AALBORG UNIVERSITY
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 an 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]. 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]. A major reason for the low user satisfaction is found in the lack of exteroceptive and proprioceptive feedback provided by commercially available devices [1, 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]. Furthermore, the user mainly rely on visual feedback [7, 8], which is a need prosthetic users have shown a strong desire to decrease in order to enhance easiness and naturalness of use [9]. In a survey by Peerdeman et al. [5], it was found that secondly to receiving proportional grasp force feedback, prosthetic positional state 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 the nerves, which conveyed that particular sensory modality in the lost limb. This is however a complicated solution and multiple aspects, like long term effect, have yet to be investigated. [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 the possibility of using multiple feedback channels [12]. As commercially available upper limb prosthetics have multiple degrees of freedom (DoF's) [16] the need for multiple feedback channels is present to accommodate the amount of information which needs to be provided in a meaningful way.

The flexibility of electrotactile stimulation makes is desirable and its use 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 with regards to 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] However, it was not tested how well these stimulation patterns could be utilized for prosthetic control
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 which parameters should be used to convey motion state is still unanswered. The current study will therefore investigate which types of electrotactile feedback supports prosthetic control most usefully when conveying proprioceptive sensory feedback of the current prosthetic state. This study 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. Often, if possible, EMG is recorded from the muscle which were used to perform movements with the natural hand and used for prosthetic control. A pattern recognition model can be trained 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.

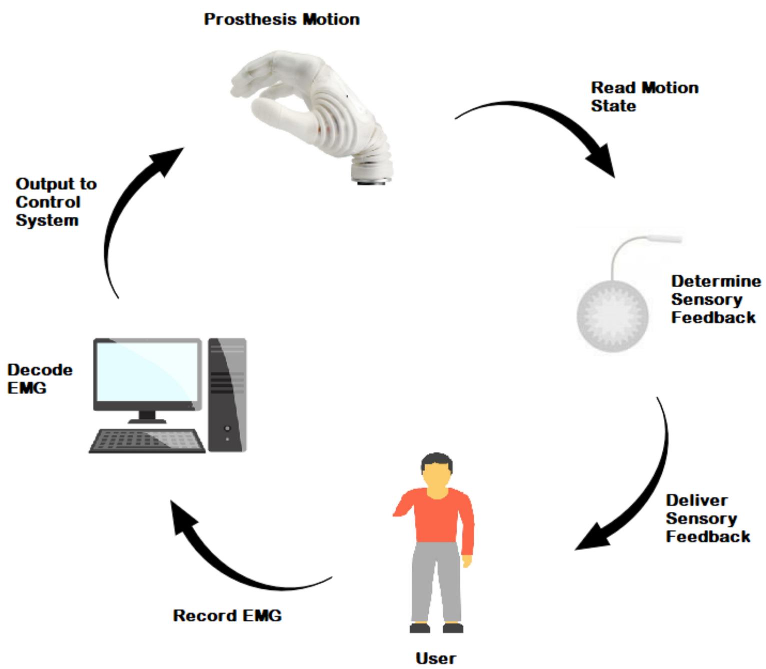

Figure 2.1: The figure shows the stages of a closed loop prosthesis. First, EMG signals are recorded from the user. The signals are decoded and an output is relayed to the control system, which is used for the prosthesis to perform a motion. The motion state is then read and sensory feedback is delivered 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 daily life use of a prosthetic device, as the use requires full visual attention attention. 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 and eventual disadvantages 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, 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

Section 2.1 presented different types of sensory feedback from which the choice of stimulation in this project can be drawn upon. Somatotopically might restore the most natural sensations, but is also the most complicated. Modality matching the feedback should instead be sought, however present tactors are larger and more power consuming than electrodes uses in electrotactile feedback. Furthermore, the dimensions of electrodes facilitates easier integration with the prosthesis as these can be placed inside the socket, along with electrodes used for acquisition. However, this requires that a solution for leakage current is found. Modulating pulse width, frequency and amplitude in electrotactile feedback gives more possibilities for 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 0.3 mA to 3 mA, pulse width from 0.1 ms to 20 ms and frequency from 40 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 multipad 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]
In summary most studies have focused on using electrotactile feedback for exteroceptive means while only [11] have investigated its use for proprioceptive feedback. However, their results encourage further investigation into how electrotactile feedback can be utilized for providing meaningful proprioceptive feedback.

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 overcome by using intermittent stimulation, and preferably, stimulation interfaces should consider conveying feedback information through diversified patterns [26, 27].
Developed feedback schemes should consider using as low amplitudes as possible to reduce the rate of sensory adaption. Furthermore, continuously changing the site of stimulation should also facilitate less adaption.

2.3 Closing the Loop

The loss of a limb 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 using substitutional sensory feedback holds the possibility of lowering need for visual attention to track correct prosthetic movement. This might furthermore improve easiness of use and embodiment, which could lower rejection rates. [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 studies like [23, 30] found closing the loop by providing grasp force 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]. However, no devices have yet to implement means of proprioceptive feedback. Additionally, 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]

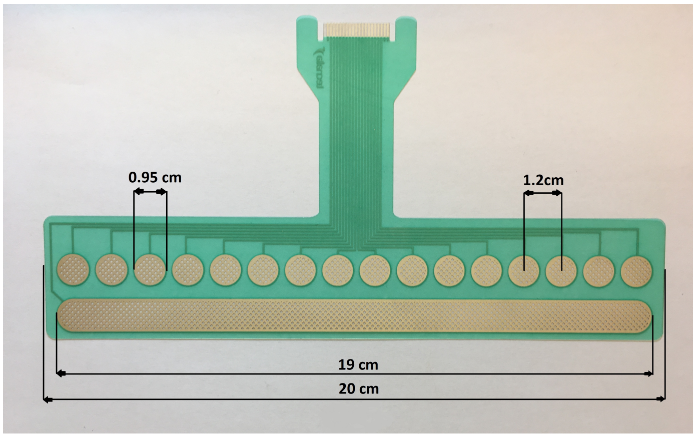

Figure 2.2: The 16 multi-pad electrode used for stimulation consists of 16 circular cathode pads, which each share a common anode.

