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STUDENT REPORT

Evaluation of Electrotactile Feedback Schemes in Combination with Myoelectric Prosthetic Control – Closing the Loop

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Part I

Paper

1 | Introduction

The loss of an upper limb can be incredibly traumatic and life changing event with the consequence of a significantly reduced quality of life due to restrictions in function, sensation and appearance [1, 2]. The loss is additionally linked to the development of multiple mental health disorders [2]. In an effort to restore pre-trauma functionality, prosthetics of various functionality and complexity have been introduced to replace the missing limb [3]. However, despite advancements in prosthetic technologies 25% of users choose to abandon their myoelectric prosthetic device [4]. An explanation for the low user satisfaction is found in the lack of exteroceptive and proprioceptive feedback provided by commercially available devices [5]. Presently, merely one commercially available device (VINCENT evolution 2, Vincent Systems Gmbh, DE), provides the user with feedback information of grasping force through a feedback interface [6].
The missing sensory feedback can cause the prosthetic hand to feel more unnatural and awkward [7]. Thus, the user has solely visual feedback to rely on [7, 8], a need prosthetic users have shown a strong desire to decrease [9]. In a survey by Peerdeman et al. [5], it was found that secondly to receiving proportional grasp force feedback, positional feedback was of highest priority. Visual independence can be achieved by providing the user with proprioceptive information through somatosensory feedback. This might facilitate the prosthetic device to be adopted by the user as an integrated part of their body, enhancing the feeling of embodiment and restoring the once physiologically closed loop [8, 10, 11, 12].
Various means of recreating the sensory feedback has been sought through either invasive and non-invasive approaches that translates information from sensors in the prosthesis to new sensory sites. Invasive methods, termed somatotopical feedback, aim to recreate the localization of the prior sensory experience by directly stimulating specific nerves in the residual limb [1, 8]. Substitution feedback utilize various tactors (pressure, vibrational, temperature, electrotactile, etc.) and their use can either be modality matched using e.g. pressure as a substitute for grasp force [13] or non-modality matched via e.g. vibration for grasp force [14, 15]. Electrotactile feedback uses small electrical currents to activate skin afferents eliciting sensory sensations, which can be modulated in multiple parameters such as pulse width, amplitude and frequency to convey feedback information along with adding the possibility of using multiple feedback channels [12]. The relevance of employing multi-channel feedback can be justified in that commercially available upper limb prosthetics have multiple degrees of freedom (DoF's) [16].
The use of electrotactile feedback has earlier been proven useful in cases of restoring force feedback through pressure sensors on a prosthetic hand or by the touch on artificial skin [17, 18]. However, the possibilities of electrotactile feedback have also been investigated in the case of improving prosthetic control. Strbac et al. [11] presented a novel electrotactile feedback stimulation interface, which could be used to convey information about the current state of a multi-DoF prosthesis. The system was comprised of four different dynamic stimulation patterns communicating the states of four different DoF's through a 16 multi-pad array electrode. The state of three different DoF's were communicated by altering

the electrodes activated in a specific pattern. The fourth pattern communicated grasp force by modulating the stimulation frequency. Tests of the stimulation design showed that six amputees were able to recognize the stimulation pattern of the four DoF's with an average accuracy of 86 %. [11]
To the authors' knowledge no one has fully closed the loop, testing the usability of electrotactile feedback for restoring proprioceptive aspects of myoelectric prosthetic control. Furthermore, based on the multiple parameters that can be modulated in electrotactile feedback, the question of what would be the optimal way to convey motion state is still unanswered. The current study will therefore investigate which types of electrotactile feedback is perceived more intuitive when conveying proprioceptive sensory feedback of the current prosthetic state. We will present two different stimulation protocols; one based on spatial activation of differently located electrode pads, and another based on delivering different levels of amplitude.

Part II

Worksheets

2 | Background

The background chapter will outline the considerations that needs to be made when testing the usability of sensory feedback configurations in combination with myoelectric prosthetic control. The feedback will be given based on which motion state a pattern recognition controlled prosthesis is in.
The main idea behind myoelectric prosthetic control is to translate recorded muscle signals (EMG signals) into a motion performed by the prosthesis. A pattern recognition model can be taught to differentiate between a set of movement classes. When receiving a segmented part of a EMG signal it then decides upon which movement class that most likely is being performed. In combination with the elicited muscle contraction level, this is used as input in the control system and the prosthesis should perform a corresponding motion. [19] In a closed loop prosthesis, the motion state the prosthesis is in can be coded to be equivalent to a certain sensory feedback. The should enable the user to interpret the sensory feedback and use as additional information to visual feedback about the prosthesis' state. [11] A closed loop prosthesis iteration can be seen in figure 2.1.
Regarding control the background chapter will explain the following: generation of EMG signals, data acquisition, data processing, pattern recognition and proportional control. Regarding sensory feedback the following will be explained: types of sensory feedback, prior investigations on sensory feedback and sensory feedback configurations.

