2010) compared to an external focus of attention. Furthermore, coaching using an internal focus exploits explicit learning processes that rely on working memory. Explicit learners have reduced performance in stressful situations (Hardy et al., 1996; R. C. Jackson et al., 2006) and when performing secondary tasks (Masters et al., 2008; Maxwell et al., 2001) compared to implicit learners. A learning paradigm that uses an external focus of attention and exploiting implicit learning processes might therefore be beneficial for learning PR control.

In this work, we examine the efficacy of serious gaming for this purpose because a game has an external focus of attention and can be designed to promote implicit learning. Serious games are (computer) games where the main goal is to teach the player a new skill and they have successfully been used to give feedback on EMG for training Direct Control (Prahm et al., 2019; Tabor et al., 2018; van Dijk et al., 2016a, 2016b). One of the main benefits of serious games is that feedback can be individually customized, which for persons with an upper limb deficiency might be important since the variability of EMG control and phantom sensations are high in this population. We suggest using a game inspired by the studies of Radhakrishnan *et al.* and Pistohl *et al.* (Pistohl et al., 2013; Radhakrishnan et al., 2008). In their studies, participants controlled a cursor in two DoFs using six surface electrodes placed on muscles in the hand and in the arm. The cursor was controlled using a direct mapping from each electrode to a direction of the

cursor. With such a mapping, trainees use an external focus of attention because they focus on cursor movement and receive implicit feedback on the relation between muscle contractions and cursor movements. By employing a similar mapping in a game, trainees will learn to move a game avatar in different directions through different muscle contractions. Choosing a particular orientation of targets to which the avatar has to move, these muscle contractions should generate separable EMG patterns. By applying these muscle contractions when training a PR classifier should thus lead to fewer misclassifications than when using muscle contractions learned using conventional training.

In comparison with previous work (Bunderson & Kuiken, 2012; Kristoffersen et al., 2019; Kuiken et al., 2016; Powell et al., 2014; Powell & Thakor, 2013; Resnik et al., 2018) this work is the first investigating the involvement of serious games in user training for PR control and compare serious games with conventional training. Furthermore, this work extends the work of Bunderson & Kuiken (Bunderson & Kuiken, 2012) by exploring additional EMG metrics while using a similar acquisition, PR setup and evaluation paradigm.

In the current study it was investigated if training with a serious game controlled with a direct mapping from electrode to avatar movement will lead to better PR control than following conventional training. The objective of this study was to determine if EMG patterns and PR control performance were different when participants trained with a serious game, compared to conventional training. We hypothesized that training with a serious game will lead to 1) more separated EMG patterns, 2) more consistent EMG patterns and 3) better PR control than conventional training.

4.2 Methods

Participants

The inclusion criteria for participants were able-bodied adults, with no neuromuscular or joint disorders in the upper body and naïve to PR control. The study took place in the laboratories of the Center of Human Movement Sciences at the University Medical Center Groningen, the Netherlands. Prior to participation all participants signed a letter of informed consent. This study was approved by the local ethics committee (ECB/2017.01.12_1).

Materials

EMG sampling

EMG was measured using eight active bi-polar electrodes (Otto Bock 13E200=50AC) placed

equidistantly around the proximal part of the participants' non-dominant forearm. The electrodes were numbered and positioned at the same location between sessions. The band of electrodes was placed on the thickest part of the forearm with the electrodes oriented as shown in Figure 1. A brace (Medical Specialties Wrist Lacer) was attached to the distal part of the same forearm and hand restricting movement of the wrist and thumb so participants produced isometric muscle contractions more alike those of an individual with an upper limb defect (Fougner et al., 2014; Smith et al., 2016). EMG was sampled at 1000 Hz. Arm dominance was determined using an adapted version of the Edinburgh inventory (Cohen, 2008; Oldfield, 1971).

Figure 1. Mapping of RMS to avatar control. Left: placement of electrodes on a right arm, with electrode 1 corresponding to RMS1, electrode 2 corresponding with RMS2 etc. For the left arm the electrodes are inverted so that electrode 1 is positioned on the volar side. Upper right: the y and x direction in 2D space was calculated as the mean RMS for three electrodes mapped to the positive y/x direction subtracted with the mean RMS for the three electrodes mapped to the negative y/x direction. Lower right: directions of the avatar. The color and the number inside of the arrows corresponds with the colored electrode number on the left-hand side of the figure.

Game

A game called MyoBox was developed and implemented for the experiment. Myobox is an abstract game (Begy, 2013; Salen & Zimmerman, 2004) inspired by games such as Labyrinth (BRIO, 1946), Marble Madness (Atari Games, 1984), and Neverball (Open source, conceived by R. Kooima, 2003). However, the game was purposefully kept as simple as possible to avoid overwhelming the player. In Myobox the player controls a ball, which functions as the avatar, in two dimensions, using EMG based control. The EMG was normalized per participant by having them perform maximum voluntary contractions (MVCs) of seven movements for three seconds each. The movements were pronation, supination, wrist flexion, wrist extension, hand open, key grip and fine pinch. The Root Mean Square (RMS) of the normalized EMG was calculated from 50 ms time windows. The RMS was mapped to control of the game avatar as depicted in Figure 1. The goal of Myobox was to collect boxes positioned on the platforms the ball could move on, while avoiding falling off the platforms, see Figure 2 A.

Figure 2. A: First orientation of Myobox. The player controls the orange ball in the bottom and is tasked with collecting the three orange boxes while staying on the light blue platform. B: First orientation of Myobox with the smallest possible platform size in the game.

Boxes could be collected by moving through them, therefore, participants had to learn how different movements of their hand and fingers would make the ball move. By learning to control the ball, participants implicitly learned to consistently generate separated EMG patterns, as movement of the ball in different directions requires EMG patterns that are different from one another. The game had four recurring orientations of the platforms, with seven levels of difficulty reflected by narrower platforms and with three boxes in each orientation and level. Every time

the player finished the fourth orientation the game restarted, but with narrower platforms, see Figure 2 B. In the beginning of the game when the platforms are wide, the player can complete the levels using two movements only. For instance, in Figure 2A the user can subsequently activate electrode 3 and 5 to move the ball through all three boxes. However, as the platforms became narrower, the player was forced to learn all eight directions to play the game.

There are other games or game-like activities in the literature that are controlled using EMG and PR for phantom limb pain treatment (Ortiz-Catalan et al., 2016) and for adapting control (Woodward & Hargrove, 2019). In these two examples the game is controlled using the output of a PR algorithm and these games were not specifically designed to train the user. Using the output of a PR algorithm, the user is constrained by the performance of the algorithm regarding which movements constitute a certain class. This requires the user to learn how to adapt to the algorithm and not how to make distinct patterns. In contrast, MyoBox is controlled without using a PR algorithm and was designed to train the user to generate distinct patterns. These distinct patterns can be used in the system training procedure and ensure that the classifier receives distinct patterns to optimize its performance. In MyoBox an exploratory game environment is provided where the user can explore all possible muscle contractions she/he can perform. The game helps the user to learn which movements are most distinct. These distinct muscle contractions can in turn be used to train the PR algorithm which might lead to better control of the prosthesis.

Pattern recognition

Pattern recognition control was based on classification using Linear Discriminant Analysis (LDA) (Duda et al., 2001). LDA is widely used in the field and is available in open source platforms such as BioPatRec (Ortiz-Catalan et al., 2013). Many researchers are therefore familiar with LDA and can relate to the performance reported in this work. EMG was recorded in the system training procedure and features were extracted and used to train the classifier. The classifier was trained on four time-domain features of the EMG recorded at 30%, 60% and 90% MVC during system training (mean absolute value, waveform length, zero crossings and slope changes (Hudgins et al., 1993)). Features were extracted from 128 ms width windows with 32 ms overlap (Amsuess et al., 2015). The features were classified into one of eight classes (7 recorded movements + rest).

System training

In the system training procedure, seven movements were recorded. In the pre-test these were: pronation, supination, wrist flexion, wrist extension, hand open, key grip and fine pinch. Before system training, these movements were first recorded at MVC to calibrate a visual cue presented as a trapezoid shape that participants had to follow during the system training to prescribe

the produced force while performing the prompted movement. The height of the plateau of the trapezoid was set at the requested force level, varying over repetitions, based on the MVC recording. During the system training, the same seven movements were recorded three times for three seconds at 90%, 60% and 30% MVC, while following the visual cue on a screen.

Pre-test

Participants performed the pre-test before training to get baseline performance measures. The pre-test started with the system training procedure, in which data to train the PR classifier was collected. Following the system training, a Motion test (Kuiken et al., 2009) was conducted, which is a virtual test to assess control performance.

Motion test

In the Motion test, participants were prompted at random to perform one of the seven movements recorded during the system training at either 30% (± 10), 60% (± 15) or 90% (± 20) MVC with a total of 21 movement trials (each movement is performed three times). A movement trial was successful if the participant could perform the prompted movement in such a way so that the classifier would correctly predict it for two seconds within a three second time-out within the given MVC margin. After the motion test, the number of successful movement trials and the online accuracy, denoting the percentage of time the classifier predicted the movement regardless of force level, was shown.

Procedure

Participants joined five training sessions on consecutive days which had a duration of either approximately 20 or 30 minutes, see Figure 3. The pre-test was performed right before the first training session. To avoid fatigue, the first training session lasted 20 minutes. On days 2-4 training sessions were 30 minutes long. On day 5 the training session lasted 20 minutes and was followed by the post-test. See Figure 3 for an overview.

	Day 1		Day 2-4	Day 5	
Game group	Pre-test: System training + Motion test using predefined movements	Training (~20 min.): 10 min. game training + (System training + Motion test)	Training (~30 min.): 20 min. game training + (System Training + Motion test)	Training (~20 min.): 10 min. game training + (System training + Motion test)	Post-test: System training + Motion test using game movements
Conventional group	Pre-test: System training + Motion test using predefined movements	Training (~20 min.): 2 x (System training + Motion test)	Training (~30 min.): 3 x (System training + Motion test)	Training (~20 min.): 2 x (System training + Motion test)	Post-test: System training + Motion test using predefined movements

Figure. 3 Procedure for the two training groups (note that system training + motion test lasted about 10 minutes).

Experimental groups

Before the pre-test, participants were randomly assigned to one of two experimental groups based on inclusion date; the first 12 participants were assigned to conventional training and the following 13 were assigned to game training.

Game training

During training sessions, the game training group played the Myobox game, that was designed for this study, for 20 minutes, except for day one where they played Myobox for 10 minutes, see Figure 3. Before the first training session participants received instructions on how to control the game. For example, participants were asked to perform wrist flexion/extension and observe the corresponding movement of the avatar. Participants were then told that a sub-aim of the game is to learn the control of at least seven directions by exploring different movements of the hand and wrist. Participants were asked to use the movements that worked best for them and felt most natural. While playing Myobox, the experimenter annotated which movements the participants used to control the avatar for each direction. After playing Myobox, if the participants could control more than seven directions, they were asked to choose the best seven directions in terms of controllability. If the participant did not learn seven directions corresponding to seven movements, extra predefined movements would be added from a predefined set (see appendix) so the total number of movements was seven. The movements learned were recorded following the system training procedure. After system training, a classifier was trained using the recorded movements. Following classifier training, the participant conducted the Motion test to assess the performance of the movements in a classifier context.

Conventional training

The conventional training group followed a training scheme inspired from two studies (Powell et al., 2014; Resnik et al., 2018), see Figure 3, in which the participants were guided by a personal coach who provided feedback, based on the coaching metrics (See Coaching metrics for conventional training group):

1. System training was performed. The system training data was used to train the classifier.
2. Using the classifier, the Motion test was performed to assess control performance
3. The pair of patterns from different movements that was least separated was calculated using (3) and the participant was asked to adapt the corresponding movements following the principle from (Powell & Thakor, 2013), see Figure 4. A spider plot (Roche et al., 2015) was shown to the participant to help the participant to visualize the conflict and the effect of the change, see Figure 4.
4. The pair of patterns from the same movement with the lowest consistency (i.e. least overlap over repetitions) was calculated using (6) and the user was asked to focus on the

corresponding movement to make repetitions more alike.

5. The pattern with the highest variability was calculated using (7) and the user was asked to focus on the corresponding movement to decrease variability.

The steps took ~10 minutes and were repeated two or three times depending on the length of the training session being 20 or 30 minutes, as described in Figure 3.