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 supination 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.

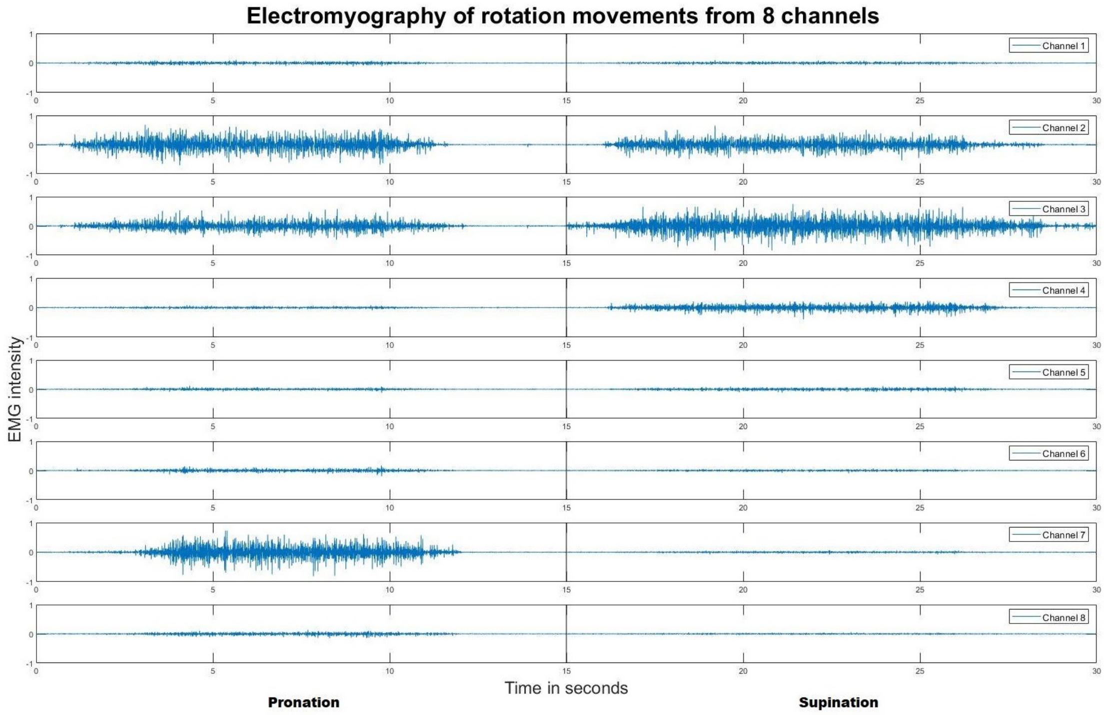

Figure 2.3: Illustration of an eight electrode channel surface EMG of the forearm during pronation (left side) and supination (right side) of the wrist.

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.

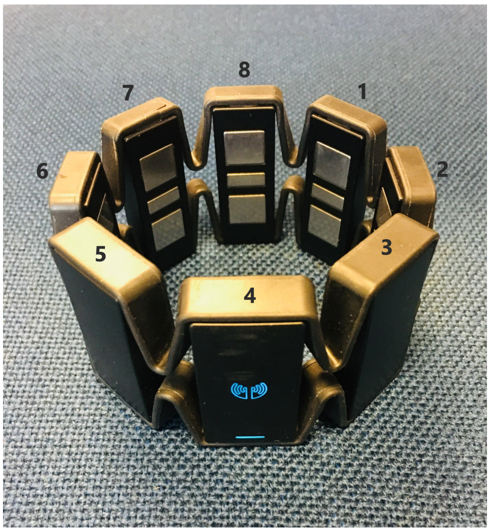

Figure 2.4: Image of the Myo armband from Thalmic Labs. Electrode channel 1 corresponds to the first output in the recording and electrode channel 2 as the second etc., as seen in figure 2.3.

2.6 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.

2.6.1 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. [1] [33]

2.6.2 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 [38]. 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 when using identical window length.

2.6.3 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

[1] FiXme Note: why? too weak

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 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.

2.7.1 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]

2.8 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.

2.9 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.

2.9.1 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. As presented in section 2.2 most studies have focused on providing exteroceptive feedback while only very few studies have investigated how proprioceptive information could be conveyed to aid prosthetic control in cases where visual attention is less wanted. 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 stated 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.

Investigating whether spatially coded or amplitude coded information assists the most when neglecting visual attention will provide insight into which parameters future configurations should encapsulates. 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

Extending the knowledge acquired involving myoelectric prosthetic control, feedback stimulation and the desire among prosthetic users for prostheses to incorporate proprioceptive feedback, the following section will document the implementation of the two feedback configurations, as well as the rest of the developed closed loop system. The methods chapter will present the following sections documenting the implementation of: study design, data acquisition, data processing, control system and validation of control, spatial configuration, amplitude configuration, configuration training, performance test and statistical methods.

4.1 Study Design

In order to investigate whether amplitude or spatial based electrotactile feedback aids prosthetic control the most when removing visual dependency an experiment had been set up. A feedback coding scheme based on spatial activation and a feedback scheme based on amplitude modulation have been developed and will be presented later in section **??**.
XX subjects were recruited and randomly assigned to one of two groups. An overview of total subject population and group demographics can be seen in table 4.1. Prior to enrollment the subjects were assessed to meet the inclusion criteria stated in the experimental protocol, which can be found in section A.1. The subjects were handed the experimental protocol prior to experiment session and gave an introduction to the background of the study and the different task the subjects would have to go through. Upon enrollment the subjects were asked to sign an informed consent form (Fordi?). The experiment has been ethically approved by (Tilføj specifikationer).