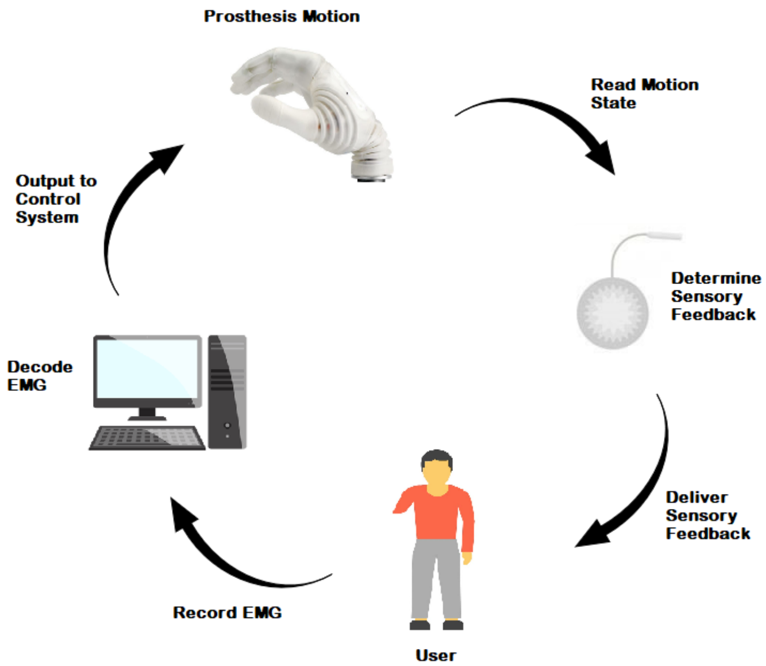

Figure 2.1: The figure shows the stages of a closed loop prosthesis. First, EMG signals are recorded from the user. The signals are decoded and an output is relayed to the control system, which is used for the prosthesis to perform a motion. The motion state is then read and sensory feedback is delivered to the user regarding which motion state the prosthesis is in.

2.1 Sensory Feedback Stimulation

It has been known for some time that vision alone does not provide a sufficient amount information to achieve efficient control of a prosthetic device. Hence, efforts have been put in investigating methods of providing proprioceptive and exteroceptive information of i.e. grasp strength and prosthetic state through the means of artificial stimulation. [1, 8] Presently, there are multiple ways of providing the user with a variety of sensory feedback. These can be divided into three categories: Somatotopically feedback, modality matched feedback and substitution feedback. [1]
This section will present general terms in sensory feedback stimulation and give a brief overview of the types of sensory feedback in order to give insight in the possibilities when providing the user of a prosthetic device with feedback.

2.1.1 Somatotopically Feedback

Somatotopically feedback aims to provide the user with a sensory experience which is perceived as natural as what was felt by their missing limb, both in location and sensation. To achieve such an experience, somatotopically feedback uses invasive approaches by making use of invasive neural electrodes and targeted reinnervation. The former is known as peripheral nerve stimulation and relies on the invasive neural electrodes being interfaced with the original neural pathways preserved proximally on the residual limb. Currently, only two different types of electrodes have been exploited: One where a cuff is placed around a nerve fascicle and another where an electrode is implanted into the nerve fiber. But to this date, none of these methods have been comprehensively studied. Targeted reinnervation also enable the possibility of stimulating the original neural pathways from the missing limb. The corresponding sensory afferents are relocated to innervate new sites which can selectively be chosen and stimulated by non-invasive tactors. Somatotopically matched feedback is hypothesized to reduce the users cognitive burden due to its 'naturalness', facilitating increased compliance and less conscience attention. [1]

2.1.2 Modality Matched Feedback

In modality matched feedback, the type of sensory experience which would have been felt by the missing limb is communicated to the user. For instance, when pressure is felt in the palm of a prosthetic hand by pressure sensors, a proportional amount of pressure is delivered to the user somewhere on the skin. Thus, the sensation is not matched in location, but only in sensation. Mechanotactile feedback which conveys pressure information is utilized by the use of i.e. pressure cuffs or servomotors. These types of tactors are very useful for modality matched feedback, but have a disadvantage by being more power consuming compared to other stimulation types. [1, 20]

2.1.3 Substitution Feedback

Substitution feedback methods convey information about the state of the prosthesis without regarding the type of sensation and location which would have been felt by the missing limb. Thereby, the sensory information is said to be non-physiologically representative. The feedback methods are often straightforward to implement, but demands a greater amount of user adaption to interpret what the feedback information represents. Often used methods for substitution feedback are vibrotactile and electrotactile feedback. [1, 20]

Vibrotactile Stimulation

Vibrotactile stimulation utilizes small mechanical vibrators to convey information to a selected area of the skin which activates cutaneous mechanoreceptors. This method is most often used to transfer tactile information in prosthetic grasping tasks. [1] A recognizable sensation is evoked using frequencies between 10 and 500 Hz. The sensory threshold varies between users and location, resulting in the need for specific user threshold calibration. [20]

Electrotactile Stimulation

In electrotactile feedback a sensory sensation is achieved by stimulating the primary myelinated afferent nerves with an electrical current. This creates what is often referred to as a tingling sensation. Electrotactile stimulation rely on small and lightweight electrodes to provide the electrical stimulation. When compared to other feedback methods as vibrational and pressure stimulation, which depend on heavier actuators and moving parts to provide the feedback, these properties can be seen as a drawback as prosthetic users strongly desire lightweight systems [8, 21]. Furthermore, through the use of electrotactile stimulation, multiple factors such as amplitude, pulse width, frequency and location of the stimulation can be controlled facilitating development of agile feedback schemes. This enables the possibility of varying the perceived feedback as either vibration, tapping or touch by modulating the signal waveform. The downside of using electrodes is the requirement for recalibration of sensory thresholds, pulse width and frequency to reproduce the same perceived stimulation every time the electrodes are placed on the user. In addition, interference between electrodes used for stimulation and recording have been found to result in noise in recorded EMG-signal used for myoelectric control. Concentric electrodes are able to limit the interference by limiting the spread of current. Concentric electrodes have also been found to increase localization and perceptibility of the induced stimuli. [1, 8, 20]

2.2 State of Art in Electrotactile Feedback

As presented in section 2.1.3 electrotactile stimulation offers a series of interesting properties which can be drawn upon when conveying complex tactile information. Therefore, the state of art methods using electrotactile sensory feedback in the current literature have been reviewed and will presented to ensure that the later derived feedback schemes extends recent evidence.