Figure. 4 Example of movement adaption and feedback given to the conventional training group. A: fine pinch grip with the non-essential fingers flexed. B: fine pinch grip with the non-essential fingers extended. Right: Example of spider plot with three movements plotted. The spider plot shows the root mean square of the EMG for each channel and serves as a simplified representation of the feature space with each movement represented by one coloured shape. Possible overlap can be visually perused and the experimenter can guide the participant to minimize it. The blue shape represents variation A of fine pinch and the green shape represents variation B of fine pinch. The red dotted shape represents an example movement that has considerable overlap with variation B of fine pinch. In this case, the experimenter would ask the participant to try variations of fine pinch such as variation A, to find the variation that causes the least overlap with the movement represented by the red dotted shape. Figure taken from (Kristoffersen et al., 2019).

Post-test

The post-test was identical to the pre-test except that the game training group used movements learned in the game instead of the predefined movements used in the pre-test. This means the two groups were performing the same task, but used different movements (i.e. where the conventional group would use movements such as pronation or supination, the game group would use movements corresponding to moving the avatar up or down etc.).

Coaching metrics for conventional training group

Metrics on EMG pattern separability, consistency and variability were calculated and used by the experimenter to coach the participants in the conventional training group, for a schematic overview see Figure 5.

Figure 5. Schematic overview over all coaching metrics and EMG-based outcome variables. Each shape represents an EMG pattern and the colour of the pattern determines the movement it belongs to. A: Example of small Mean Semi-principal Axis (MSA) and small Within-class Distance (WD). B: Example of Large MSA and small WD. C: Example of large MSA and large WD. MSA

measures variance and can be depicted as the size of an EMG cluster. WD measures pattern consistency between repetitions of the same movement. D: Example of long (top, dark green and brown) and short (right side, beige and pink) Inter-class Distance All Neighbours (IDAN) measured from the grey example class. E: Example of Inter-class Distance Nearest Neighbour (IDNN) and Most Separable Dimension (MSD) measured from the green example class. E, top left: long IDNN and short MSD (yellow). E top: Short IDNN and short MSD (red). E right: short IDNN and long MSD (blue). IDAN, IDNN and MSD all measure pattern separability. IDAN measures the average distance to all neighbours. IDNN measures the distance to the nearest neighbour. MSD measures the length of the most separable dimension.

Feedback on EMG pattern separability

To measure EMG pattern separability, the distance between EMG patterns of different movements was measured. We defined the separability metric Inter-class Distance Nearest Neighbor (IDNN) as the distance between two patterns defined as half the Mahalanobis distance in feature space between the centroids of movements i and j (Kristoffersen et al., 2019):

$$dist_j^i = \frac{1}{2} \sqrt{(\mu_{Ti} - \mu_{Tj})^T * S_{Ti}^{-1} * (\mu_{Ti} - \mu_{Tj})} \quad (1)$$

$$dist_i^j = \frac{1}{2} \sqrt{(\mu_{Tj} - \mu_{Ti})^T * S_{Tj}^{-1} * (\mu_{Tj} - \mu_{Ti})} \quad (2)$$

$$IDNN_i = \min_{j=1, j+1, \dots, 7} \frac{dist_j^i * dist_i^j}{dist_j^i + dist_i^j} \quad (3)$$

Where μ_{Ti} and μ_{Tj} denote the feature vector centroids of the training data from movement i and j , respectively. S_{Ti} and S_{Tj} are the covariance of the training data from movement i and j , respectively.

Feedback on EMG pattern consistency

To measure EMG pattern consistency, we measured the distance between EMG patterns from repetitions of the same movement. We defined the consistency measure Within-class Distance (WD) as the distance between two patterns defined as half the Mahalanobis distance in feature space between repetition r and k of movement j (Kristoffersen et al., 2019):

$$dist_{kj}^{rj} = \frac{1}{2} \sqrt{(\mu_{Trj} - \mu_{Tkj})^T * S_{Trj}^{-1} * (\mu_{Trj} - \mu_{Tkj})} \quad (4)$$

$$dist_{rj}^{kj} = \frac{1}{2} \sqrt{(\mu_{Tkj} - \mu_{Trj})^T * S_{Tkj}^{-1} * (\mu_{Tkj} - \mu_{Trj})} \quad (5)$$

$$WD_j = \sum_{k=1}^3 \frac{dist_{kj}^{rj} * dist_{rj}^{kj}}{dist_{kj}^{rj} + dist_{rj}^{kj}} \quad (6)$$

Feedback on EMG pattern variability

To measure EMG pattern variability, we measured the size of the EMG patterns for each movement using the Mean Semi-principal Axis (MSA) measure defined by (6):

$$MSA_j = \left(\prod_{k=1}^{32} a_k \right)^{\frac{1}{32}} \quad (7)$$

Where a_k is the geometric mean of the semi-principal axes of the 32-dimensional hyperellipsoid.

Outcome variables

The outcome variables used in this study measure EMG separability, EMG consistency and control performance. EMG variability was not used as an outcome measure even though it was used as feedback for the conventional training group. We used EMG variability as feedback since it has been used in previous research (Bunderson & Kuiken, 2012; Powell & Thakor, 2013). However, no evidence has been found that it relates to performance which is why we did not formulate a research question and a hypothesis related to EMG variability.

Differences in separability of EMG patterns

To assess the differences in separability of EMG patterns, we measured EMG pattern separability between the two training groups. We defined three measures for pattern separability; Inter-class Distance Nearest Neighbor Total ($IDNN_{Total}$), Inter-class Distance All Neighbours (IDAN)

and Most Separable Dimension (MSD) (Kristoffersen et al., 2019). Notation of (8), (9) and (10) follows that of (1) and (2).

$$IDNN_{Total} = \frac{1}{7} \sum_{i=1}^7 IDNN_i \quad (8)$$

$$IDAN = \frac{1}{7} \sum_{i=1}^7 \left(\frac{dist_j^i * dist_i^j}{dist_j^i + dist_i^j} \right) \quad (9)$$

$$MSD = \frac{1}{7} \sum_{i=1}^7 \max_{d=1, \dots, 32} \left(\min_{j=1, j+1, \dots, 7} \frac{dist_j^i * dist_i^j}{dist_j^i + dist_i^j} \right) \quad (10)$$

For MSD the feature vectors of dist (μ_{Ti} and μ_{Tj} in (1) and (2)) are calculated for each of the 32 dimensions (4 features times 8 channels, $d=1, \dots, 32$) and the dimension where the distance is the largest (max) is then used to calculate MSD

Differences in consistency of EMG patterns

To assess differences in consistency of EMG patterns, we measured EMG pattern consistency by measuring the WD over all movements and taking the mean. We define WD_{Total} as:

$$WD_{Total} = \frac{1}{7} \sum_{j=1}^7 WD_j \quad (11)$$

Differences in PR control

To assess differences in PR control, we computed the online accuracy from the Motion Test. The online accuracy was defined as the percentage of time during which the participants performed the movement so that the classifier could correctly identify whether such movement was (or was not) performed with the level of force required. Online accuracy was chosen as it is the most used metric for measuring control performance when performing screen-based tests (Ortiz-Catalan et al., 2013).

Data analysis

Differences in age and gender distribution between the groups were analysed using Chi-Square tests. All outcome variables $IDNN_{Total}$, $IDAN$, MSD , WD_{Total} and online accuracy were analysed using repeated measures ANCOVAs using pre-test values of number of successful movement trials as the covariate (see section “Motion test”). The within-subjects factor was test (pre-test vs post-test), and group (game vs conventional) was the between-subjects factor. Post-hoc testing was done using T-tests with Bonferroni correction and was performed when the results of the ANCOVAs were significant. The level of significance was set at $\alpha < 0.05$. Results are reported using mean $\pm$ standard error of the mean (SEM).

4.3 Results

Twenty-five people participated in the study (Game: N=13, 6 women and 7 men, age=21.3±0.44 (mean ±SEM); Conventional: N=12, 7 women and 5 men, age=22.33±1.06). No significant differences in the age or the gender distribution of the participants were found between groups. At the post-test, all participants in the game group used movements learned in Myobox.

Differences in separability of EMG patterns

The covariate, number of successful movement trials in the pre-test, was not significantly related to IDNN_{Total}, IDAN and MSD. No significant effects were found for IDNN_{Total}. The analysis on IDAN revealed no significant main effects. Interestingly it showed a significant interaction effect for test and group ($F(1,22) = 9.165$; $p = .006$). Post-hoc testing revealed that participants in the game group increased their IDAN significantly ($t(12) = -5.086$; $p > .001$, $r = .82$), while the conventional training group did not ($p = .135$). See Figure 6. No significant effects were found for MSD.

Figure 6. Inter-class Distance All Neighbours (IDAN) for each session for all participants (N = 25). For the conventional training group data from the last system training is shown per session. The bottom and top

box edges denote the 25th and 75th percentile respectively. The white dot denotes the median and the black diamond the mean. Outliers are marked with black plus signs. Abbreviations: Conventional (Conventional training), Game (Game training).

Differences in consistency of EMG patterns

The covariate, number of successful movement trials, was not significantly related to WD_{Total} . No significant effects were found for WD_{Total} , see Figure 7.

Figure 7. Within-class (WD) for each session for all participants (N = 25). For the conventional training group data from the last system training is shown per session. The bottom and top box edges denote the 25th and 75th percentile, respectively. The white dot denotes the median and the black diamond the mean. Outliers are marked with black plus signs. Abbreviations: Conventional (Conventional training), Game (Game training).

Differences in PR control

The covariate, number of completed movements, was significantly related to online accuracy ($F(1,22) = 17.52$; $p > .001$, $\eta^2 = .443$). The analysis on online accuracy revealed a significant main effect of test ($F(1,22) = 8.03$; $p = .01$, $\eta^2 = .267$) with an increase between pre- and post-test ($62\% \pm 2.27\%$; $78\% \pm 3\%$, Figure 8). The main effect of group and the interaction effect were not significant. However, as can be seen in Figure 8, the conventional group appears to reach a skill ceiling at the second session and do not appear to improve much in the following sessions. The game group on the other hand show some improvement over all sessions especially for the worst performers. Furthermore, at the post-test the worst performer in the game group had an online accuracy that was more than 40% lower than the best performer in the game group.

Figure 8. Online accuracy for each session for all participants ($N = 25$). For the conventional training group data from the last system training is shown per session. The boxes show data from all participants, where the bottom and top edges denote the 25th and 75th percentile, respectively. The white dot denotes the median and the black diamond the mean. Outliers are marked with black plus signs. Abbreviations: Conventional (Conventional training), Game (Game training),

4.4 Discussion

The results showed, in line with our hypothesis, that participants who trained with a serious game generated EMG patterns that were significantly more separable than those of participants who underwent conventional training. However, participants in the game group did not achieve more consistent patterns nor better control of the classifier output, as measured by online accuracy, compared to those in the conventional group. This is surprising, as previous research has identified the separability of EMG patterns as the metric that explained the superior performance of those skilled in PR control compared to novices (Bunderson & Kuiken, 2012).

Serious games can be used to train PR control

Participants in the game group improved control of the classifier output to the same extent as participants in the conventional training group. This shows that game-based training with an external focus of attention exploiting implicit learning processes can be used to train PR control. However, some participants were having difficulties to transfer their skills from the game to the test. While the results for the game group are promising, some improvements are still needed if game training should replace conventional training. If skill transfer can be improved, there is a great potential using games like MyoBox for user training for PR control, as the generated EMG patterns are on average almost 50% more separable and for the best performers more than twice as separable compared to the best performers in the conventional training group.

That serious games show potential for user training for PR control might benefit users if transfer has been improved. A major benefit of using games with an external focus of attention and implicit learning is that the training exploits stages of motor control that are presumed to require less cognitive effort (Kal et al., 2013), which might be beneficial as patients have reported that PR control takes a lot of cognitive effort during training (Franzke et al., 2019) and use (Moran et al., 2019; Resnik et al., 2018). In addition, game-based training can offer individualized feedback that is tailored to the participants skills and learning goals and can be done at home without additional clinical resources. Furthermore game based training can result into higher training exposure, as training is more motivating (K. Lohse et al., 2013). The motivational aspect can be further improved by using commercial games for training by applying the continuous RMS control scheme used in Myobox. Commercial games provide entertainment beyond what can be developed in clinical practice and users can play a game of their favourite genre. These games are also more likely to make the trainee reach the flow state (Csikszentmihalyi, 1990), in which an appropriate challenge makes the trainee completely focused on the task at hand. The learning rate is improved when trainees are in the flow state (Vervaeke et al., 2018; Wulf & Lewthwaite, 2016). However, care should be taken so that the commercial games still require

that the user controls the avatar in all directions as to promote the generation of separated EMG patterns. Moreover, transfer of abilities in those games need to be explicitly tested (van Dijk et al., 2016a, 2016b).