Table 4.1: Overview of total subject population and group demographics.

	Age, mean(std)	**Gender n(%)**	
		Female	Male
Total (n = X)	X(X)	X(X)	X(X)
Group 1 (n = X)	X(X)	X(X)	X(X)
Group 2 (n = X)	X(X)	X(X)	X(X)

The experiment was designed such that the each subject was trained and tested in using both feedback schemes along with control during a one session experiment. A graphical illustration of the main stages that the subject went through can be seen in figure 4.1. For all subjects data used to build the control system was acquired first. Secondly, the subjects were given time to familiarize with the control system and next the achieved control was assessed through a target reaching test. Finally, sensory thresholds used for feedback were determined for the subject. Subjects assigned to group 1 went through four steps of training and test using scheme 1 followed by the same four steps using scheme 2. The opposite was applicable for group two which started with scheme 2 followed by scheme 1. The next sections will further document the implementation and execution of the experiment.

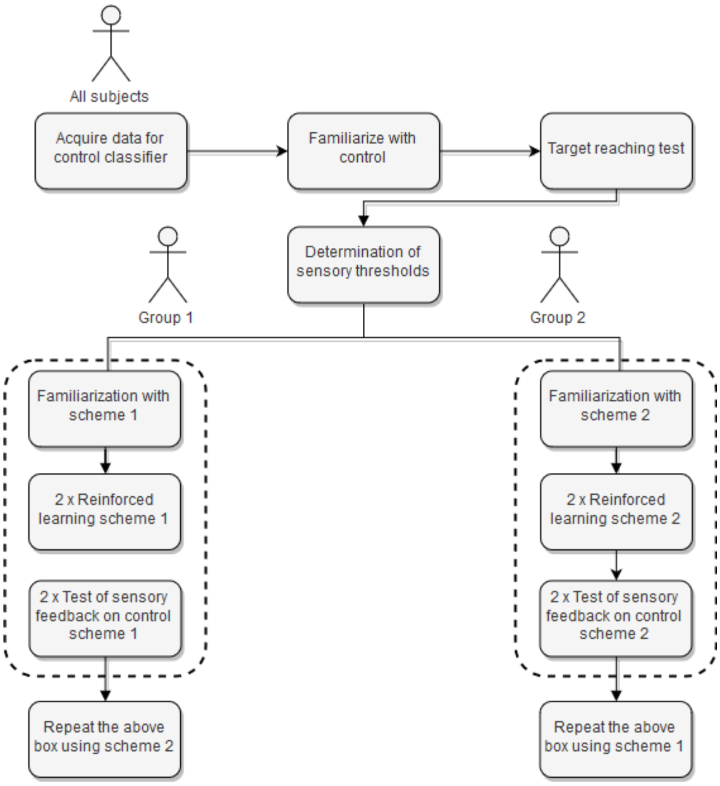

Figure 4.1: Graphical illustration showing the stages of the experiment. Firstly, the stages common for all subjects followed by the group dependent stages.

4.2 Acquiring Control System Data

As presented in section 2.7, 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 while the subject performed the movements: wrist pronation, writst 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, however, including transient state might make for a more robust classifier as the delay until steady state is reached is eliminated [49, 50].

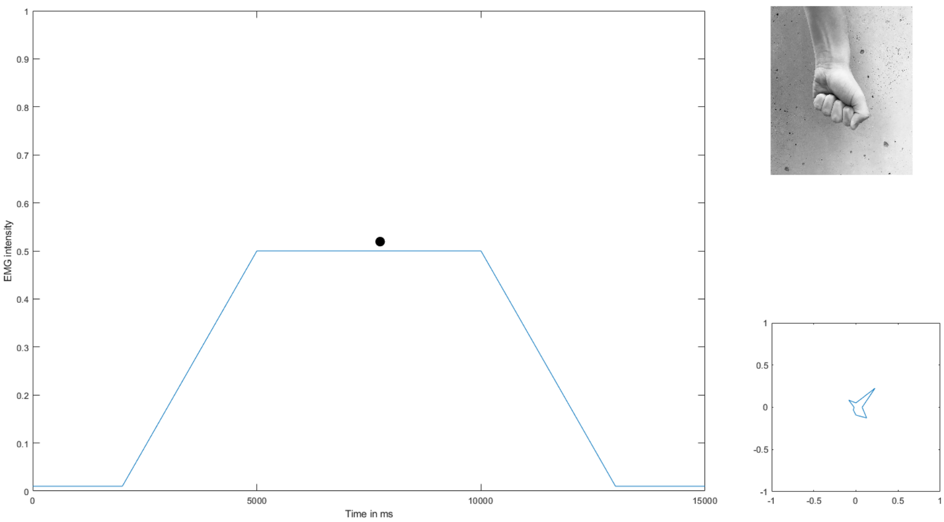

Figure 4.2: The trapezoidal plot (left) and contraction validation plot (right) used during acquisition of the training data. The line in the trapezoidal plot represented the contraction amplitude requested and the green cursor represented the currently elicited contraction intensity.

To feed the classifier with training data representing muscle contractions with varying force, different fractions of maximum subject contraction force were recorded. In the process of obtaining training data for each movement the same four were carried out: a prolonged maximum voluntary contraction (pMVC) recording and a 40 %, 50 % and 70 % fraction of pMVC recording. The pMVC 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 pMVC 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 pMVC were done using a developed graphical user interface (GUI), which can be seen on figure 4.2. The image shows the trapezoidal trajectory the subject 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 positively along the x-axis in relation to time. The height of the trapezoid represented either the 40 %, 50 % or 70 % fractions of

the pMVC. 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, summing to a total time of 15 seconds. However, only data recorded during the steady state and the last and first second of the incline and decline transition phase, respectively, were extracted and used to train the classifier.
The additional plot seen on the right in figure 4.2, 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 the amplitude of the channels responsible for the performed movement shifted rapidly, or if channels not responsible for the performed movement were active, it would indicate that the subject did not perform a pure contraction and the recording would have to be redone.