Multiple studies have investigated the use of electrotactile feedback regarding both how distinguishable sensations are evoked and how to convey sensory feedback in different coding schemes for improving myoelectric prosthetic control [8]. In 2015 Shi and Shen [22] investigated how subjects would perceive the effects of varying amplitude, frequency and pulse width of an electrical stimulation in various combinations. Results showed that appropriate sensations from electrical stimulation would be achieved by varying amplitude from 0.2 mA to 3 mA, pulse width from 0.2 ms to 20 ms and frequency from 45 Hz to 70 Hz. Furthermore, varying these ranges properly would make it possible to have proportionally increased stimulation grades felt by the subject. Additionally, the authors stated the importance of electrode size, as stimulation through to big or to small electrode diameters could result in sensations of pain or discomfort. [22]
Several studies [7, 10, 23, 24] using electrical stimulation have investigated its use in conveying grasping force/pressure feedback. Jorgovanovic et al.[23] investigated users' recognition of grip strength, when controlling a joystick controlled robotic hand, through varying the pulse width and keeping the frequency and intensity constant at 100 Hz and 3 mA, respectively. Results showed that providing electrotactile feedback improved the users' ability to move objects with the robotic hand. [23] Similar result were found by Isakovic et al. [24], who also showed that electrotactile feedback supported a faster learning than no feedback in grasp force control, and that electrotactile feedback might facilitate short-term learning.
A study by Xu et al. [10] tested and evaluated different types of pressure and slip information feedback through electrotactile stimulation and compared this to visual feedback and no feedback. The study recruited 12 subjects, 6 able bodied, and provided electrotactile feedback by keeping the intensity and frequency constant and then varying the pulse width between 0 μs and 500 μs indicating changes in grasp force. In this case, visual feedback was found to outperform electrotactile feedback. [10]
Pamumgkas et al. [7] also tested the use of electrotactile feedback to convey information from pressure sensors located in a robotic had. Their setup used six feedback channels corresponding to a pressure sensor in each of the fingers and one in the palm. Pressure information in the sensors were given in three discretized frequency levels of 100 Hz, 60 Hz and 30 Hz for the fingers and 20 Hz for the palm. Reported results stated that the subjects learned how to appropriately use the feedback when picking up objects of various sizes. Furthermore, the subjects reported that they preferred having electrotactile feedback accompanied by visual feedback opposed to only having visual feedback. [7]
The purpose of restoring the sensation that would be experienced by touch of the skin has also been pursued in more elaborate efforts through artificial skin [17, 18]. In these cases, a grid of 64 pressure sensors were used to translate information of touch into 32 electrotactile electrodes placed on the arm of the subjects.
The use of electrotactile feedback has proven useful in cases of restoring the haptic feedback through pressure sensors on a prosthetic hand or by the touch on artificial skin. However, the possibilities of electrotactile feedback have also been investigated in the

case of improving prosthetic control. In 2016, Strbac et al. [11] presented a novel electrotactile feedback stimulation system, which could be used to convey information about the current state of a multi-DoF prosthesis. The system comprised of four different dynamic stimulation patters communicating the states of four different DoF's through a 16 multi-pad array electrode, possibly restoring both proprioception and force. The state of the three of the DoF's were communicated by altering the electrodes activated in patterned fashion and the fourth DoF by modulating the stimulation frequency. Tests of the stimulation design showed that six amputees were able to recognize the four DoF's with an average accuracy of 86 %. [11]

2.2.1 Sensory Adaptation in Electrotactile Feedback

Before implementing a electrotactile feedback interface, it is important to consider the effect electric stimulation might impose on the sensory system.
Adaption is defined as a changing sensory response to a constant stimulus, and all sensory systems have shown adaptive tendencies. This could result in unreliable effects during prolonged electric stimulation. Hence, it is crucial to consider stimulation parameters which reduce adaption. Sensory adaption usually occurs within minutes, and reaches a maximum after 15 minutes. Furthermore, the adaption rate is related to the stimulation amplitude as adaption occurs faster when closer to the pain threshold. Low frequencies (<10 Hz) show less adaption compared to higher frequencies (>1000 Hz). The adaption response is found to be exponential in decay and recovery. [25, 26] However, sensory adaptation can be defeated by using intermittent stimulation, and preferably, stimulation interfaces should consider conveying feedback information through diversified patterns [26, 27].