More separated patterns do not lead to better control

While participants in the game group had more separable EMG patterns, their control performance, as measured by the online accuracy, was not better than that in the conventional training group. This relation was suggested by Bunderson and Kuiken (Bunderson & Kuiken, 2012), but very few studies have investigated if it holds true. We suggest that future research investigates the relation between EMG pattern separability and online accuracy and whether there are other metrics that correlate with online accuracy.

However, that higher EMG pattern separability does not necessarily translate to higher online accuracy does not mean that there is no relation between more separated patterns and control, as they both increased significantly from pre- to post-test. It might be the case that beyond a certain threshold, more separated patterns do not lead to better control, e.g. if patterns do not overlap, it might not improve control to separate them further. Nevertheless, this is speculation as our data cannot confirm this. Another possible reason why the game group did not perform better than the conventional training group is that the conventional training group had more training in performing the Motion test since the training and test platform were the same. A question for future research is which type of training will have the best skill-transfer if the test in the pre- and post-test will be different from the test used during training. Especially, if the task involves functional prosthesis use where non-stationarity effects such as limb position and weight will have a greater impact on control. In such a task, more separated patterns might eventually lead to better control.

(Dis)advantages of conventional versus game training

PR control is often described as being intuitive, because this control is based on (phantom) movements that match the mode of the prosthesis. One of the aims of conventional training is to adapt the intuitive muscle contractions to make them more separable from one another. A downside of this approach is that the more the intuitive muscle contractions are adapted, the less intuitive they become (Resnik et al., 2018). We argue that these adaptations and the way they are being taught is one of the main reasons that PR control achieves comparable performance to conventional myoelectric prosthetics (Kuiken, Miller, et al., 2016; Resnik et al., 2018) or lower (Mastinu et al., 2018; Roche et al., 2015; Vujaklija et al., 2017). Game based training instead utilizes the adaptability of people and let them define their own muscular contractions that they can use for control. One of the benefits with game-based training is that an external focus

of attention and implicit learning processes can be exploited.

A disadvantage of the control scheme used in the game is that movements that generate symmetrical patterns, e.g. EMG activity on both sides of the arm, will not lead to avatar movement and thus might not be used even though they are separated from other patterns. This means that some separated patterns might go unused, which might limit the number of DoFs a user can control. From our experiences such EMG patterns might come from a co-contraction or a (phantom) fist. We suggest that if game training fails to provide the number of desired DoFs, muscle contractions that result in symmetrical EMG patterns should be added under the supervision of a therapist during system training. In this way, the therapist can verify that the added muscle contraction does not interfere with the trained muscle contractions. For the same reason, we included “fist” as the first muscle contraction to be added in case the participant did not learn enough muscle contractions while playing Myobox. It should be noted however, that all participants in the game group used muscle contractions learned while playing Myobox at the post-test, i.e. that the fist muscle contractions never had to be manually added in this fashion.

Transfer

In the current study, training was similar to the Motion test that was used to assess the training effect. However, the requirements for good functional prosthesis use, which is the ultimate end-goal of training, are quite different from the Motion test. Good functional prosthesis use requires matching the aperture of the hand to the size of the object being grasped (Bouwsema et al., 2010) and fine control of the speed of the hand (proportional control) (Bouwsema et al., 2014). The Motion test contains none of these requirements. Therefore, it is not certain that a high performance in the Motion test leads to a high performance when controlling a PR controlled prosthetic hand. This also means, that training as presented in this study might not lead to an improved functional prosthesis use. The reason that we used the Motion test for both training and testing was because this study investigated changes at the EMG level and not at the functional level. Therefore, transfer effects were not investigated. To increase the chance that there will be transfer of training to functional prosthesis use, we do have some suggestions on what training should entail. First, training should require the user to adjust an aperture to match objects. Second, training should require the user to adjust the speed when adjusting an aperture. A game using augmented feedback i.e. feedback on the procedural aspects of the task demands, to reinforce these constraints has shown promising results training able-bodied participants to operate a one DoF prosthetic simulator (van Dijk et al., 2016b). We suggest implementing these recommendations in future versions of Myobox to improve transfer.

Limitations

This study had some limitations. Participants were able-bodied and the outcome measures did not measure functional prosthetic use. We recruited able-bodied participants to measure the effect of game training in a homogenous population before moving on to a heterogeneous patient population. In this way, we can ensure that game training might have an effect before spending resources recruiting patients. However, this still means that our results cannot be directly applied to prosthetic control for individuals with upper limb absence. In addition, the training and test platform was the same for the conventional training group and partly so for the game group. As a consequence, participants might have improved during testing. However, considering that all training was performed between the two tests we believe this had a very minor influence on the results as exposure to the test was low compared to the training.

4.5 Conclusion

A serious game with an external focus of attention using implicit learning can be used by PR control trainees to generate EMG patterns more separated than those learned from conventional training. Participants training using the game reached similar consistency in generating EMG patterns and similar control of the PR classifier output as participants who followed conventional training even though they did not receive coaching. Serious game training therefore appears to be a viable alternative to conventional training schemes.

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Appendix

Extra predefined movements for game group:

1. Fist
2. Stretch fingers
3. Wrist flexion
4. Wrist extension
5. Flex pinky finger
6. Key grip
7. Fine pinch
8. Pronation
9. Supination

USER TRAINING FOR MACHINE LEARNING
CONTROLLED UPPER LIMB PROSTHESES:
A SERIOUS GAME APPROACH

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Abstract

Background: Upper limb prosthetics with multiple degrees of freedom (DoFs) are still mostly operated through the clinical standard Direct Control scheme. Machine learning control, on the other hand, allows controlling multiple DoFs although it requires separable and consistent electromyogram (EMG) patterns. Whereas user training can improve EMG pattern quality, conventional training methods might limit user potential. Training with serious games might lead to higher quality EMG patterns and better functional outcomes. In this explorative study we compare outcomes of serious game training with conventional training, and machine learning control with the users' own one DoF prosthesis.

Methods: Participants with upper limb absence participated in 7 training sessions where they learned to control a 3 DoF prosthesis with two grips which was fitted. Participants received either game training or conventional training. Conventional training was based on coaching, as described in the literature. Game-based training was conducted using two games that trained EMG pattern separability and functional use. Both groups also trained functional use with the prosthesis donned. The prosthesis system was controlled using a neural network regressor. Outcome measures were EMG metrics, number of DoFs used, the spherical subset of the Southampton Hand Assessment Procedure and the Clothespin Relocation Test.

Results: Eight participants were recruited and four completed the study. Training did not lead to consistent improvements in EMG pattern quality or functional use, but some participants improved in some metrics. No differences were observed between the groups. Participants achieved consistently better results using their own prosthesis than the machine-learning controlled prosthesis used in this study.

Conclusion: Our explorative study showed in a small group of participants that serious game training seems to achieve similar results as conventional training. No consistent improvements were found in either group in terms of EMG metrics or functional use, which might be due to insufficient training. This study highlights the need for more research in user training for machine learning controlled prosthetics. In addition, this study contributes with more data comparing machine learning controlled prosthetics with Direct Controlled prosthetics.

5.1 Introduction

In recent years, multiarticulate myoelectric prosthetic hands controlled using machine learning (ML) algorithms have been brought from the labs to the clinics by both commercial enterprises (Coapt Engineering, n.d.; Infinite Biomedical, n.d.; OttoBock, n.d.) and research groups (Kuiken, Miller, et al., 2016; Mastinu et al., 2018; Resnik et al., 2018; Roche et al., 2015; Vujaklija et al., 2017). ML control can reveal the full potential of multiarticulate hands, as the clinical standard two-site “Direct Control” (DC) scheme is currently one of the main limiting factors in prosthetic control. In contrast to DC, ML control does not require isolated subsequent electromyographic (EMG) signals derived from two electrodes to control all available grip modes, but utilizes more intuitive control generated by patterns of muscle contractions (Franzke et al., 2019). However, ML control currently suffers from robustness issues while DC is faster in tasks that only require one degree of freedom (DoF) (Kuiken, Miller, et al., 2016; Resnik et al., 2018).

The benefit of ML control is that the user does not need to actively switch between DoFs or grips. Unlike DC, ML control is not based on a direct mapping from each muscle to a direction in a DoF: It performs a complex mapping between EMG activity and control commands, thus allowing the user to generate a potentially larger set of control commands. EMG patterns are measured on the residual muscles in the stump using an array of electrodes, commonly between four to eight, then features are calculated from the EMG and used as input for a learning algorithm which maps the features to prosthetic control commands. ML control should lead to the utilisation of at least a few DoFs and grips. Use of more DoFs might reduce compensatory movements of the trunk and shoulders which are areas with many complaints for people with upper limb absence (Postema et al., 2016). Therefore, ML control might lead to better function and reduce the risk of pain and further impairment.

Independent of whether DC or ML control is used, user training is required to skilfully control a myoelectric prosthesis. For DC, training focuses on contracting the two muscles used independently from each other and on executing switching commands. For ML control training focuses on adapting the (phantom) movements used for control to achieve the most distinct EMG patterns, and on performing the movements consistently (Powell & Thakor, 2013; Roche et al., 2015; Simon et al., 2012). A coach assists the trainee in selecting how the movement(s) should be adapted by studying the feature space. Such adaptations mostly focus on the non-essential fingers e.g. flexing the little finger while performing a pinch. Adaptations retain the basis of the original movement (e.g. thumb and index finger touching), but by adding the non-essential part (e.g. flexing the little finger) the generated EMG pattern changes and becomes more distinct from other movements. We refer to this training scheme as conventional training.

Conventional training has some drawbacks. Firstly, training requires a coach, which restricts training to the clinic leading to increased costs and limited training exposure. Furthermore, coaching relies on declarative statements such as “when doing the pinch, flex the phantom little finger” which induces an internal focus of attention (i.e. focus on body parts) that, compared to an external focus of attention (i.e. focus on the result), may lead to slower and less accurate motor performance as well as increased cognitive effort (Wulf & Lewthwaite, 2010). Lastly, the possible separation of EMG patterns is limited by using movements that correspond to the actuation of the prosthesis (e.g. phantom fine pinch leads to prosthetic fine pinch). Possible movements which are not prioritised due to limited functional benefits might generate more separable EMG patterns than the movements which resemble the actuation of the prosthesis (Kristoffersen et al., 2020; Na et al., 2017).

As an alternative to conventional training, we suggest the use of serious games. Serious games have as purpose to teach or train a skill while keeping the trainee engaged with entertaining challenges and individualised feedback (Garcia-Agundez et al., 2019; Garcia-Hernandez et al., 2019; van Diest et al., 2013). Other benefits of serious games are that the trainee focuses on the screen which induces an external focus of attention. Furthermore, serious games can facilitate implicit learning as the game gives a safe environment that allows for experimentation so that the trainee can find the best solution to the challenge without being told to explicitly. Serious games have been used to train proportional control and switching grip modes, as commonly used in commercial upper-limb prosthetics (Prahm et al., 2019; Tabor et al., 2018; van Dijk et al., 2016b).

We have previously used a serious game to train ML control in able-bodied participants (Kristoffersen, Franzke, van der Sluis, Murgia, et al., 2020). We found that game training led to more separable EMG patterns than conventional training with coaching, while performance was similar when evaluating real-time classifier performance using a screen-based test. However, since the participants were able-bodied it is unknown if these results are also applicable to individuals with upper limb absence (ULA), since the neuromuscular changes caused by amputation affects the EMG (Campbell et al., 2020; Kristoffersen, Franzke, van der Sluis, Bongers, et al., 2020). Furthermore, it is also unknown if and to what extent game performance transfers to functional prosthesis use, as transfer to functional use has not been explicitly tested with serious games and is the most important metric to gauge a new training scheme. The purpose of this exploratory study was to compare game training with conventional training using coaching for individuals with ULA when learning ML based control, using measures of functional prosthesis use. Specifically, we asked if game-based training leads to 1) more separated and consistent EMG patterns, 2) a higher rate of improvement in EMG pattern separability and consistency

as result of learning, 3) use of more degrees of freedom and 4) better outcomes in functional prosthesis use, compared to conventional training with coaching. In addition, we performed baseline measurements using the participants' own prosthesis to contribute with additional data for comparing DC with ML control as proposed by Resnik *et al.* (Resnik *et al.*, 2018).

5.2 Methods

Participants

The study was approved by the ethics committee of the University Medical Center Groningen (METc 2018.268). To be eligible for inclusion the participants had to meet the following criteria: Adults with unilateral upper limb absence at the transradial or wrist level. Both individuals with an upper limb deficiency caused by amputation or congenital deficiency were included. Individuals had to use DC. All participants gave written informed consent before the start of the first session. After training was completed, participants were awarded a gift voucher for their participation.