4.3 Data Processing

The following sections will cover which filtering, segmentation and feature extraction solutions that were decided to implement, based on the background information presented in section 2.6.

4.3.1 Filtering

Due to the EMG-bandwidth being 10-500 Hz and taking the MYB specifications into consideration the only interest was to remove low-frequency artefact noise. Hence, a 2^{nd} order Butterworth high-pass filter with a cut-off at 10 Hz was implemented. The order of the filter was chosen, as fast update time was highly desired in the online prosthetic control, and a higher order might have slowed the update due to a longer computation time. The choice of implementing a Butterworth filter was due to the desire of avoiding phase shift inside the EMG bandwidth, as this could distort the fidelity of some of the extracted features.

4.3.2 Segmentation

In online myoelectric prosthetic control, quick update time is important to maintain naturalness in the prosthesis motion, while still ensuring robust classification. A windowing of 200 ms with 50 % overlap was therefore chosen. This would update the prosthesis motion state every 100 ms and segment 40 samples per window to feed the classifier. In initial tests, this proved adequate to yield smooth and reliable prosthesis motions, when using the MYB for EMG acquisition.

4.3.3 Feature Extraction

For this project it was decided to extract the space domain features recommended by Donovan et al. [37], due to the increased classification accuracy obtained compared to using Hudgins features when applying the MYB for data acquisition. The features for-

mulated in [37] were MAV, Mean MAV (MMAV), Scaled MAV (SMAV), Correlation Coefficient (CC), Mean Absolute Difference Normalized (MADN), MAD Raw (MADR) and Scaled MADR (SMADR). Additionally, it was decided to extract the Hudgins feature, WL, to exploit frequency related information of the signal in the classification. All these features will be explained in the following text.
MAV is a commonly used feature to represent information on muscle contraction intensity and how much force a subject needs to produce to perform a movement at a given intensity. Its changes are linearly proportional with contraction intensity; the more intense the contraction is the higher the feature value will be and vice versa. For one window in the i^{th} channel, MAV is calculated as:

$$MAV_i = \frac{\sum_{n=1}^{ws} |x_i[n]|}{ws} \tag{4.1}$$

where $x_i[n]$ denotes the n^{th} raw sample from channel i and ws denotes window size or number of samples in one window.
Scaling MAV with the mean of MAV across all channels will remove the dependency of specific movement intensity - some movements produce higher mean intensities than others at the same fraction of the MVC. The average of MAV across all channels is denoted MMAV and is calculated as:

$$MMAV = \frac{\sum_{i=1}^{8} MAV_i}{8} \tag{4.2}$$

MAV scaled by MMAV is denoted SMAV and is calculated as follows for each window in the i^{th} channel:

$$SMAV_i = \frac{MAV_i}{MMAV} \tag{4.3}$$

Each EMG channel in the MYB records a mixture of sources. Some individual sources can affect multiple channels, which will increase the correlation between channels, while other more local sources might only affect a single channel, which decreases the correlation. To represent the correlation between channel i and the neighbouring channel $i+1$, Donovan et al. proposed the calculation of a correlation coefficient (CC), which is expressed as:

$$CC_i = \frac{\sum_{n=1}^{ws} X_i[n]X_{i+1}[n]}{ws} \tag{4.4}$$

where $X_i[n]$ is the n^{th} sample from channel i in one window after the sample has been normalized. The normalization is done by subtracting the mean of raw samples from each samples followed by dividing the resulting values with their standard deviation.
In an effort to further represent the relationship between channels, the mean of the absolute value of the difference between normalized channel values was calculated. This is referred to as mean absolute difference normalized (MADN), and is expressed as:

$$MADN_i = \frac{\sum_{n=1}^{ws} |X_i[n] - X_{i+1}[n]|}{ws} \tag{4.5}$$

To decrease the computational denseness of first calculating the normalized values as done with CC and MADN, MAD was calculated using just the raw samples. This is referred to as MADR and is expressed as:

$$MADR_i = \frac{\sum_{n=1}^{ws} |x_i[n] - x_{i+1}[n]|}{ws} \tag{4.6}$$

Similar to MAV, MAD is affected by movement intensity and is therefore scaled by MMAV, which results in the final space domain feature SMADR:

$$SMADR_i = \frac{MADR_i}{MMAV} \tag{4.7}$$

Finally, to increase the amount information the classifier based its decisions upon, the Hudgins feature WL was included. WL represents both amplitude and frequency content of the signal by measuring the length of the signal in channel i in one window:

$$WL_i = \sum_{n=1}^{ws-1} |x_i[n+1] - x_i[n]| \tag{4.8}$$

To avoid redundancy in signal representation only SMAV, CC, MADN SMADR and WL were used to train the classifier and for online control.

4.4 The Prosthetic Control System

Having extracted features from the three EMG datasets of one movement for each of the four movements, the control system could be build in order to achieve real-time recognition of movements. The following sections will explain the implementation of the control system and how the achieved level of control was assessed for each subject.

4.4.1 Building the Control System

The implementation of the control system was divided into two parts. To achieve recognition of performed movement a classifier was trained, however this only produces a recognition of a movement and does not reflect the intensity of which the movement is being performed with. Therefore, following the recognition of performed movement a linear regression model was implemented to achieve proportional control.