2.3 Closing the Loop

The loss of a limp does not only result in loss of motor function as sensory function also gets impaired. Providing an amputee with a prosthetic device, which does not provide sensory feedback, only restores one half of the once closed limb control loop. To close the loop the prosthetic device needs to contain proprioceptive and exteroceptive sensors, whose recorded information should be conveyed to the amputee in a intuitive and meaningful way [28]. This can be achieved using methods of sensory substitution mentioned in section 2.1.3.
Closing the loop is a well recognized need amongst prosthetic users and might improve easiness of use and embodiment, which might lower rejection rates. Furthermore, the need for visual attention to track correct prosthetic movement would be lowered. [11] However, the advantages of closing the loop by providing sensory substitution feedback have been contradictory [23]. In 2008, Cipriani et al. [29] investigated the use of vibroctacile feedback for improving prosthesis grasp function and did not find any improvement when providing the sensory feedback. Later findings by Witteveen et al. [30] disproved this as they found that when providing information of grasp force and slip through vibrotactile

feedback improved a virtual grasping task.
Even though most studies find closing the loop by providing sensory feedback helpful (review by Stephens-Fripp et al.) [8], currently only one commercial feedback providing device, the VINCENT evolution 2 (Vincent Systems Gmbh, DE) is available [6]. Addtionally, closed loop control systems bypassing human interaction have also been investigated and implemented by commercial manufacturers i.e. Otto Bock and RSL steeper. Actuators are made to autonomously adjust grip force based on sensors located in the prosthetic hand, thereby not involving the user in the final execution of the task. [10] Such an approach might improve reliability of the prosthesis, but does not provide proprioceptive and exteroceptive feedback to the user, hence not promoting embodiment.

2.4 Feedback Stimulation Setup

To elicit electrotactile stimulation in this project, the MaxSens stimulation device will be used along with a 16 multi-pad electrode. The following section will provide a short overview of the stimulation device and multi-pad electrode specifications.

2.4.1 Stimulation Electrode

The 1×16 multi-pad stimulation electrode, can be seen in figure 2.2. It is made of 16 circular cathodes, which each share a common long anode. The electrode consists of a polyester layer, an Ag/AgCl conductive layer and a insulation coating. The electrode to skin contact is improved by applying conductive hydrogel pads to the electrode pads. [11]

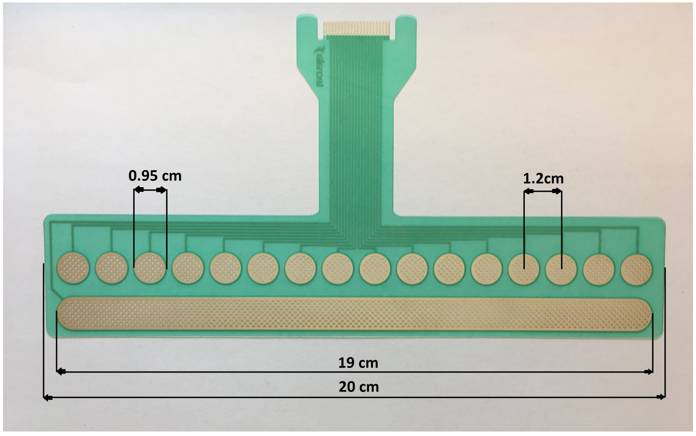

Figure 2.2: The 16 multi-pad electrode used for stimulation consists of 16 circular cathode pads, which each share a common anode.

2.4.2 MaxSens Stimulation Device

The stimulation device is made by MaxSens, Tecnalia, San Sebastian, Spain. Communication between PC and the stimulation device can be achieved either through Bluetooth or USB serial connection. The device can be controlled through a series of commands. The MaxSens device allows for independent control of the 16 pads in the electrode. It generates biphasic stimulation pulses where the pulse width can be controlled within a 50 - 1000 μs range with 10 μs steps, frequency ranges from 1 - 400 Hz with 1 Hz steps and current amplitude ranges from 50 - 10000 μA with 0.1 μA steps. Whereas current amplitude and pulse width can be controlled independently for each pad, the pad frequency is set globally limiting all pads to have same frequency.

2.5 Electromyography

The control of a myoelectric prosthesis is based on recorded myoelectric signals. [3] Enabling the use of myoelectric signals for control of functional prosthetics requires a theoretical background knowledge of the signals origin and how it can be acquired. The following section will describe myoelectric signals and how they are acquired through the acquisition method of electromyography (EMG).
The process of executing a voluntary movement can be explained through electric potentials and the excitability of skeletal muscle fibers. The nerve impulse carrying excitation information of a voluntary muscle contraction will travel from the motor cortex down the spinal cord to a alpha motor neuron. The alpha motor neuron will activate and direct an nerve impulse along its axon to multiple motor endplates, which each innervate a muscle fiber. The motor neuron and the muscle fibers it innervates is in collection called a motor unit. [31]
The nerve impulse initiates the release of neurotransmitters forming an endplate potential. The muscle fibers consist of muscle cells, which each are surrounded by a semi-permeable membrane. The resting potential over the membrane is held at a equilibrium, typically at -80 mV to -90 mV, by ion pumps, which passively and actively control the flow of ions through the membrane. The release of neurotransmitters affects the flow through the ion pumps resulting in a greater influx of Na^+. This results in a depolarization of the cell membrane. However, only if the influx of Na^+ is great enough to create a depolarization surpassing a certain threshold, an action potential is formed. The action potential is characterized by the cell membrane potential, which changes from around -80 mV to +30 mV. The created action potential will propagate in both directions on the surface of the muscle fiber. This process happens across all muscle fibers in a motor unit. The action potential is also known as a motor unit action potential (MUAP), and it is the superposition of multiple MUAPs that is recorded through surface EMG. [31, 32]
Acquisition of EMG-signal can either be carried out through surface EMG or intramuscular EMG. The latter measures MUAPs through needles inserted into the muscle and can and collect MUAPs from single muscle fibers individually. Surface EMG is acquired through electrodes on the skin surface. [33] Using surface EMG requires preparation of the skin surface to minimize impedance and maximize skin contact. Hence, the skin should be clean and dry before electrode placement. To further minimize skin-electrode impedance removal of excess body hair or flaky skin and cleansing the area using alcohol swabs should be considered. [31, 33] In this project MUAPs will be recorded through surface EMG. An example of a surface EMG recording of two different movements (pronation and supina-