Prosthesis and Socket

This study used the Michelangelo Hand (Otto Bock, Germany, Ref: 8E500=R-M) which was fitted with a custom wrist flexion/extension unit and a wrist rotation unit (AxonRotation, Otto Bock, Germany, Ref: 9S503). The Michelangelo hand could perform open hand, fine pinch, lateral pinch, wrist rotation and wrist flexion/extension.

The sockets were 3D-printed using antibacterial thermoplastic (Otto Bock, Germany, Ref: 616T269) based on a 3D scan of the participant's stump. The printed socket was adjusted by a certified orthopaedic technician for optimal fit. A connector for the Michelangelo hand was attached to the socket using a bespoke adapter made in Cellacast (Lohmann & Rauscher, Germany, Ref 25 202). Furthermore, eight bipolar Otto Bock Myo plus Electrodes with amplifiers (Otto Bock, Austria, ref: 13E401=G140-60) were placed equidistantly (i.e. not targeted) around the socket using a numbered positioning band (Otto Bock, Austria, Ref: 623F50) according to the manufacturer's specification (Otto Bock, 2019) avoiding the location corresponding to the ulnar bone. The battery pack was strapped on the upper arm using an adjustable Velcro band placed proximal from the elbow joint. See Figure 1.

Figure 1. An example of the complete prosthetic setup as used in the study attached to a left arm. While all participants used the same setup, the positioning of the amplifiers and adapter differed slightly between participants to accommodate for a different anatomy.

The socket and the battery pack were worn during training, but the Michelangelo hand was only worn during functional training (see section Functional Training) and when performing the pre/post-test (see Pre/post-test).

Machine Learning

The ML control system consisted of three components: (1) feature extraction, (2) regression between EMG features and hand movement commands, (3) post-processing of movement commands to improve usability and suppress possible errors.

To compute features, the eight-channel raw EMG data were windowed into overlapping windows of 128 ms with a step size of 50 ms; in a real-time application this allows to transmit control commands at 20 Hz with less than 200 ms delay. Hudgins-style time-domain features (Hudgins et al., 1993), namely the framewise mean absolute value, zero crossing rate, waveform length, and slope sign change, were computed and z-normalized before further processing.

A feed-forward neural network was used as a regressor to compute hand movement commands from the pre-processed EMG data. The neural network used two fully connected hidden layers with 50 and 25 neurons respectively, each followed by a tanh nonlinearity, and a final linear layer with as many output neurons as hand movements. Thus, for each window of EMG data, four vectors with desired strengths corresponding to each possible DoF/grip (fine/lateral pinch, wrist rotation, wrist flexion/extension, hand open) was computed, enabling simultaneous proportional control of all DoFs. Each vector was represented as a number between -100 and 100, where negative/positive values represented the two directions of a DoF and 0 represented no activation of the DoF. The neural network was trained on mini-batches of 64 EMG windows

using a mean squared error regression loss and the ADAM optimizer (Kingma & Ba, 2015), with early stopping on a randomly chosen validation set of 10% of the entire training data. In the case that the vectors representing fine/lateral pinch and hand open both differed from zero, the vector with the lowest absolute value was discarded as the prosthetic hand cannot close in a pinch and open at the same time.

Training data for the algorithm were recorded using the following EMG recording procedure. For each movement, the maximum voluntary contraction was performed to establish a baseline. Following baseline measures, each movement was recorded three times, where the participant was asked to follow a trapezoidal reference line (Amsuss et al., 2014) with a maximum of 30%, 60% and 90% maximum voluntary contraction for five seconds. During this recording, the contraction force was estimated from the real-time EMG activity and plotted on a screen visible to the subject together with the reference force, thus providing biofeedback to the subject. Over the course of user training, the EMG recording procedure was repeated several times, as described below.

Initially, hand open and fine pinch were trained, thus making the control comparable to DC and making the initial use of the system easier for the user. As participants progressed through the training scheme, more movements were added, namely whenever both the participant and the experimenter considered control to be robust using a qualitative assessment. Apart from the pre-training (see Pre-training) the algorithm was always trained on data from the most recent five EMG recording procedures. Five was chosen as a compromise in order to supply the algorithm with sufficient data and at the same time account for changes in the EMG patterns resulting from user training. The EMG recording procedures were performed with the arm in one of three postures: hanging down by the side, resting on the armrest of the chair or reaching in front with the arm stretched out. At least one set of data from each posture was used to train the algorithm.

A moving average post-processing filter was implemented, where the average was taken over the last four regression outputs; this setup was found useful to suppress recognition outliers and provide a smoother hand control.

Study design

Participants were randomly assigned to either the game training group or the conventional training group using a computer program. Participants in both groups followed the same training scheme, but with different content during training. The scheme consisted of 11 sessions. In the first session the stump of the participant was scanned, so a 3D-printed socket could be

made (see Materials) and the baseline measure was performed (see Baseline). In the 2nd session the participant performed pre-training (see Pre-training). In the third session, the pre-test was performed (see Pre/Post-test). Session 4-10 were training sessions (see Training). The last session was a post-test that was identical to the pre-test. Pre-training (session 2) and post-test (session 11) were scheduled within one month leading to two to three training sessions per week, see Figure 2. This scheme was a compromise between having enough sessions to detect a difference and making recruitment of participants feasible (Powell et al., 2014; Resnik et al., 2018).

Figure 2. Overview over the sessions.

Baseline measurement

The participant performed the baseline measurement using their own DC prosthesis. The baseline consisted of two parts; the spherical subset of the Southampton Hand Assessment Procedure (SHAP) (Light et al., 2002) and The Clothespin Relocation Test (CRT) (Kuiken et al., 2005; Kyberd et al., 2018). The spherical subset of the SHAP consists of 4 tasks: moving the light sphere, moving the heavy sphere, pouring water from a carton, and opening a jar. The time for each SHAP task was recorded and converted to a score between 0 and 100 where 100 represents able-bodied performance. We used the method described by Burgerhof *et al.* to calculate the SHAP score (Burgerhof et al., 2017). The CRT was setup with 6 pins, 3 yellow pins (resistance 4.44 N) placed on the vertical bar and 3 red pins (resistance 8.89 N) placed on the horizontal bar. Participants were asked to move one red pin to the other horizontal bar, then move a yellow pin down the vertical bar followed by another red pin etc. The time to move all clothespins and the number of dropped clothespins were recorded. The participant was not given a time penalty for dropping pins.

Pre-training

Pre-training started by briefly introducing the participant to ML control and how it differs from DC. Pre-training differed depending on group allocation, either the game training group or the conventional training group. Participants in the game training group trained using the MyoBox game (see game training group) for ten minutes, followed by three EMG recording procedures for open hand and fine pinch. Participants in the conventional training group trained with a coach for ten minutes to find two phantom movements or muscle contractions that could be used to activate the open hand and fine pinch commands of the prosthesis. After the ten minutes with the coach, the participant performed three EMG recording procedures for open hand and fine pinch.

At the end of pre-training for participants in both groups, the Michelangelo hand was connected to the socket. The participant was then given five minutes in which they could get acquainted with the hand and the control.

Pre/Post-test

Before starting the pre-test and post-test, two EMG recording procedures were performed to get 'fresh' data. The movements recorded before the pre-test were the same as in the pre-training. Data from the preceding five EMG recording procedures were combined to train the ML algorithm.

The contents of the pre-test and post-test were identical and consisted of the SHAP and CRT as in the baseline measurements. The test order was randomised between participants but was kept the same for each participant between the pre- and post-test.

User training

User training sessions lasted between 45 and 60 minutes depending on the amount of rest needed by the participant. The participant could rest between each part of the training if needed. Initially, training focused on adding wrist rotation in addition to hand open and fine pinch. When the participant had good control over these two DoFs, lateral pinch would be added and lastly wrist flexion/extension. At the end of each training session the participant performed five minutes of functional training (see Functional training).

Game training group

The game training group trained using two games named MyoBox and Prosthesis Gripper. Myobox was designed to maximise separation of EMG patterns (Kristoffersen et al 2020) and Prosthesis Gripper was designed to train functional prosthesis use. Prosthesis Gripper was

originally designed for DC (Heerschop et al., 2020; van Dijk et al., 2016b), but was adapted for ML control. In each session, participants played both games for approximately 10 minutes.

In MyoBox players controlled a ball which functioned as the game avatar using EMG. The goal of the game was to collect boxes by hitting them with the ball while staying on the platforms, see Figure 3 upper right. The ball was controlled using a direct mapping between the root mean square (RMS) of the EMG of each electrode and avatar direction, see Figure 3. The direction was calculated as:

$$y = \frac{RMS_2 + RMS_3 + RMS_4}{3} - \frac{RMS_6 + RMS_7 + RMS_8}{3} \quad (1)$$

$$x = \frac{RMS_1 + RMS_2 + RMS_8}{3} - \frac{RMS_4 + RMS_5 + RMS_6}{3} \quad (2)$$

Where y is the vertical direction and x is the horizontal direction. RMS_x corresponds to the arrows and numbers in Figure 3.

To obtain the goal in Myobox, players had to explore different muscle contractions and learn which muscle contractions made the ball move in the desired direction. As the participant learned the control and progressed through MyoBox, the game became more difficult by decreasing the platform width. In this way, participants had to control the ball with higher precision to avoid falling off the platform, see Figure 3 upper right. Since participants would learn to control the ball in the game without initially connecting the muscle contractions they learn to the actuation of the prosthesis, this mapping strategy might be unintuitive at first. However, it has been shown to be potentially more robust (Kristoffersen, Franzke, van der Sluis, Murgia, et al., 2020) and consequently the risk that the neural network makes a misclassification might be smaller. As a result of the mapping, the EMG patterns generated by the muscle contractions used to control the ball in different directions were distinct. These patterns were later used to train the ML algorithm. For more details about MyoBox see also (Kristoffersen, Franzke, van der Sluis, Murgia, et al., 2020).

After playing MyoBox, an ML algorithm was trained using the muscle contractions learned by playing MyoBox. The real-time control output of the ML algorithm was then used to play the game Prosthesis Gripper. Prosthesis Gripper trained two aspects: proportional control and grasping.

Proportional control was trained using a tracking task, where the participant had to control the game avatar left or right, see Figure 4A1. In the beginning of training when focus was on training wrist rotation, the muscle contractions corresponding to wrist rotation moved the avatar left and right. Similarly, when focus was on training wrist flexion/extension, the muscle contractions

corresponding to wrist flexion/extension moved the avatar left and right. In the tracking task, participants controlled the avatar, so it followed a light that moved from the centre of the screen to one of the sides. When the avatar was close enough, a beam would show, and the participant was awarded points, see Figure 4A2. If the avatar were too far away from the light, the participant would lose points. When the light reached the edge of the screen it would stop moving. When this happened, the participant had to get the avatar under the light for one second after which the light would disappear and be replaced by a dispenser indicating the start of training for grasping, see Figure 4B.

Figure 3. Mapping of RMS to avatar control. Left: placement of electrodes on a left arm, with electrode 1 corresponding to RMS_1 , electrode 2 corresponding with RMS_2 etc. Upper right, A: First orientation of Myobox. The player controls the orange ball at the bottom and is tasked with collecting the three orange boxes while staying on the light blue platform. Upper right, B: First orientation of Myobox with the smallest

possible platform size in the game. Lower right: directions of the avatar. The colour and the number inside of the arrows correspond with the coloured electrode number on the left-hand side of the figure.

Figure 4. Prosthesis Gripper with inserts showing different game situations. Main screen shows the gripper about to grasp a blue box which corresponds to fine pinch. Bottom right corner shows the required grip. Top right corner shows the score, which was always visible. Insert A1, tracking task where the avatar must follow the light. Insert A2, a beam shows when the avatar is close enough and points are awarded and written on screen (green numbers). Insert B, after the tracking task is completed, the player must activate the grip corresponding to the colour of the dispenser at the top. This must be done before the hourglass shown on the dispenser runs out. Insert C, when the object has been grasped, it turns green and the player must release it again. Insert D, when the object is released, a thousand points is awarded. Insert E, if the gripper is opened too much, sparks showed, and the gripper would force close.

Grasping was trained with a stationary game avatar being a gripper. First, the participant had to activate the grip corresponding to the colour of the dispenser at the top of the screen (blue for fine pinch, red for lateral pinch, see Figure 4), within ten seconds. A grip was activated when the ML algorithm output for that DoF was ± 25 while all other DoFs were between 0 and ± 24 . If the grip was not activated within ten seconds, the game would go back to proportional control training. When the grip was activated, the dispenser would drop an object. The object fell towards the gripper and the participant had to first open the gripper and then grip it using the correct grip based on the colour of the object. The gripper could maximally open up to 1.7 times the width of the object. If the gripper was opened more than 1.5 times the width of the object, sparks would show, see Figure 4E. If the gripper was fully opened, it would force close itself. This constraint was added to the game to avoid that the participants fully opened the gripper every

time, as skilled prosthesis users match the opening of the hand to the size of the object they are grasping (Bouwsema et al., 2010). In addition, some of the objects were fragile (indicated with cracks, see Figure 4E) and when such an object was presented the participant had to be careful not to close the gripper too forcefully, otherwise the object would break. When an object was successfully grasped, the participant had to release it again to earn points and proceed to proportional control training, see Figure 4C-D.