Classification of Movement

Real-time classification of movements was accomplished by implementing a LDA classifier. As presented in section 2.7 the classifier needed to be trained using data from each movement. Hence, the five features extracted for each of the 40 %, 50 % and 70 % fraction of the pMVC for one movement were assembled into one labeled training matrix. The same was done for the three remaining movements. A fifth class was labeled rest and its training matrix only contained the features from the single rest acquisition.

3 intensities for each movement 4 movements + 1 rest 5 features 8 channels

Proportional control

4.4.2 Assessment of Subject Control

After the acquisition of data training data and the training of the classifier, two stages were the subject could familiarize themselves with the control and test how well they were able to use the control system, were implemented. It was highly critical that the subject was able to achieve sufficient control such that it would not be due to insufficient control, that a subject was not able to reach a target during test of the feedback schemes. However, as the classifier only had five classes, representing five very independent movements, to distinguish between, the classifier achieved high classification accuracy. Therefore, the need for subject training could be kept to a minimum. [1].

Familiarization with Control

Target Reaching Test

[1] FiXme Note: This was furthermore supported by the results from pilot studies

5 | Results

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A | Appendices

A.1 Experiment Protocol

Project Title
Evaluation of electrotactile feedback schemes in combination with myoelectric prosthetic control - closing the loop.

Information on Investigators
The investigators are biomedical engineering Master students at Aalborg University.

Background
Losing an upper limb can be hugely debilitating and can result in lowered quality of life due to restrictions in function, appearance and sensation. As a mean to regain the functionality, transradial amputees can receive a functional prosthesis, where the majority are controlled by muscles signals, or myoelectric (EMG) signals. However, still 25% of myoelectric prosthesis users reject their device, where a major reason for the low satisfaction is due to lack of sensory feedback. Many advancements have been made in the academic community to improve function accuracy. However, combining function with sensory feedback, thus closing the motor/sensory loop, is still a scarcely investigated area. Therefore, this experiment will combine the control of a prosthesis with sensory feedback delivered via electrotactile stimulation electrodes placed on the forearm. During the experiment the subjects will test two different feedback configurations while controlling a virtual prosthesis, represented as a cursor on a computer screen. The subject can move the cursor in a two-dimensional coordinate system, where the axes represents a degree of freedom (DOF) each (wrist rotation and opened/closed hand).

Purpose
The purpose of the experiment is to compare how subjects' perform in an evaluation test when receiving feedback from two different electrotactile stimulation configurations, respectively, in a closed loop virtual prosthesis. This might provide information on which feedback that seems more intuitive to use in practice in a prosthesis.

Research Aim
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.

Experiment Duration
To be estimated.

Inclusion Criteria

The subject must be:

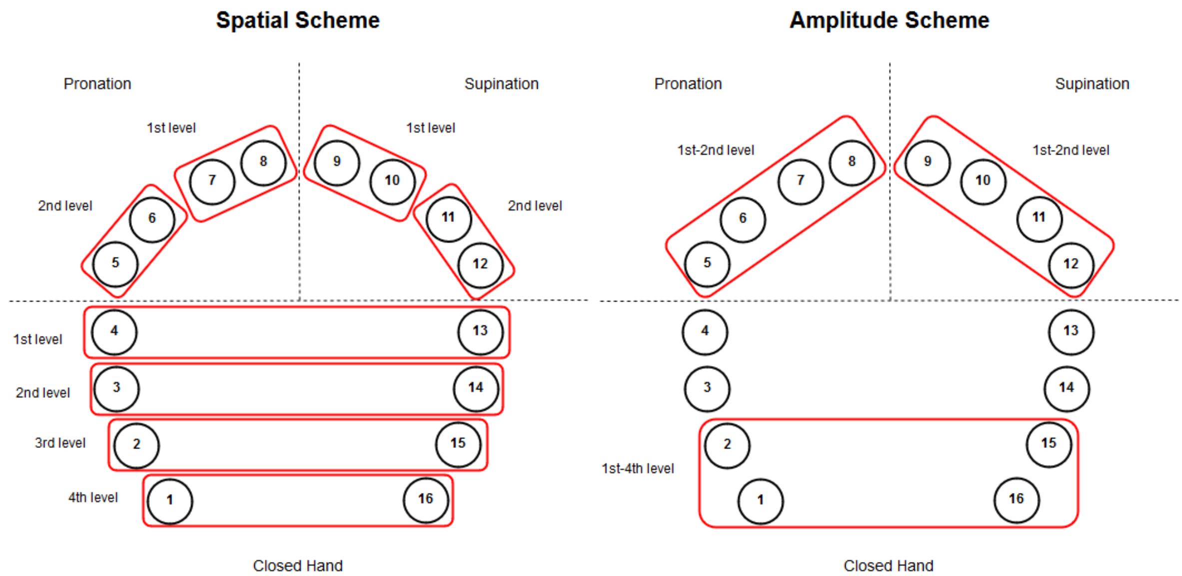
- able bodied.
- at least 18 years of age.
- able to understand, read and speak English and/or Danish.
- assessed by the investigators to comply with the instructions given during the experiment.

Exclusion Criteria
The subject must:

- not have any diseases/conditions that may influence sensory perception.
- be willing to receive low amplitude current stimulation.
- assessed by the investigators to have robust prosthetic control during the experiment.
- be willing to give informed consent.