tion of the wrist) can be seen in figure 2.3. Here, the surface electrodes are placed at the circumference of the forearm of the subject. It can be seen that some electrode channels are more or less active when comparing the two movements. This corresponds to different muscles being more or less contracted depending on which movement that is performed. This enables the recognition of which movement is being performed. A prerequisite for this to work is that the electrode placement must be identical throughout the recording.

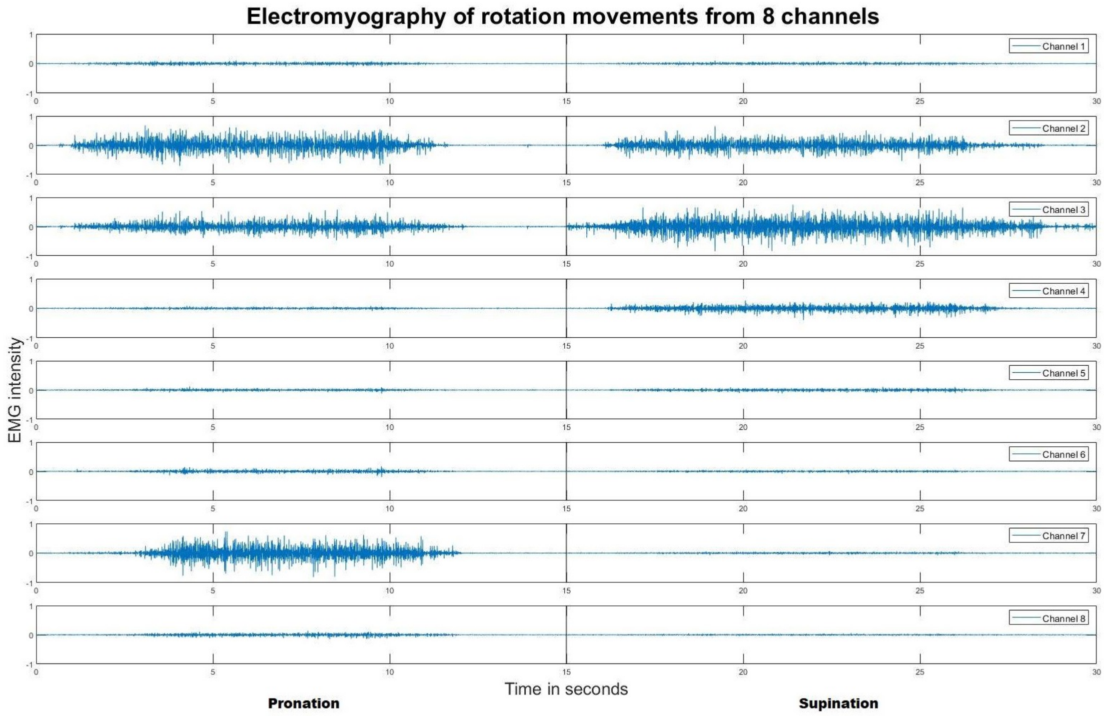

Figure 2.3: Illustration of an eight electrode channel surface EMG of the forearm during pronation (left side) and supination (right side) of the wrist.

2.5.1 Data Acquisition

Before a user can utilize a myoelectric prosthesis the control system needs to be taught how certain movements look like represented as EMG signals. This process is called training the control system. The acquisition of training data from the user is therefore the first step in training the control system.

In the acquisition of EMG signals the Myo armband (MYB) from Thalmic Labs will be used. It contains eight dry stainless-steel electrode pairs placed inside the armband. The advantage of using dry electrodes is that they do not need to be disposed after use, in contrary to conventional gel electrodes. Thus, the MYB can be reused for all subjects participating in the project, which enables less time consuming experiments. An additional usability advantage is that it communicates wirelessly to external devices via

Bluetooth 4.0, leaving no loose wires to possibly limit mobility or distort connection.
The MYB acquires EMG signals in an 8-bit resolution. Instead of acquiring the signal in millivolts, the output is scaled to decimal numbers between -1 and 1. However, the amplitude of the EMG signal output is still proportional to muscle contraction intensity. To avoid signal frequencies from the power grid to interfere with the EMG signal, an analogue 50 Hz notch filter is built in the MYB. This is, however, the only analogue filter implemented in the MYB, and as it has a sample rate of 200 Hz, which is inside the EMG spectrum (10-500 Hz), the acquired EMG signal will likely be aliased. The implementation of a digital anti-aliasing filter would therefore be a trivial task and extracting features that represents the frequency content of the signal might not be useful. However, a comparison study showed that using the MYB in a Linear Discriminant Analysis (LDA) control scheme can archive similar performance accuracy compared to using conventional gel electrodes with a sample rate of 1000 Hz [34]. Additionally, the MYB contains a 9 axes inertial measurement unit, but will not be utilized in this project and will therefore not be further elaborated on.
During initialization of the MYB the user has to follow two calibration steps: the warm up and the synchronization. In the warm-up step, the MYB is establishing a strong electrical connection between the skin and the armband, which reduces skin-electrode impedance and enables the electrodes to transduce properly. This happens as the user's skin becomes more moist from light sweating, which works similar to the gel in conventional EMG electrodes. During the synchronization step the MYB determines its orientation in space, its position and on which arm it is placed, based on a wrist extension movement the user must perform. The MYB works most optimally when tightly fit. To ensure a close fit, a set of clips can be used if necessary.