Conventional training group

Training for the conventional training group followed three steps: EMG recording procedure, two times Motion Test and coaching. The system training procedure was conducted as described in the Machine Learning section of this paper. The Motion Test (Kuiken et al., 2009) is a computer-based test designed to assess the control a participant has over the ML output, but in this study it was used as a training tool. In the Motion Test the participant conducted several movement trials. In each movement trial, the test prompted the participant with a movement at a specific force level that the participant had to perform. The participant had to perform the movement in such a way that the ML algorithm output was the highest for the prompted movement at the correct force level for two seconds within a six second duration window. The force level corresponded to the force levels used during the EMG recording i.e. 30%, 60% and 90% with a margin of 15%, 20%, and 30% respectively. The number of movement trials depended on the number of trained movements. Each trained movement resulted in three movement trials corresponding to the trained force levels. The Motion Test was performed two times in a row. After the second Motion Test, the participant received coaching from the experimenter. The coaching was based on a spider plot which showed a simplified representation of the feature space. The representation showed the RMS of the EMG patterns, see Figure 5.

The coaching followed the work of Powell and Thakor (Powell & Thakor, 2013). The principle was to make EMG patterns as separate as possible by adapting the phantom movement of the participant. For participants with no phantom limb sensation, Powell and Thakor suggested that participants “mimic the muscle activity of their intact limb”. The coach asked the participant to perform variations of the phantom movements (muscle contractions) used for training. As an example, when performing a fine pinch, the index, ring and little finger can be either flexed or extended (or a combination thereof). When the participant performs the different variations of a fine pinch, the coach will observe the feature space as shown in Figure 5 and determine which variation is most separate from the other movements. Coaching was given by two Dutch students in Human Movement Science (University of Groningen) who had been trained to this effect. Coaching was always done under supervision of either MBK or AWF.

In each session, the three steps i.e. EMG recording, two times Motion Test and coaching, were repeated three times. See Figure 6 for an overview over both training groups.

Figure 5. Example of the spider plot used in conventional training. The spider plot shows the RMS of the EMG for each channel and serves as a simplified representation of the feature space with each movement represented by one coloured shape. Possible overlap can be visually perused, and the coach can guide the participant to minimize it.

Functional training

Functional training consisted of grasping an object from a table and placing it on a box (height 21cm) and grasping an object from the box and placing it on the table. Three objects were used; a plastic lid, a 0.5 L plastic bottle filled with water and a plastic single-use cup. The training protocol was:

1. Grasp bottle placed horizontally on the box, rotate and place vertically on the table
2. Grasp plastic lid placed vertically from the table, rotate and place horizontally on the box
3. Move plastic cup placed on the table to the box.

The protocol was repeated for 2.5 minutes while sitting in front of the table. After a break, the protocol was repeated for 2.5 minutes while standing in front of the table. The different objects and their orientations were chosen to promote the use of wrist rotation and the different grips. If participants tried to perform the protocol using only one grip and compensatory movements, they were encouraged to use wrist rotation or other grips.

Figure 6. Overview of the training sessions for the training groups. Length of each activity is written above the pictograms. Top row: Game training starting with Myobox, followed by three times EMG recording, Prosthesis Gripper and ending with functional training. Bottom row: Conventional training starting with three times combined EMG recording, Motion Test and coaching and ending with functional training.

Data analysis

To answer the research questions related to the separability and consistency of EMG patterns metrics measuring these properties were calculated and reported for each participant. The separability metrics were the Inter-class Distance Nearest Neighbour (IDNN) and Inter-class Distance All Neighbours (IDAN). The consistency metric was the Within-class Distance (WD). We report the mean of each of these metrics per session. These three metrics were taken from (Kristoffersen et al., 2019).

To answer the research question related to the number of DoFs used, the number of DoFs used by each participant at the post-test was reported, since this differed from the pre-test.

To answer the research question related to functional outcomes, the scores of the SHAP and CRT were reported for each participant separately using the ML controlled prosthesis and the participants' own DC prosthesis (baseline).

5.3 Results

Eight participants were recruited, and four participants completed the training protocol, see Table 1. Participant P6 had to cancel his last training session and therefore trained one session less than the other participants. Four participants did not complete the training protocol due to poor socket fit, fatigue, or issues with scheduling appointments (Table 1).

Table 1. Characteristics of the participants.

Acronym	Sex	Age	Acquired limb loss?	Own prosthesis	Group	Completed
P1	F	52	Yes	Conventional 1 DoF	Game	No. Was excluded before pre-test due to poor socket fit
P2	F	39	No	Conventional 1 DoF	Conventional	Yes
P3	M	59	No	Conventional 1 DoF	Game	Yes
P4	M	47	Yes	Conventional 1 DoF	Conventional	No. Dropped out during pre-test due to fatigue
P5	M	49	Yes	Multi-articulate multiple DoFs	Conventional	Yes
P6	M	56	Yes	Multi-articulate multiple DoFs	Game	Yes
P7	M	52	Yes	Conventional 1 DoF	Game	No. Dropped out after baseline measure due to scheduling conflicts
P8	M	74	Yes	Conventional 1 DoF	Conventional	No. Dropped out during baseline measure due to fatigue

M: Male, F: Female, DoF: Degree of Freedom, DoFs: Degrees of Freedom P: participant number

EMG pattern separability and consistency

To answer research questions 1 and 2 related to EMG pattern separability and consistency we plotted the EMG metrics calculated from the pre-test, each training session and post-test in Figure 7 and 8. Figure 7 shows the WD, which is a measure of the consistency of the EMG patterns where lower WD corresponds to more consistent EMG patterns, for individual participants. Most participants had erratic changes in WD except for participant P3 (game) who after the second training session showed a steady reduction in WD. On the group level there appear to be no clear difference between both groups in terms of reduction of WD or rate of improvement.

Figure 7. Within-class Distance (WD) per participant. Lower WD indicates better performance. Participants in the game group are plotted in solid colour, while participants in the conventional group are plotted with dashed lines. Participant P6 had to cancel his last training session (session 7) so participant P6 has no data for this session. All sessions except for the Pre-test used two DoFs.

Figure 8 shows the IDNN and IDAN metrics which measure the separability of EMG patterns. Higher IDNN and IDAN correspond to more separable EMG patterns. Most participants showed a minor increase in IDNN and IDAN except for participant P5 (conventional) who achieved high IDNN and IDAN during training until the post-test.

Functional outcomes

The results from the spherical subset of the SHAP are shown in figures 9 and 10 and the results from the CRT are given in Figure 11. Training in either group did not appear to have improved performance in a consistent manner. Furthermore, baseline measurements with the user's own prosthesis appeared to be consistently superior to either test using ML. Note that all participants controlled one DoF at the pre-test and two DoFs at the post-test.

Figure 8. Left: Inter-class Distance Nearest Neighbour (IDNN) per participant. Right: Inter-class Distance All Neighbours (IDAN) per participant. Higher IDNN/IDAN indicate better performance. Participants in the game group are plotted in solid colour, while participants in the conventional group are plotted with dashed lines. Participant P6 had to cancel his last training session (session 7) so participant P6 has no data for this session. All sessions except for the Pre-test used two DoFs.

Figure 9. Times for completing each of the four SHAP tasks per participant. Participants in the game

group are in solid colour, while participants in the conventional group are shaded. Baseline was conducted before training using the participants' own DC prosthesis. Pre- and post-test was conducted using the Michelangelo hand controlled with ML. In the pre-test all participants used one DoF and in the post-test participants used two DoFs.

Figure 10. SHAP scores for the spherical subset of the SHAP per participant. Higher scores reflect better performance. Participants in the game group are in solid colour (P3, P6), while participants in the conventional group are shaded (P2, P5). Baseline was conducted before training using the participants' own DC controlled prosthesis. Pre- and post-tests were conducted using the Michelangelo hand controlled with ML. In the pre-test all participants used one DoF and in the post-test participants used two DoFs.

Figure 11. Times for completing the clothespin relocation test per participant. Lower time scores indicate better performance. The number written above each bar indicates how many pins were dropped (maximum = 6). Participants in the game group are in solid colour (P3, P6), while participants in the conventional group are shaded (P2, P5). Baseline was conducted before training using the participants' own DC controlled prosthesis. Pre- and post-tests were conducted using the Michelangelo hand controlled with ML. In the pre-test all participants used one DoF and in the post-test participants used two DoFs. Participant P3 was unable to grasp any of the yellow clothespins at the pre-test, so the time is for the red clothespin only.

5.4 Discussion

The aim of this explorative study was to assess if game-based training leads to 1) more separated and consistent EMG patterns, 2) a higher rate of improvement in EMG pattern separability and consistency as result of learning, 3) use of more degrees of freedom and 4) better outcomes in functional prosthesis use, compared to conventional training with coaching.

Separability and consistency of EMG patterns

In terms of EMG separability, participants P2, P3 and P5 all show a trend towards higher separability, but the increase was not very consistent over the training sessions. Especially participant P5 showed a major increase in separability during training, but at the post-test his separability was almost the same as it was at the pre-test. For participant P3, the increase in IDAN was promising for game-based training, as an increase in IDAN was also found in able-bodied participants who trained using games (Kristoffersen, Franzke, van der Sluis, Murgia, et al., 2020). Game training using movements that do not match the actuation of the prosthesis (e.g. prosthetic fine pinch is not activated by phantom fine pinch) can lead to more separable EMG patterns. A similar strategy could also be applied to conventional training, but it might have limited efficacy due to the internal focus of attention and the declarative statements of the coach.

In terms of EMG consistency, only participant P3 had a consistent decrease (lower is better) from the 2nd training session. From these results we see no indication that game-based training could lead to more separated and consistent EMG patterns. Furthermore, we see no indication that game-based training could lead to a higher rate of improvement in EMG pattern separability and consistency. However, neither conventional nor game training seemed to lead to consistent improvements which might be due to the number of training sessions (discussed later) or the robustness of ML control. If ML control is not robust, participants will hardly improve but instead spend their training time adapting to the system. From this perspective, it might be better to not retrain the ML algorithm as often as it was done in this study, and instead have the participant spend more time learning the peculiarities of a trained ML algorithm for a longer period of time. However, this also means that performance will be limited by the quality of the trained ML algorithm and a ML algorithm that is not well trained might be unusable. Future research should investigate how learning is affected by keeping the ML algorithm (near) constant and compare with a ML algorithm that is retrained at every session.

Use of more degrees of freedom

All participants controlled two DoFs at the post-test. From these results we see no indication that game training could lead to the use of more DoFs than conventional training. This can however be expected given our results that game training did not seem to lead to more separable EMG patterns.

None of the participants was sufficiently skilled at controlling two DoFs at the time the training was completed, so adding the third DoF was not considered. From our experience in running the experiment, we consider it more important that participants have robust control of a few DoFs, than adding additional DoFs that might deteriorate control. However, we would argue that in the long run users benefit from the use of more DoFs.

Functional outcomes

Functional outcomes did not seem to improve as a result of training for either group. Therefore, we see no indication that game training leads to better functional outcomes. It is important to underline that the post-test was performed using an extra DoF (compared to the pre-test) which might have reduced the robustness of the control. We observed that some participants prioritised using the additional DoF over completing the tasks as fast as possible. While participants knew that the outcome of the tasks was time, they also were encouraged to utilise both DoFs during functional training. It can be hypothesized that participants who used two DoFs might have had a reduced amount of compensatory movements. Compensatory movements can lead to overuse resulting in pain and reduced mobility (Datta *et al.*, 2004; Jones & Davidson, 1999; Østlie *et al.*, 2011). Reducing compensatory movements might therefore be a more important goal than reducing completion times in functional tasks. Outcome measures evaluating the movement quality should therefore be part of future studies.

Length of training

To our surprise, training did not seem to lead to consistent improvements in terms of EMG patterns nor led to improved performance in functional tests. Comparable results were obtained in the study by Resnik *et al* (Resnik *et al.*, 2018) where improvements in the Jebsen Taylor Hand Function page turning test showed erratic behaviour. This is in contrast with the study by Kuiken *et al* (Kuiken, Miller, *et al.*, 2016) where training led to improved functional performance. However, the participants in the study of Kuiken *et al* trained for at least four hours prior to a one-month home trial which is considerably more than in the current study and in the study by Resnik *et al*. It is likely that with additional training and use, participants in our study would have improved and eventually achieved better performance with ML control. We suggest future studies include more training and home training in order for participants to achieve good control.