Experiment Description

The main aim of the experiment is for the subject to be able to correctly interpret the two sensory feedback schemes when combined with myoelectric prosthetic control. The grid illustrated in figure A.2 is the map the subject will be able to navigate inside. Each square in the map will deliver a different stimulus corresponding to the motion state of the virtual prosthesis, represented as the black cursor. The square with center in the origin (square with cursor inside in figure A.2) corresponds to resting state and will provide no sensory feedback. The remaining squares in the first row will deliver stimuli corresponding to only the wrist rotation degree of freedom, and the remaining squares in the third column will deliver stimuli only corresponding to the closed hand DOF. The remaining squares will deliver a stimulation based on a combination of the two DOFs. The further away from resting state a square is, corresponds to the angular degree of the prosthesis state in relation to the performed movement (see figure A.1).
The arrows in the upper right corner of figure A.2 represent the hand movements needed to be performed to move the cursor in the corresponding direction. The control system will only respond to single DOF movements. Thus, the cursor is only able to move along one axis at a time and not diagonally. The subject will control the cursor with the dominant arm through an EMG electrode armband. The subject will receive stimulation from an electrode consisting of 16 electrode pads placed around the contra-lateral forearm (see illustration in figure A.1).



(a) Illustration of the spatial scheme.

(b) Illustration of the amplitude scheme.

Figure A.1: Figure (a) shows the spatial scheme, which is based on different electrodes being activated depending on the level of the grid square the cursor is located in. The highest number of possibly activated electrodes is four at a time. Figure (b) shows the amplitude scheme. Here, the amplitude of the active electrodes will increase with the increase of the level of the target location. The highest number of possibly activated electrodes is eight at a time.

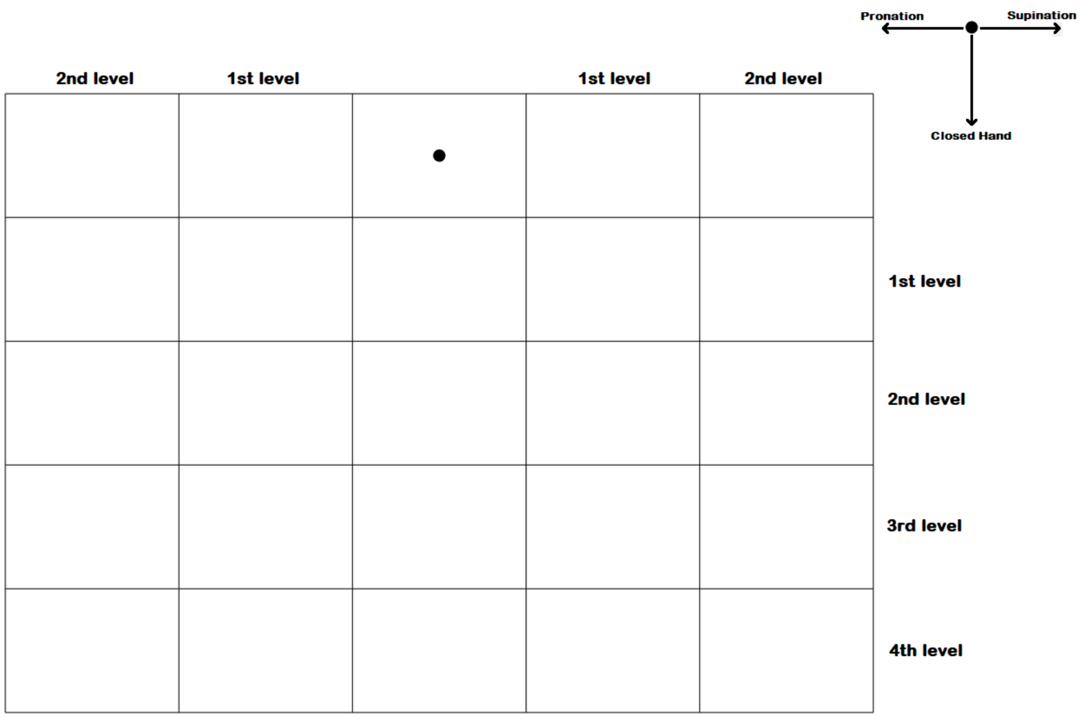


Figure A.2: Image of the grid map and cursor used in the experiment. Performing supination moves the cursor the right, pronation moves it to the left and closing the hand moves it down. Opening the hand moves the cursor up, and is used as a correction movement if a wrong movement has been made.

Hand Movements Used for Prosthetic Control

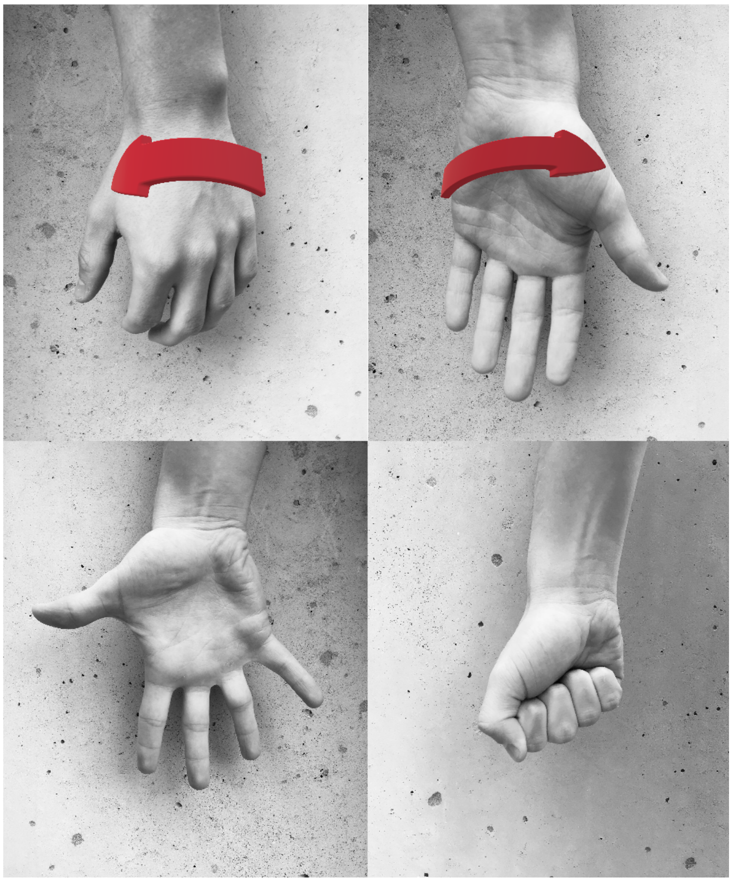


Figure A.3: Image of the hand movements used in the experiment for myoelectric prosthetic control. From top left corner: Wrist pronation, wrist supination, opened hand and closed hand.