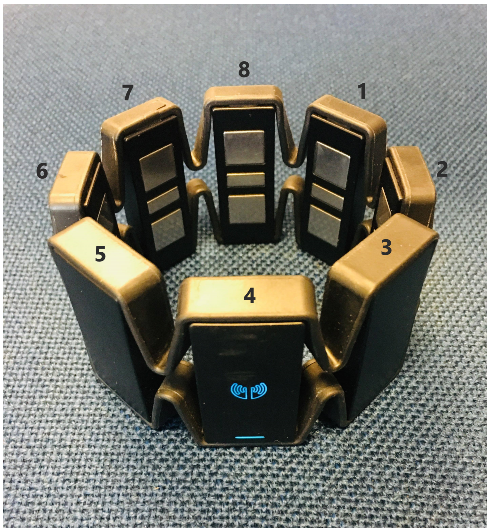

Figure 2.4: Image of the Myo armband from Thalmic Labs. Electrode channel 1 corresponds to the first output in the recording and electrode channel 2 as the second etc., as seen in figure 2.3.

2.6 Prosthetic Control Strategies

Needs to be written

2.7 Data Processing

In order to use the acquired data most optimally in the myoelectric prosthetic control scheme the data must be processed. In this processing, undesired frequencies are filtered out and features that represents the data are extracted from segments of the data in order to obtain more information about the movement than what is only contained in the raw EMG signal. This data processing will be covered in the following sections.

2.7.1 Filtering

To remove unwanted frequencies from the EMG signal, it should be filtered. According to the Nyquist Theorem, the rate the signal is sampled with must be at least twice the highest frequency contained in the signal to archive a non-aliased digital recording. However, as mentioned in section 2.5.1, the MYB samples with a rate lower than the highest frequency in the EMG spectrum, without having any analogue bandpass filter implemented. The rationale behind incorporating a digital anti-aliasing filter is therefore defeated. Implementing a digital high-pass filter with a corner frequency at 10 Hz to remove low frequency artefacts would, however, be desirable. [33]

2.7.2 Feature Extraction

Instead of only utilizing the raw EMG signal in a control scheme, features are extracted to exploit more representations of the EMG signal that optimally results in robust control. Various independent features can be extracted from the signal either from the time domain, frequency domain or the time-frequency domain. Most commonly features from the frequency and time domain are used. When extracting frequency domain features it is required for the EMG signal to transformed into the frequency domain. This takes more computation time compared to extracting features directly from the time domain. For this reason features in the time domain are usually favoured. [35] Especially used are the Hudgins features: Mean Absolute Value (MAV), Zero Crossings (ZC), Slope Sign Changes (SSC) and Waveform Length (WL) [36]. However, both ZC and SSC represent the frequency content of the signal, which most likely has been distorted by the low sample rate. When using the MYB for EMG acquisition an alternative set of features has been suggested by Donovan et al. to extract from the data [37]. These features are so called space domain feature, since they exploit the relationship between the output from the electrode channels. When evaluating data acquired from the MYB the space domain features increased classification accuracy by 5 % in a LDA-based control scheme compared to using the Hudgins features [37]. A final consideration to make when choosing features is to avoid redundancy as they then would not provide additional information about the signal.

2.7.3 Segmentation

The extraction of features are done in discretely segmented windows of data, instead of calculating the features from instantaneous values. In online control, the length of windows is a compromise between classification accuracy and delay in prosthetic control. Often an window overlap is implemented. This is a technique applied to ensure short delays, while still enabling a high classification accuracy. When applying an overlap values from the previous window is reused in the current window. The amount of overlap chosen is significant for the performance of the control scheme. Generally, it is recommended to have window lengths of 150-250 ms and use a 50 % overlap. Choosing a large overlap will result in short delays, but worse classification accuracy and vice versa. When using the MYB it is important to take the low sample rate into consideration, as a window will contain less data compared to if the sampling was appropriate to the EMG frequency properties. [38] Short windows will therefore likely result in worse classification accuracy compared to appropriately sampled data segmented in identical window length.

2.8 Pattern Recognition

For a myoelectric prosthesis to know which movement to perform, it needs to know how to differentiate between the movements it will be trained to perform. For this purpose classification is a commonly applied model. The classification model, or classifier, is fed known data consisting of features extracted from the raw EMG signals, which were recorded while the user was performing different movements. If each of the known feature data sets related to each movement is known they can be labelled appropriately, and the classifier will then learn which data represents which movement. Each label is known as a class and the process of labelling the data is called supervised learning. The known data is also called training data, hence this process is called training the classifier. If the classifier is trained properly, it is able to categorize unknown data accurately into the correct class. This is what happens online in each segmented data window when using a pattern recognition-based myoelectric prosthesis. The classifier is, however, only able to categorize unknown data into one of the trained classes. [39]
A frequently used supervised classifier for myoelectric prosthetic control is the LDA classifier. An advantage of using LDA is that it enables robust control, while having a low computational cost [40]. LDA will be used in this project to determine motor function and an overview of the theory behind LDA will be given in the following section.