Comparing Direct Control and Machine Learning control

To provide additional data for comparing DC with ML control, we performed baseline measurements as proposed by Resnik *et al.* (Resnik et al., 2018) using our participants' own DC prostheses. Similarly, to Resnik *et al.* we found that DC control seems to outperform ML control. However, it should be noted that all participants in our study had several years of experience using their own DC prosthesis and were naïve to both the prosthesis hand used in the current study as well as ML control. Therefore, it is possible that with sufficient training participants would have been able to achieve better performance with ML control than with DC. A study by Kuiken *et al.* supports this claim (Kuiken, Miller, et al., 2016). In their study, they showed that after one month of home use, participants tended to have better performance using ML control than DC. Future research should investigate longer training periods and/or home trials using the same prosthesis and control algorithm. A serious game as proposed in this study might be beneficial for such studies as participants can train at home without supervision using such games.

Recommendations for future studies

During this study we learned several new things we believe are helpful for future training studies using ML control. Firstly, pre-training before performance assessments ensures that participants have some basic control and understand the basic concepts of ML control. Secondly, the importance of the socket fit should not be underestimated. Any non-ideal fit in terms of user comfort or electrode-skin contact will likely have a drastic negative impact on control performance. In pilot testing we had used sockets made of plaster under the guidance of an orthopaedic technician and while initial results were promising, the plaster sockets were not robust enough when applying weight to the prosthesis which led to noise in the EMG and discomfort. We therefore advise any research group to manufacture professional sockets in trials with prolonged (home) use. Thirdly, increasing DoFs gradually appeared to be a good way to ease participants into ML control and made the transition from DC to ML control easier. Lastly, including functional training as part of the training scheme gave participants the opportunity to learn how external factors like weight and posture affects control which helped them to adapt.

Limitations

The main limitations of this study are the limited sample size and the number of training sessions. While we recruited eight participants, half of them dropped out of the study for various reasons. Unfortunately, due to limited resources, we were unable to find new participants to replace those that dropped out of the study. In terms of the number of training sessions, we made a trade-off between resources, providing sufficient training and making participant recruitment feasible. We believe recruiting participants will become more difficult if more training sessions

are added, but from our results it is also evident that additional training sessions are needed. We suggest that future research combines training sessions with a lengthy home trial. In our case, a home-trial was not feasible due to time constraints, limited financial resources, hardware availability and safety issues. Given that there are now at least two commercial ML control systems on the market in Europe and in the US, it should be feasible in future research to conduct a lengthy home-trial. Finally, our study only provides quantitative data which does not capture the users' satisfaction with the training scheme and the control. Such data could be measured using qualitative methods such as questionnaires which might reveal a preference for either control method which is not directly related to the functional performance we captured.

5.5 Conclusions

To conclude, we have shown that serious games might be used for ML control training with the target population, as we found similar results in the game group compared to the conventional group. In addition, we found no consistent improvement in terms of EMG separability and consistency and no improvements in functional outcomes. However, control of two DoFs might require more training than what was provided in this study and with more training improvements in EMG metrics and functional outcomes might improve. Furthermore, we have provided additional data and knowledge regarding ML control versus DC which adds to the data from previous research by Resnik *et al* and Kuiken *et al*. Research efforts should be combined to reach larger sample sizes in order to provide more evidence for different training schemes.

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In Memoriam

The work presented in this chapter would not have been possible without the invaluable assistance of Jessie Geene. Jessie helped us creating the sockets for our participants and was always very helpful answering our questions and helping us with practical matters.

6

DISCUSSION & CONCLUSION

*This period in history may be an appropriate
time to evaluate priorities and to cast them
into a future perspective.*

R. Wirta, Pattern-Recognition Arm
Prosthesis: A Historical Perspective -
A Final Report, 1978

The goal of this thesis was to investigate current training methods and develop new training methods based on serious games.

To investigate current training methods, we decided to recruit able-bodied participants. The reason for recruiting able-bodied participants was to ensure that we would be able to recruit a sufficient high number of participants. As a first step we assessed how much the myoelectric signals of able-bodied individuals differ from those of individuals with upper limb absence. In chapter 2 we compared the myoelectric signals of the able limb and the remnant limb of individuals with upper limb absence and found a significant difference between the two. Furthermore, we found that restricting the able limb by using a wrist brace reduced this difference. While our results are preliminary, we found that there are differences between able-bodied individuals and individuals with upper limb absence. We also found that these differences can be somewhat mitigated. I think this is important, as the recruitment of able-bodied participants is required to reach sufficient sample sizes to conduct preliminary research. In addition to restricting the able limb by using a wrist brace, I would recommend that future studies employ prosthesis simulators/bypass sockets (Paskett et al., 2019) to measure functional performance with able-bodied participants. However, I want to emphasise that after conducting preliminary research with able-bodied participants, steps should be taken to recruit individuals with upper limb absence to verify results obtained with able-bodied participants.

6.1 Current training methods

Our initial investigation of current training methods concerned three groups of able-bodied participants who received one of three levels of feedback: no external feedback, visual feedback or visual feedback with coaching (chapter 3). This study was setup to disentangle the feedback commonly used in conventional training which consists of visual feedback with coaching. Our hypothesis was that the group with visual feedback and coaching would outperform the no external feedback and visual feedback groups. Furthermore, we expected to see group specific changes to the myoelectric signals as a result of training. To our surprise, we found no significant differences between the groups in terms of performance. In addition, the only difference we found in terms of the myoelectric signals was for the no external feedback group which had

higher signal variance and amplitude compared to the visual feedback group. That the visual feedback group achieved similar results as the visual feedback with coaching group shows that machine learning myoelectric control can be learned without a coach. This is essential for a serious gaming approach as one of the main benefits of serious gaming is that it can be done at home at the discretion of the user. Furthermore, the visual feedback group received implicit feedback and had an external focus of attention (as there was no coach asking them to focus on their body) which shows that similar feedback and focus of attention can be used by a serious game.

6.2 Serious gaming for training distinct and repeatable signals

In chapter 4 conventional training (i.e. visual feedback and coaching) was compared with a serious game called Myobox. Myobox is a serious game in which the player controls a ball in two dimensions (see chapter 4, Figure 1) in order to pick up boxes that are placed on a platform above a void. Myobox is controlled using the myoelectric signal and requires that the player generates the correct signal to control the ball towards the boxes while staying on the platform. The more distinct signals the player can generate, the higher the precision of the control. We hypothesised that playing Myobox would teach players to generate more distinct signals (i.e. training A depicted in chapter 1, Figure 4B) which is a presumed requirement for machine learning myoelectric control (Bunderson & Kuiken, 2012; Nilsson et al., 2017a; Powell et al., 2014). Our results showed that Myobox players significantly increased the distinguishability of their myoelectric signals while the participants in the conventional group did not. However, while we found no significant differences in terms of performance between the two groups, there was high variability in the group that played Myobox. This was surprising, as higher distinguishability has been assumed to correlate with better performance (Bunderson & Kuiken, 2012; Nilsson et al., 2017a; Powell et al., 2014). There are a few possible explanations to this discrepancy: firstly, it might be that when the myoelectric signals reach a certain level of distinguishability, further separation does not lead to better performance. This could be the case when the machine learning algorithm has near-perfect offline accuracy and the user is able to replicate the signals well (which is not uncommon in a laboratory setting). Another reason might be that the task specificity was not high enough between playing Myobox and performing the recording session/Motion test which caused a lack of transfer. Anecdotally, we observed that some participants could not generate a certain myoelectric signal without the focus and feedback of the game. This is an example of lack of transfer and an example that trainees can become so dependent on the feedback in the game that they cannot perform without it. One way to improve transfer is to increase task specificity between the training task and the goal task. However, achieving high task specificity between training to generate distinct and repeatable myoelectric signals and the recording session/Motion test is not trivial as the feedback and task constraints are very different. One

of the ways task specificity could be improved is by making the task in Myobox more similar to the recording session. In the recording session, participants had to modulate their myoelectric signal so it followed a trapezoidal reference (chapter 3, Figure 1). A similar task could be added to Myobox, where the player would need to modulate their myoelectric signal while controlling the ball in the right direction. Another option would be to add the feedback of Myobox to the recording session or even record the signals while the player is playing Myobox in order to skip the recording session entirely. While I believe all of these options are viable, we instead decided to add a new game to our training scheme which focused on transfer to functional prosthesis use.

6.3 Serious gaming for functional prosthesis use

For training functional use we adapted a serious game called Prosthesis Gripper where players were able to transfer their skill from the game to functional prosthesis use with a direct controlled prosthesis mounted on a prosthesis simulator (van Dijk et al., 2016b). In Prosthesis Gripper (chapter 5, Figure 4) players control a gripper using machine learning myoelectric control and the goal of this game is to catch boxes of varying widths by opening the gripper sufficiently (but not too much) and close it on the box at the right time with the right grip. Players who play Prosthesis Gripper learn to adapt the aperture of the prosthetic hand to match the width of the object, which is a characteristic of skilled prosthesis users (Bouwsema et al., 2010).

Prosthesis Gripper was adapted so that it was controlled using a machine learning algorithm and different movements were added as Prosthesis Gripper only required opening and closing the hand. Prosthesis Gripper was tested in conjunction with Myobox where Myobox trained the user to generate appropriate myoelectric signals before the recording session (i.e. training A depicted in chapter 1, Figure 4B) and Prosthesis Gripper trained the control of the machine learning algorithm trained on those same signals (i.e. training B depicted in chapter 1, Figure 4B).

This serious gaming scheme with two games was compared to conventional training in chapter 5 where individuals with upper limb absence was recruited. The serious game group and the conventional training group received pre-training before baseline measurements, and they trained for an additional seven sessions over a month. Both groups used the neural network developed by the INPUT project (see chapter 5 for details) and each training session ended with functional training with the prosthesis donned. We found that training did not lead to improvements for either group in terms of improved myoelectric signals or in functional outcomes. The lack of improvement after training might be due to insufficient training as discussed in chapter 5, but it might also be because training was ineffective or because machine learning myoelectric control is not suitable for functional use. Whether training or machine

learning myoelectric control (or both) is the cause of the lack of improvement, it means that machine learning myoelectric control is not intuitive and is not ready for clinical use.

6.4 The assumption of machine learning myoelectric control

The upper limb prosthetic field has not really discussed the underlying assumption of machine learning myoelectric control. The assumption, that every user intent (or movement) is manifested as a unique, repeatable myoelectric signal.

The human motor system has an abundance of DoFs (Bernstein, 1967). These Dofs are the result of the number of muscles and joints and the interplay between them. There are various hypotheses regarding how the motor control system decides which DoFs it should use, which is also known as the Degrees-of-Freedom problem. However, so far no consensus has been reached on the solution to the Degrees-of-Freedom problem. This abundance of DoFs means that for the same task, the motor system might change which DoFs to use, while at the level of the performance no change is observed. All the causes for these changes in DoFs is not known, but known examples are environmental changes and fatigue. Nevertheless, for machine learning myoelectric control changes in DoFs manifests itself as changes in the myoelectric signals. These changes are at odds with the assumption of machine learning myoelectric control that user intent is manifested as a repeatable myoelectric signal. To the best of my knowledge, this has not been studied.

Besides the Degrees-of-freedom-problem, people do not have very good control of their myoelectric signal even under laboratory conditions. A study by Johnson and colleagues (Johnson et al., 2017) compared myoelectric control with torque control and torque control + noise. The noise was modelled after the noise seen in myoelectric signals. Their results show that even though EMG and torque + noise had very similar signal to noise ratios, the control of torque + noise was significantly better than control of the myoelectric signals. Importantly, subjects in the study improved their control in the torque + noise condition throughout the experiment, meaning that the torque + noise condition was learnable. In contrast, the subjects in the myoelectric signal condition did not improve their performance. This result illustrates that the problems of myoelectric control are beyond noise and might relate to people's ability to consciously generate specific myoelectric signals. This finding might be problematic for machine learning myoelectric control as it requires that people can learn to generate several specific myoelectric signals. Ultimately, this might mean that machine learning myoelectric control might not progress beyond two or three degrees of freedom.