Experiment Procedure

Before the final evaluation test is carried out the subject will be trained in controlling the cursor via EMG signals, trained in interpreting the sensory feedback and trained in interpreting the sensory feedback while controlling the cursor. The evaluation test is a target reaching test, where the subject needs to move the cursor to a highlighted target consisting of one of the grid squares. The cursor will not be visible, thus, the subject will have to only rely on the information received from the sensory feedback.
During the experiment the subject must let the dominant arm hang relaxed down the side of the torso and the contra-lateral arm placed on a table without putting pressure on the stimulation electrode, as seen in figure A.5. The subject must be seated during all procedures. The following order represent the chronology of the procedures the subject needs to undergo; the steps will be divided in solely control, solely sensory feedback and feedback with control.

Control

1. Record EMG signals needed to build the prosthetic control system. To do this the subject must first perform five movements used as reference signals: 15 seconds rest, 15 seconds prolonged maximum voluntary contraction (pMVC) of wrist supination, 15 seconds pMVC of wrist pronation, 15 seconds pMVC of opened hand and 15 seconds pMVC of closed hand. Between each contraction the subject will get a 15 seconds break to avoid fatigue. Secondly, the subject must perform movements from which the recorded signals are used to build the control system. Here, the subject controls a cursor as seen in figure A.4, and must match the cursor with trapezoidal trajectory. The cursor moves horizontally with time and the subject control the contraction intensity vertically. The subject must perform three contractions per movement: 40 %, 50 % and 70 % of the pMVC. The plateau of the trapezoidal trajectory corresponds to the designated fraction. Between each performed movement, the subject gets a 15 seconds break to avoid fatigue. Lastly, a 15 seconds rest is recorded.

2. Train the subject's ability to control the cursor via letting the subject move freely around inside the grid map for three minutes.

3. Perform target reaching test to evaluate the subject's ability to control the cursor. The designated target will be one of the squares in the grid highlighted in red. To reach a target the cursor must enter the target and dwell inside it for 1.5 seconds. Then a bell sound will occur and a new target appears. The time limit for reaching a target is 30 seconds. The starting point is always the resting state square (first square in third column), and the cursor will, thus, return to starting point when a target is reached or then the time limit is reached. A total of 16 targets will appear before this test is through.

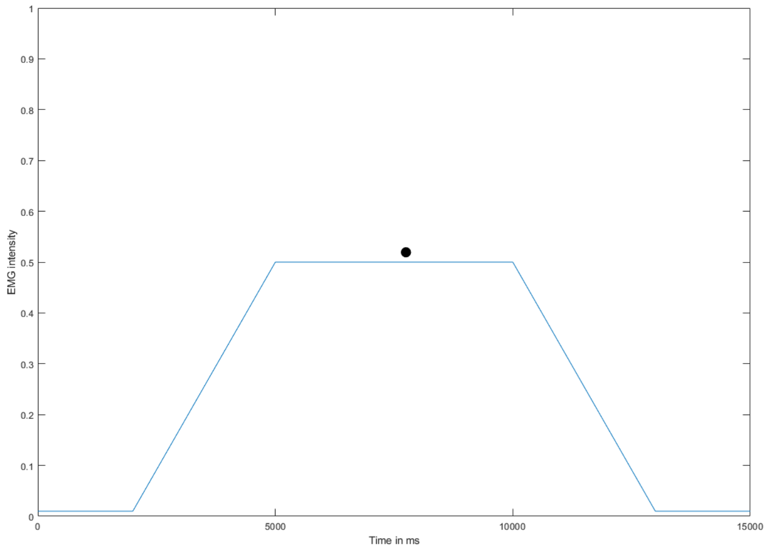


Figure A.4: Image of the trapezoidal trajectory used when recording EMG signals used to build the control system. The subject controls the black cursor in height by increasing contraction intensity.

Sensory Feedback

1. Record current amplitude thresholds needed to build the sensory feedback schemes. For each electrode the subject must first note when the stimulus is felt clearly. When all thresholds are set, the sensation of neighbouring electrodes are compared to ensure homogeneity in the sensation. Afterwards the same procedure is performed for the subject's tolerance threshold.

2. Train the subject's ability to interpret sensory feedback of feedback one of the schemes. This is done by exposing the subject to feedback from all grid squares. The subject will experience the transitions from square to square until the designated square is reached. The path taken to reach the designated square is the direct route (full length in one direction and then the other), but which direction that will be travelled first is predetermined by the investigators.

3. Perform reinforcement learning on 16 grid different squares. The path taken to reach the designated square is the direct route, but which direction that will be travelled first is predetermined by the investigators. During this step the subject must look away from the computer screen. When a designated square is reached, the subject will be asked where the cursor is located. After answering the subject will be informed on whether is was correct, and told the correct location, if the answer was incorrect.

4. Perform validation test on the 16 squares from step 3. The order of the squares and the route to each square will vary from step 3. During this step the subject must look away from the computer screen. When a designated square is reached,

the subject will be asked where the cursor is located. After answering the subject will not be informed whether the answer was correct or not.