2.8.1 Linear Discriminant Analysis

LDA determines decision boundaries between the desired number of classes, where the distance between the decision boundary and the centroid of the class feature values is maximized. Such a decision boundary is defined as a linear combination of the feature values and a weight w:

$$g_j(x) = weight_j x + bias_j \tag{2.1}$$

where $weight_j$ decides the orientation of the decision boundary of class j, and $bias_j$ is a bias that decides the position of the decision boundary of class j in relation to origo.
The decision rule of a LDA classifier is based on which class that has the highest probability of having produced the input feature values; also called the posterior probability. Given this decision rule, LDA can be derived from the Bayes theorem, which expresses the posterior probability as:

$$P(\omega_j|x) = P(x|\omega_j)P(\omega_j) \tag{2.2}$$

where $P(x|\omega_j)$ is the class conditional probability, the probability that a feature value from class j appears, and $P(\omega_j)$ is the prior probability, the probability that class j appears. This can be written as the function:

$$g_j(x) = P(x|\omega_j)P(\omega_j) \tag{2.3}$$

An constraint in LDA is that each class is Gaussian distributed and all classes share the same covariance matrix. The class conditional probability can therefore be written as the multivariate normal distribution, in which the class conditional covariance matrix can be written as the common covariance matrix. This leaves the following function:

$$g_j(x) = \mu_j \Sigma^{-1} x' - \frac{1}{2}\mu_j \Sigma^{-1} \mu_j' - ln(P(\omega_j)) \tag{2.4}$$

where μ_j and Σ^{-1} are the mean vector for class j and the common covariance matrix, respectively. The function in equation (2.4) can be written in the common linear discriminant classifier form as in equation (2.1). [41]
Thus, a posterior probability is calculated for each class based on the decision boundaries, and according to the decision rule, the class with the highest probability of having produced the input feature values will be chosen as the determined motor function. However, LDA only determines the movement class, but does not enable control of the motion speed the actuator must perform. For this purpose an additional control scheme must be applied to activate the determined motor function in a proportional matter. [42]

2.9 Proportional Control

After the motor function has been determined, a mapping of a control output needs to be performed. The advantage of providing a continuous output to the actuator proportional to the contraction intensity compared to a one-speed controller is that the user has the possibility of grasping objects quickly, while still being able to perform more slow and dexterous tasks. Additionally, proportional control resembles the human neuromotor system, which makes it more intuitive. [42]
A widely used proportional control scheme is linear regression [42]. Here, a dependent output value can be calculated based on a function of an independent input value. In the case of using several electrode channels as when using the MYB, the output needs to be computed based on several independent values. For this purpose multivariate linear regression would be appropriate:

$$\hat{Y} = \alpha + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_i X_i + \epsilon_i \tag{2.5}$$

where $\hat{Y}$ is the control output and X_i is the independent input values, where the index i will correspond to the number of electrode channels in the MYB. α and β are the estimated value of $\hat{Y}$ at $X = 0$ and estimated regression coefficients, respectively. The absolute values of the recorded EMG signals can be used directly as the independents input value in such a proportional control scheme. [43] However, a regression model needs to be estimated for each motor function in the control system. Then the appropriate regression model will be selected based on the classification output.

2.10 Performance Evaluation

Evaluating the performance of a derived control system can be achieved through the completion of various tasks. If available, the system can be interfaced with a myoelectric prosthesis, and based on the completion of tasks mimicking daily life functionality (e.g. grasp and movement of objects), performance can be evaluated [44]. Otherwise, virtual environments have been widely used showing movements of virtual prostheses [45] or by moving a cursor to targets resembling motor function, where performance can be quantified through measurements based on Fitts' Law [46, 41, 47]. In this project, performance evaluation will be carried out in a virtual environment through a Fitts' Law based target reaching test. The next section will present metrics representing aspects of performance.

2.10.1 Fitts' Law Test

Various versions of the Fitts' Law test focusing on different performance metrics have been derived to quantify performance of myoelectric control. The metrics are used to describe different aspect of completing a movement task.
When designing the test, the Index of Difficulty (ID) is often calculated for each target in

order to asses how difficult it is to reach the given target. The ID is based on the distance to the target and target width. An obvious measure to observe is the completion rate (CR), which is the ratio of reached targets compared to the total number of targets. This describes the overall ability the user has when using the control system.
Throughput (TP) describes the achieved speed and accuracy by using the relationship of time used to reach a target compared to the target ID. Path efficiency (PE) can be used to observe how efficiently continuous movement control is achieved by comparing the distance travelled to reach a target and comparing it to the most direct route. To observe how well the user can keep the system at rest and control velocity, stooping distance (SD) and overshoot (OS) can be measured. The former measures the distance travelled at times where no movement is intended, and the latter tracks the number of times the user reaches a shown target, but leaves before completion. [41]

3 | Study Objective

In summary, there is still a need for myoelectric prosthetic devices to fully close the neural loop by providing amputees with proprioceptive feedback to lower the need for visual attention. Using the modality of electrotactile stimulation as a mean of transferring information of the prosthetic state offers multiple stimulation parameters which can be modulated through several channels enabling possibilities for intuitive and meaningful sensory feedback.
However, even though several opportunities present themselves in modulating the stimulation amplitude, frequency and active channels, it would be of great interest to investigate which would lead the sensory feedback to be perceived most intuitively. As presented in section 2.4 the frequency cannot be controlled individually for each pad in the electrode, thus a feedback scheme modulating frequency will no be investigated in this study. This leaves the following study objective:

Test and evaluate two novel stimulation schemes, one based on modulating amplitude and one based on spatial localization of activation, for conveying sensory feedback of the prosthesis state in a closed loop prosthetic control system.