6.5 Tasks, not movements

Machine learning myoelectric control works at the level of movements. The recording session procedure for machine learning myoelectric control follows a procedure in which the movements of the hand is the basis. The user is asked to perform a movement such as “open hand” in a steady or varying contraction (e.g. when the hand is opened, the user must stretch the fingers to keep the contraction) for a few seconds. This is repeated a few times with breaks in between for each movement. The resulting dataset contains one sub-dataset per movement. This means that the algorithm is trained to recognise movement intent. However, in accordance with self-organising theories of motor control, people do not think in terms of movements, but in terms of actions and tasks. By movement I refer to the displacement of (prosthetic) body parts whereby an action is the step towards completion of a task. As an example: people who are thirsty think that they need to grasp the glass and drink. They do not think that they need to (1) extend their elbow while extending their fingers, (2) flex their fingers around the glass and flex their elbow, (3) open their mouth and pronate their forearm and (4) swallow.

Instead of thinking that the user should be able to control two degrees of freedom (four movements), maybe they should be able to perform four tasks? Tasks could be grasping, drinking, eating, and holding. Such tasks might generate more repeatable myoelectric signals in real-life than those of static movements, because the task constraints are the same when recording the myoelectric signals and when performing functional tasks. While this would be a major departure from how machine learning is done for upper limb prosthetics, it has been done for lower limb prosthetics (e.g. (Young et al., 2014)). For lower limb prosthetics control using machine learning it is common to detect the type of gait instead of the movement of the user. Gaits include walking and ascending/descending stairs and ramps. The job of the machine learning algorithm is to first detect the correct gait and then detect where in the gait cycle the user is. Whether such an approach would lead to transfer and thus more robust control for upper limb prosthetics compared with the current state of the art is unknown, but I think it would be very interesting to investigate.

6.6 Brave New World

Several challenges on training machine learning myoelectric control as well as challenges in the machine learning myoelectric control paradigm itself have been formulated in this thesis. However, there are also some very exciting developments that might improve the lives of people with upper limb loss by making prosthetic control more intuitive.

Firstly, I want to mention the introduction of machine learning myoelectric control to the market. Until a few years ago machine learning myoelectric control did not exist outside of academia

which meant that studies would have small sample sizes and use non-standardised hardware/software. Now that machine learning myoelectric control is offered to end-users, there is hope that larger studies using the same hardware will be conducted which might reveal information on the basis of which to solve some of the problems experienced today.

Secondly, I want to mention the introduction of new control paradigms that are not based on classification. A limitation of most implementations of machine learning myoelectric control is that they are based on classification which means that the output is binary. In practice this means that very small changes in the myoelectric signal can make the difference from one prosthesis movement to another. This puts a high strain on the precision of the user. Hahne and colleagues have demonstrated that machine learning based on linear regression is a viable alternative (Hahne et al., 2018). The benefit of linear regression is that the output is a vector containing a value for each DoF. The resulting output is thus on a scale and a small change in motor control should only lead to a small change of the output. This should lead to more intuitive control, as the control is more gradual and it should be more clear for the user how a change of motor control changes the control of the prosthesis. Another benefit of linear regression is that a skilled user can do simultaneous movements such as closing the hand while flexing the wrist¹. Simultaneous movements are also possible using the neural network regressor developed as part of the INPUT project, but none of our participants managed to utilise it. Another interesting line of research is the one of Dyson and colleagues (Dyson et al., 2020). They have introduced (based on the same work that inspired the design of the Myobox game) an abstract decoder for myoelectric control. This abstract decoder requires that the user learns to activate their muscles individually which is unintuitive at first. However, with training they have shown promising results in virtual tasks with patients and have demonstrated transfer to similar virtual tasks. This is an example of a control paradigm which abandons the idea that control should be “natural” (i.e. that phantom hand open leads to prosthetic hand open). However, as long as the control can be learned I do not think this is a problem as people have a good capacity to learn things even though they are not natural.

Lastly, I want to mention the introduction of implanted systems with sensory feedback. Ortiz-Catalan and colleagues demonstrated a bone-anchored “osseointegrated” human-machine gateway (Ortiz-Catalan et al., 2014, 2020). This system allows a connection between electrodes implanted on the muscles and nerves to communicate directly with the prosthesis. Measuring the myoelectric signal directly on the muscle instead of on the skin gives a much higher signal to noise ratio and less crosstalk compared to measuring the myoelectric signal on the skin. In

¹ This is also possible with classification schemes but requires that the system is trained on the combined movement e.g. open hand + flex wrist.

addition, all the non-stationarity problems, caused by limb movement, sweat and temperature changes are eliminated. The system is also more comfortable than conventional systems since it does not rely on a socket to attach the prosthesis to the body. Lastly, the system is also capable of giving sensory feedback via cuff electrodes on the median and ulnar nerve. Improved myoelectric signals that are robust combined with sensory feedback should lead to more intuitive control. The downside of this system is that it requires surgery which is not an option for everyone.

6.7 Conclusion

The goal of this thesis was to investigate current training methods and develop new training methods based on serious games. I found that current training methods led to changes in the myoelectric signals, but coaching was not required for these changes to happen. A serious game called Myobox was developed and playing the game led to distinct myoelectric signals. Another serious game called Prosthesis Gripper was adapted to train functional use. However, in the target population training with the games or current training methods did not lead to improved functional control of a machine learning myoelectric controlled prosthetic hand. This result illustrates the challenges of training machine learning myoelectric control, but also other challenges in the field of machine learning controlled upper limb prosthetics. Serious games might be beneficial in learning machine learning myoelectric control, but at the moment it is not clear how one learns machine learning myoelectric control. The focus for future research should therefore be to better understand how machine learning myoelectric control is learned. Until we understand how machine learning myoelectric control is learned, it is unlikely that the clinical reality of myoelectric prosthesis users will change. However, there have been several promising developments that might lead to intuitive, and maybe even, natural control.

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Summary

The aim of this thesis is to investigate current training methods for learning to control a state-of-the-art hand prosthesis and develop new training methods based on serious games. State-of-the-art prosthetic hands are controlled using the myoelectric signal (electromyography, EMG) which is a small electric current that can be measured using electrodes that are placed on the skin above muscles when muscles are activated. By placing electrodes on the affected limb of a person with upper limb absence a myoelectric signal can be measured when they contract a muscle in the affected limb. By using machine learning (artificial intelligence) methods, the movement intent of the user can be determined by analysing the myoelectric signal. The intent can then be translated into a control command for the prosthetic hand. However, the myoelectric signal must satisfy certain requirements for the machine learning algorithm to successfully decode the movement intent. The requirements are that for each movement intent the myoelectric signal must be distinct and repeatable. While laboratory results using machine learning control looks promising, the results of real-world tests show that machine learning control is not very robust. The main reason for this disparity is due to non-stationarities affecting the myoelectric signal. Such non-stationarities include limb position, sweat and fatigue, which all cause changes in the myoelectric signal. A lot of research has been conducted to mitigate the non-stationarities, but an alternative route is to train the user to generate myoelectric signals that are more distinct and repeatable, which makes them more robust to the non-stationarity changes. User training has not received a lot of attention in the literature, but usually user training is conducted with a coach that guides the user on how to contract their muscles to improve their myoelectric signals. However, coaching has some limitations such as low training exposure and the use of explicit feedback and internal focus of attention (focus on body parts). An alternative way of training is the use of serious games. Serious games are games that are entertaining while teaching the player a skill which is applicable in real-life. The benefits of serious games is that they do not require a coach, can provide instantaneous implicit feedback, and leads to an external focus of attention (focus on the task/goal). The goal of this thesis is to investigate current training methods and develop new training methods based on serious games.

The first chapter is a general introduction to upper limb prosthetics and motor learning. The chapter briefly describes the types of upper limb prosthetics, its history and how machine learning has been applied and the challenges faced. It continues with a brief description of motor learning theories and details how conventional user training for a machine learning myoelectric controlled prosthesis is performed. It ends with a description of serious games that have been applied to prosthetic training in research and why the transfer of skills from game to real-life should be prioritised.

The second chapter is an investigation into how the myoelectric signal of an able limb can be made more like the myoelectric signals of the affected limb of an individual with upper limb absence. Most research in upper limb prosthetics is conducted on able-bodied participants as the population of individuals with upper limb absence is scarce. However, there is more and more evidence suggesting that the myoelectric signals of able-bodied participants differ from the myoelectric signals of individuals with upper limb absence. It has been hypothesised that the myoelectric signals can be made alike by restricting the hand and wrist of able-bodied participants. To test this hypothesis, the myoelectric signals of individuals with acquired limb loss were compared between the affected and unaffected limb in two conditions: with the unaffected limb restricted or not. This comparison was performed in three different arm postures: down, front and up. It was found that the unaffected limb generated more distinct myoelectric signals. Furthermore, restriction lowered the separability of the unaffected limb in the arm down posture. This indicates that limb restrictions make the myoelectric signal of able-bodied participants more similar to those of individuals with upper limb absence.

The third chapter investigates the role of feedback for conventional training for machine learning controlled myoelectric prosthetic hands and how myoelectric qualities, such as signal distinguishability and repeatability, correlate with task performance. Three levels of feedback were compared: no external feedback, visual feedback, and visual feedback with coaching. Able-bodied participants were recruited and assigned to one of the three training groups. All participants trained a machine learning myoelectric control task on a screen for five consecutive days. We hypothesised that higher levels of feedback would lead to better outcomes and that the distinguishability and repeatability of the myoelectric patterns would differ between the groups. We found that all participants improved after training and that higher levels of feedback did not lead to improved task performance compared with lower levels of feedback. However, we did find that training with no external feedback led to higher myoelectric signal amplitudes than the other types of feedback. We found no correlation between myoelectric signal qualities and task performance. The chapter concludes that the mechanisms behind user training for machine learning myoelectric controlled prosthetics is not straightforward, but that training seems to be possible without a coach.

The fourth chapter compares conventional training employing visual and coaching feedback with a serious game that was developed for the study. The serious game was called Myobox and was controlled using the myoelectric signals of the player. The goal of the game was to move a ball over a platform and collect boxes by hitting them with the ball while avoiding falling into a void. The ball was controlled using a direct mapping from each electrode to a direction of the ball. Unlike conventional training, Myobox players use an external focus of attention as

they focus on the screen and not on their bodily movements. Furthermore, Myobox players receive implicit feedback which helps them improve without instructing them on how to do so. The game was designed to train the player to generate more distinct myoelectric signals. Able-bodied participants were recruited and trained for five days following either conventional training or serious game training. We found that both groups improved after training while we found no difference between the groups. Furthermore, we found that the myoelectric signals of participants who followed serious game training were 51% more distinct than the myoelectric signals of participants who followed conventional training. The chapter concludes that serious gaming using an external focus of attention and implicit learning can be considered a viable alternative to conventional training.

The fifth chapter investigates training of functional prosthesis use with either conventional training with visual and coaching feedback or serious game training. In addition, the chapter also compares functional performance of the participants' own prosthesis and the machine learning myoelectrical controlled prosthesis they are trained to use. Serious game training consisted of two different games: Myobox (chapter four) and Prosthesis Gripper. Prosthesis Gripper was adapted from previous research where it had successfully shown to promote skill transfer to functional prosthesis use with a conventional one degree of freedom myoelectric prosthesis. In Prosthesis Gripper, players control a gripper, and the goal of the game is to catch objects falling from the ceiling by opening the gripper sufficiently (but not too much) and close the gripper using the right grip. Some of the objects are fragile and, in this case, players must be careful not to use too much force, otherwise the object will break. Both groups also donned a prosthesis and trained functional prosthesis use by moving objects. The prosthesis had three degrees of freedom and two grips and was controlled with a novel neural network algorithm. Participants with upper limb absence were recruited for this study and they participated in eleven sessions. The sessions were: One session for 3D-scanning their stump for making a socket, one session for fitting the prosthesis and pre-training, one session for pre-test, seven training sessions and one post-test session. The fitting session and the post-test session were conducted within a month from each other. We found that training did not lead to consistent improvements in functional prosthesis use or in the metrics of the myoelectric signals. In addition, we found that participants had consistently better task performance using their own prosthesis. The chapter concluded that more research in user training for machine learning controlled myoelectric prosthetics is needed.

The sixth and last chapter summarises the thesis and discusses the wider implications of the results which is that machine learning myoelectric control is not intuitive and will probably not progress beyond control of three degrees of freedom. The underlying assumptions of

machine learning control are discussed, and a new perspective focusing on tasks instead of movements is introduced which might lead to more robust control. Lastly, an outlook on some recent promising developments, such as new control paradigms and implanted systems are highlighted. Finally, the thesis concludes that serious games might be beneficial for training machine learning controlled myoelectric prostheses, but that the underlying mechanisms are unclear and a better understanding of how machine learning myoelectric control is learned in general is needed.