Sensory Feedback with Control

1. Train the subject's ability to control the cursor while receiving sensory feedback via letting the subject move freely around inside the grid map for three minutes.
2. Perform target reaching test where the cursor is invisible to evaluate how well the subject can utilize the sensory feedback regarding the cursor location. This test has the same format as the target reaching test from the control procedure step 3.
3. Redo sensory feedback steps and sensory feedback with control steps with sensory feedback from the remaining scheme.

Experiment Setup

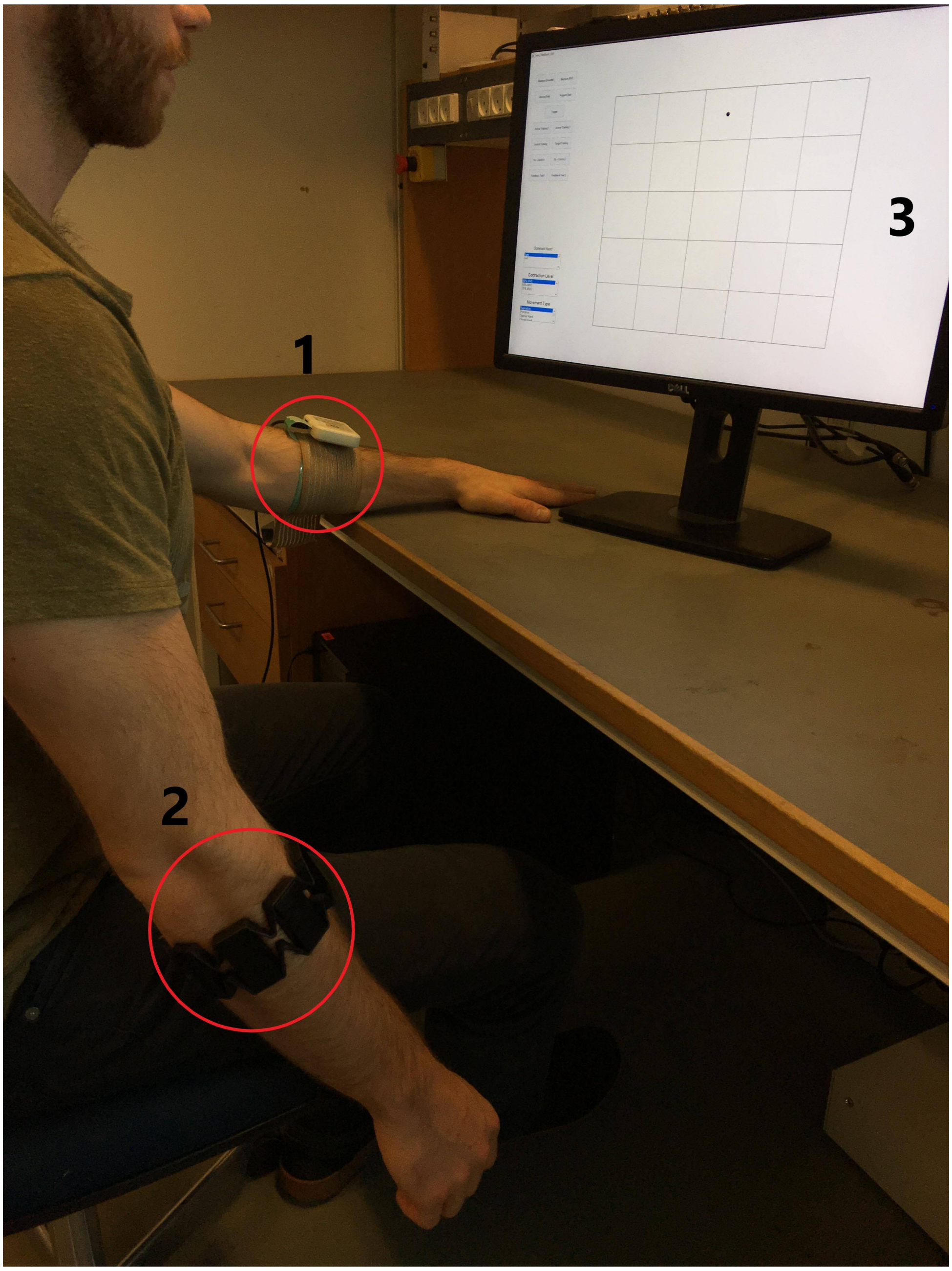


Figure A.5: Image of the experimental setup. 1) is the stimulation device with the stimulation electrode placed under the brown armband, 2) is the electrode armband used to record EMG signals and 3) is the computer screen used to guide the subject and display tasks.

A.2 Experiment Introduction Letter

Project Title
Evaluation of electrotactile feedback schemes in combination with myoelectric prosthetic control - closing the loop.

Experiment Purpose
The purpose of the experiment is to compare how subjects' perform in an evaluation test when receiving feedback from two different electrotactile stimulation configurations, while controlling a virtual prosthesis. The results might provide information on which feedback that seems more intuitive to use in a real prosthesis.

Experiment Overview
The experiment will take place in the laboratory building $D3-107$ at Aalborg University. The duration of the experiment is approximated to 2 hours and 30 minutes. During the experiment a myoelectric armband will be placed on the dominant forearm and will be used to record muscle activity during the performance of four different hand gestures. Subsequently, a test of the ability to reproduce the gestures will be made.
Afterwards, an electrode armband, capable of delivering electrical stimulation at 16 different locations will be placed on the non-dominant arm. A test to determine the electrical perception and tolerance level for the subject will then be carried out. The subject will then be made familiar and trained in understanding two different feedback configurations representing possible states which the virtual prosthesis might produce. A test of the subjects ability understand the feedback while making the trained hand gestures will be made right after familiarization and training for each feedback configuration.
On the day of the experiment please refrain from using any types of sensory deprivation drugs (painkillers and the likes). Any form of reimbursement will not be provided at the end of the experiment.