4 | Methods

4.1 Acquiring Training Data

As presented in section 2.8, for the classification scheme to differentiate between movements, it has to be trained with EMG data from each movement. Training data was acquired using the MYB placed on the forearm and recorded the movements of pronation, supination, open hand, closed hand and rest. The subsequent section will document how the data used for training the classifier was acquired.
First, a baseline recording was made, where the subject was instructed in keeping the hand perfectly still. The baseline consisted of a 15 second recording and was subtracted from each of the other recordings to reduce baseline noise. If the signal was below the baseline amplitude it was set to zero.
During a muscle contraction two main states can be recognized; a transient state, described by inconsistent myoelectric activity as the muscle length is changed and steady state, where a constant firing rate is reached. [48] Classification is often based solely on steady state data and even though incorporating transient state in the training data has been found to decrease classifier accuracy [48], including transient state might make for a more robust classifier as the delay until steady state is reached is eliminated [49, 50].

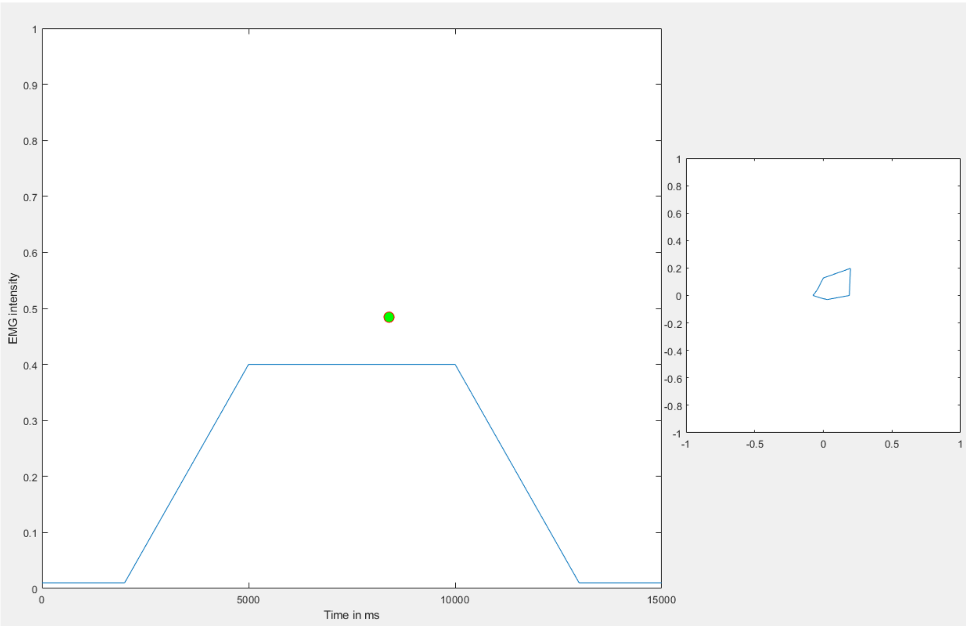

Figure 4.1: The trapezoidal plot (left) and contraction validation plot (right) used during acquisition of the training data. The line in the trapezoidal plot represented the contraction amplitude requested and the green cursor represented the current elicited contraction intensity.

To feed the classifier with training data representing muscle contractions with varying

force, different fractions of maximum subject contraction force were recorded. The process of obtaining training data for each movement the same four step process of a Maximum Voluntary Contraction (MVC) recording and a 40 %, 50 % and 70 % fraction of MVC recording. The MVC was recorded for 15 seconds where the subject was instructed to elicit the contraction with a maximum contraction force which could be held steady, without fatigue, over the course of the 15 seconds. This resulted in an MVC for each channel in the MYB. The absolute of the EMG signal for each channel was computed and a mean across all channels was calculated. The mean was used as reference when recording the subsequent training data.
Acquisition of the 40 %, 50 % and 70 % fraction of MVC, were done using a developed graphical user interface (GUI), which can be seen on figure 4.1. The image shows the trapezoidal figure, which line the subjects were instructed to follow using the green cursor, which was a representation of the mean intensity across all channels of the elicited muscle contraction. The cursor would automatically move forward along the x-axis in relation to time. The height of the trapezoid represented either the 40 %, 50 % or 70 % fractions of the MVC. Data were recorded during 2.5 seconds rest periods in the beginning and end, a 2.5 incline transition, 5 second steady state and 2.5 second decline transition, summiting to a total time of 15 seconds. However, only data recorded during the steady state and last and first second of the incline and decline transition phase, respectively, were extracted and to be used for training the classifier.
The additional plot seen on the right in figure 4.1, plotted the amplitude of each of the eight channels in the MYB and were used by the investigators to assess whether the performed movements were done correctly. If sudden shifts in the amplitude or the channels activated were present, this would indicate that the subject did not perform a pure contraction and the recording would have to be redone.

5 | Results

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A | Appendices