Samenvatting

Het doel van dit proefschrift is de huidige trainingsmethoden waarmee een state-of-the-art handprothese aangestuurd wordt te onderzoeken en om nieuwe trainingsmethoden te ontwikkelen waarbij serious games gebruikt worden. State-of-the-art prothese handen worden aangestuurd met behulp van een myo-elektrisch signaal (elektromyografie, EMG). Het EMG is een elektrisch stroompje dat kan worden gemeten met elektroden die op de huid boven de spieren worden geplaatst als de onderliggende spieren geactiveerd worden. Door elektroden te plaatsen op de aangedane arm van een persoon met een amputatie of aangeboren defect van de bovenste extremiteit, kan een myoelektrisch signaal worden gemeten wanneer spieren in de aangedane extremiteit geactiveerd worden. Door machine learning (kunstmatige intelligentie) methoden te gebruiken, kan de bewegingsintentie van de gebruiker vastgesteld worden via het analyseren van het myo-elektrische signaal. Deze bewegingsintentie kan vervolgens worden vertaald in een commando die naar de prothese wordt gestuurd. Het myo-elektrische signaal moet wel voldoen aan bepaalde vereisten voor het machine learning algoritme om de bewegingsintentie met succes vast te stellen. De vereisten zijn dat voor elke bewegingsintentie het myoelektrische signaal onderscheidend en herhaalbaar moet zijn. Hoewel machine learning-besturing in laboratorium testen veelbelovend lijken, laten de resultaten in de praktijk zien dat machine learning-besturing niet erg robuust is. De belangrijkste reden voor dit verschil wordt veroorzaakt door afwijkingen in het EMG signaal als gevolg van de ledematen, zweet en vermoeidheid. Een manier om deze afwijkingen te verminderen is de gebruiker te trainen om myo-elektrische signalen te genereren die onderscheidend en herhaalbaar zijn, waardoor ze minder afwijkingen bevatten. Gebruikerstraining heeft niet veel aandacht gekregen in de literatuur, maar meestal wordt gebruikerstraining gegeven met een coach die de gebruiker begeleidt bij het aanspannen van zijn spieren om de myoelektrische signalen te verbeteren. Coaching heeft echter enkele beperkingen, zoals een lage trainingsfrequentie en het gebruik van expliciete feedback met een interne focus (focus op lichaamsdelen). Een alternatieve manier van trainen is het gebruik van serious games. Serious games zijn games die leuk zijn om te doen, terwijl ze de speler een vaardigheid leren die in het echte leven kan worden toegepast. De voordelen van serious games zijn dat er geen coach nodig is, dat direct impliciete feedback kan worden geven en waarbij de speler een externe focus gebruikt (focus op de taak / het doel). Het doel van dit proefschrift is om de huidige trainingsmethoden te onderzoeken en nieuwe trainingsmethoden te ontwikkelen waarbij serious games gebruikt worden.

Het eerste hoofdstuk is een algemene inleiding over protheses van de bovenste ledematen en motorisch leren. Dit hoofdstuk beschrijft in het kort de typen protheses van de bovenste ledematen, de geschiedenis ervan en hoe machine learning reeds is toegepast in prothesegebruik

en de uitdagingen van deze toepassing. Het gaat verder met een korte beschrijving van motorische leertheorieën en dit hoofdstuk beschrijft hoe de huidige training voor een machine learning myoelektrisch gestuurde prothese wordt uitgevoerd. Het eindigt met een beschrijving van serious games die zijn toegepast bij prothese training in onderzoek en waarom de transfer van vaardigheden van game naar real-life prioriteit moet krijgen.

Het tweede hoofdstuk onderzoekt hoe het myoelektrische signaal van een niet-aangedane arm meer gelijkend kan worden gemaakt aan het myoelektrische signaal van de aangedane arm van een persoon met een armamputatie. Het meeste onderzoek op het gebied van protheses van de bovenste ledematen wordt uitgevoerd bij gezonde deelnemers, aangezien de populatie van personen met een armamputatie schaars is. Er is echter steeds meer bewijs dat de myoelektrische signalen van niet-aangedane deelnemers verschillen van de myoelektrische signalen van personen met een armamputatie. Uit de literatuur is de hypothese af te leiden dat de myoelektrische signalen hetzelfde kunnen worden gemaakt door de hand en pols van gezonde deelnemers te beperken. Om deze hypothese te testen, werden de myoelektrische signalen van individuen met een armamputatie vergeleken met de aangedane en niet-aangedane armen in twee omstandigheden: met de niet-aangedane arm beperkt (door het dragen van een brace) of niet. Deze vergelijking werd uitgevoerd in drie verschillende posities van de arm: naar beneden, naar voren en naar boven. Het bleek dat de niet-aangedane arm meer onderscheidbare myoelektrische signalen genereerde (een betere separability). Bovendien nam de separability van de signalen af in de niet-aangedane arm in de neerwaartse houding. Dit geeft aan het myoelektrische signaal van niet-aangedane deelnemers meer gelijkenis vertoont met dat van personen met een armamputatie als de arm beperkt wordt door een brace.

Het derde hoofdstuk onderzoekt de rol van feedback bij conventionele training van machine learning gecontroleerde myoelektrische protheses en hoe myoelektrische eigenschappen, zoals signaal-separability en herhaalbaarheid (repeatability), correleren met taakuitvoering. Drie feedbackniveaus werden vergeleken: geen externe feedback, visuele feedback en visuele feedback met coaching. Gezonde deelnemers werden gerekruteerd en toegewezen aan een van de drie trainingsgroepen. Alle deelnemers trainden gedurende vijf opeenvolgende dagen, waarbij ze een taak op een scherm uitvoerden met behulp van machine learning. Onze hypothese was dat hogere feedbackniveaus zouden leiden tot betere resultaten van de training en dat de separability en repeatability van de myo-elektrische patronen zou verschillen tussen de groepen. We vonden dat alle deelnemers verbeterden na de training, maar dat hogere feedbackniveaus niet leidden tot betere resultaten in vergelijking met lagere feedbackniveaus. We ontdekten echter dat training zonder externe feedback leidde tot hogere myoelektrische signaalamplitudes dan de andere soorten feedback. We vonden geen verband

tussen de kwaliteit van de myoelektrische signalen en de prestaties op de uitgevoerde taken. Het hoofdstuk concludeert dat de mechanismen achter gebruikerstrainingen voor machine learning myoelektrisch gestuurde protheses niet eenvoudig zijn, maar dat training mogelijk lijkt te zijn zonder een coach.

Het vierde hoofdstuk vergelijkt huidige training met visuele en coach feedback met een serious game die voor het onderzoek is ontwikkeld. De serious game heette Myobox en werd bestuurd met behulp van de myoelektrische signalen in de arm. Het doel van het spel was om een bal over een platform te sturen en zo dozen te verzamelen door ze te raken met de bal, zonder dat de bal van het platform viel. De bal werd bestuurd via een directe koppeling van elke elektrode met een richting die de bal kon opgaan. In tegenstelling tot de huidige training hebben Myobox-spelers een externe focus door zich te concentreren op het scherm en niet op hun lichamelijke bewegingen. Bovendien ontvangen Myobox-spelers impliciete feedback die hen helpt zich te verbeteren zonder hen te instrueren hoe ze dat moeten doen. De game is ontworpen om de speler te trainen meer verschillende myoelektrische signalen te genereren. Gezonde deelnemers werden gerekruteerd en gedurende vijf dagen getraind met een huidige training of een serious game-training. We vonden dat beide groepen verbeterden na de training waarbij we geen verschil vonden tussen de groepen. Verder vonden we dat de myoelektrische signalen van deelnemers die een serious game training volgden in 51% van de gevallen meer onderscheidend waren dan de myoelektrische signalen van deelnemers die een conventionele training volgden. Het hoofdstuk concludeert dat serious gaming waarbij gebruik wordt gemaakt van een externe focus of control en impliciet leren, kan worden beschouwd als een goed alternatief voor conventionele training.

Het vijfde hoofdstuk onderzoekt functioneel prothesegebruik na huidige training met visuele en coachende feedback in vergelijking met serious game training. Daarnaast vergelijkt het hoofdstuk ook het functioneel gebruik van de eigen prothese van de deelnemers met de machine learning myoelektrisch gestuurde prothese waarmee ze zijn getraind. Serious game training bestond uit twee verschillende spellen: Myobox (hoofdstuk vier) en Prothese Gripper. Prothese Gripper is een aangepaste versie van een serious game, die gebruikt is in eerder onderzoek. Met dit spel was aangetoond dat het de transfer bevordert van vaardigheden die nodig zijn voor het gebruik van een conventionele myo-elektrische prothese met één vrijheidsgraad. In Prosthesis Gripper besturen spelers een gripper, en het doel van het spel is om voorwerpen te vangen die vanuit het plafond vallen. Hiervoor dient een speler de gripper voldoende (maar niet te veel) te openen en de gripper te sluiten met de juiste greep. Sommige objecten zijn kwetsbaar en in dat geval moeten spelers oppassen dat ze niet te veel kracht gebruiken, anders breekt het object. Beide trainingsgroepen (huidig vs serious game) droegen een prothese en trainden

het functionele gebruik van de prothese door objecten te verplaatsen. De prothese had drie vrijheidsgraden en twee grepen en werd bestuurd met een nieuw neurale netwerk algoritme. Deelnemers met een armamputatie of een aangeboren armdefect werden gerekruteerd voor deze studie en zij namen deel aan elf sessies. De sessies waren: een sessie voor het 3D scannen van hun stomp voor het maken van een koker, een sessie voor het aanmeten van de prothese en pre-training, een sessie voor de pre-test, zeven trainingssessies en een post-testsessie. De aanmeet sessie en de posttest sessie werden binnen een maand na elkaar afgenomen. We vonden dat training niet leidde tot consistente verbeteringen in het gebruik van functionele prothesen of in de eigenschappen van de myo-elektrische signalen. Bovendien vonden we dat deelnemers consequent betere testresultaten hadden met hun eigen prothese. Het hoofdstuk concludeerde dat er meer onderzoek nodig is naar gebruikerstraining voor myo-elektrische prothesen door machine learning aangestuurd.

Het zesde en laatste hoofdstuk vat het proefschrift samen en bespreekt de bredere implicaties van de resultaten, namelijk dat machine learning myoelektrische controle niet intuïtief is en waarschijnlijk niet verder zal gaan dan de controle van drie vrijheidsgraden. De onderliggende aannames van machine learning worden besproken en er wordt een nieuw pad geïntroduceerd dat de nadruk legt op taken in plaats van bewegingen, wat zou kunnen leiden tot meer robuuste controle. Ook wordt een vooruitblik gegeven op enkele recente veelbelovende ontwikkelingen, zoals nieuwe besturingsparadigma's en geïmplanteerde systemen. Ten slotte concludeert het proefschrift dat serious games gunstig kunnen zijn voor het trainen van myo-elektrische prothesen aangestuurd door machine learning, maar dat de onderliggende mechanismen onduidelijk zijn en dat er een beter begrip nodig is van hoe machine learning myoelektrische

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Moving abroad is an adventure. Moving to Groningen in the “north”¹ was the kind of adventure where you meet a lot of wonderful people.

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¹ The local slogan is *er gaat niets boven Groningen* meaning nothing is above Groningen (figuratively and literally). However, as a Dane I have never lived more south than Groningen.

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EDUCATION

2016 → 2020 PhD from University Medical Centre Groningen, The Netherlands.
Thesis title: Serious gaming for learning the intuitive, non-natural control of prosthetic hands

2013 Master's degree in medialogy from Aalborg University, Denmark.
Medialogy is a interdisciplinary study programme on interactive digital media and teaches programming, math, interaction design, computer vision, statistics and perception & cognition.

2012 Programmer at the Danish Academy for Digital Interactive Entertainment (DADIU), Denmark. DADIU puts students from different background in teams with the purpose to create a computer game. My main responsibilities included audio programming and artist support.

SELECTED JOB EXPERIENCES

2020 → Current PostDoc, Center for Bionics & Pain Research, Sweden.

2013 → Current Research & Development Engineer at Integrum AB, Sweden.
Note: On a part-time consultancy basis since 2016.
Responsibilities: Software development, development and maintenance of IT.

2013 → 2016 Guest Researcher at Chalmers University of Technology, Sweden.
Integrum and Chalmers were collaborating on research and I was awarded a guest researcher position to facilitate cooperation.

AWARDS

2020 Best paper of the year award from the Extremities, Pain and Disability (EXPAND) research group.

2014 Winner of the European Youth Award in the Healthy Life category.

SELECTED VOLUNTARY WORK

2017 Secretary of Groningen Organisation for PhD Education and Recreation.
Arranging recreational and educational events for PhD students from all the faculties of the University of Groningen.

2013 Treasurer of Liberal Alliances Ungdom (English: Liberal Alliance's Youth).
Financial administration for a youth political organisation which at the time had more than 500 members and 10 local divisions.

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REFERENCES

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