1 | Introduction

1.1 Introduction

The general challenge for users living with prosthetics it to be able to consistently produce distinguishable muscle patterns, for the prosthetic system to recognize. [**Powell2014**] Prosthetics are becoming exceedingly good in performance, however lack of functionality and discomfort of prosthetics are among the most commonly stated reasons for users to reject their prosthetic [**Reiber2010**]. Commercial available prosthetics range from passive cosmetic prosthetics to functional low degree of freedom (DOF) cable-driven prosthetics and switch controlled myoelectric prosthetics. In recent years several complex multi DOF prosthetic hands have been developed. Examples of this are the the Vincent hand by Vincent Systems, iLimb hands from Touch Bionics, the Bebionic hands from RSL Steeper and the Michelangelo hand from Otto Bock [**Belter2013**]. Despite the efforts to advance and improve the functionality of prosthetics, a critical bottleneck still exist: the ability to properly control the prosthetic [**Hwang2017**]. Most commercially available myoelectric controlled prosthetics rely on switch control which is a robust control scheme, but is slow and non-biologic/robotic in movement. In the research area of myoelectric prosthetics newer control schemes have been developed.These control schemes are classification and regression. Classification have been used for many years in research but is to date only used in one commercially available prosthetic. When using classification as a control scheme the classification attempts to classify similar patterns in electromyography (EMG) signals, between previously acquired data and new data [**Mendez2017**]. The regression control scheme determine the output signal for a input based on a regression line. This provide a continuous output value contrary to classification which provide a single value. [**Hahne2014**] Both types of control schemes have become exceedingly good at correctly estimating muscle patterns. [**Hahne2014**, **Bruun2017**, **Englehart2003**, **Scheme2015**] However, there still exist a challenge for the users to be able to consistently produce distinguishable muscle patterns. [**Powell2014**] In resent years many advancements have been made in research on system training. System training is the training of the control system to recognize the input signals from the user [**Fougner2012**]. This area focus on the design of the hardware and software side of the system in EMG prosthetics. Jiang et. al [**Jiang2012**] argue that a change should be made in the focus of research on myoelectric prosthetics in relation to improving control. The awareness in the research area show a very single-minded approach to possible improvements of control, and thus mainly system training have been researched. Jiang et. al [**Jiang2012**] discuss that the awareness of possible other practical implementation have been underestimated. One such implementation which have been addressed in only a few studies is user training [**Fang2017**, **Powell2014**, **Pan2017**]. Contrary to system training, user training focus on the user's ability to control a prosthetic [**Founer2012**]. User training differ from regular use of a prosthetic in that the training is usually part of the initial period, where the system is being adjusted to the individual user. Here different types of feedback can be used to inform the user on how well it performs movement or how well the system recognizes the users performed movements. In a 2014 study Powell et. al [**Powell2014**] provided to user with real-time visual feedback of a virtual prosthetic. This type of feedback is similar to the visual feedback a prosthesis user would receive using a normal prosthesis, albeit without the sensory feedback of the weight of the prosthesis. Pan et. al [**Pan2017**] provided a visual feedback of an arrow to be moved on a 2D plane. The arrow was controlled by two DOF's; one controlled the horizontal position of the arrow, while the other could rotate the arrow [**Pan2017**]. Fang et. al [**Fang2017**] provided real-time visual feedback of subjects performed movement in relation to the classes defined in the system. The feedback visualized a map of clusters of different classes which subjects could match the position of a cursor to. When subjects could match the cursor to the centroid of a cluster the performed movement corresponded the best with the class of that movement. [**Fang2017**]

Studies investigating the effect of user training shows promising results, however, as Jiang et. al [**Jiang2012**] discuss the myoelectric prosthetic research area might have been too focused on system training in resent years and could overall benefit from an expansion of research interests to include previously underestimated implementations or completely new approaches. A 2013 study by Scheme et. al [**Scheme2013**] proposed a novel approach of utilizing confidence-based rejection to improve system training of myoelectric control. Here a classification control scheme were provided with confidence scores to assist in acceptance or rejection of the class output. The confidence scores were calculated from a modification of Bayes' theorem. Scheme et. al [**Scheme2013**] showed a significant improvement in performance with the use of the rejection-capable system when compared to the normal classification scheme. A similar approach could be used in user training by providing the confidence scores of the classification to the user as a form of feedback. Thus, this study propose a novel method of providing users with feedback based on confidence scores for different classes in a classification control scheme during user training. Contrary to current feedback methods in user training this approach could enable users to better understand how the classification works based on their performed movements. During user training this could improve the way users perform specific movements in order to enable the system to better recognize and classify movements correctly.

2 | Background

2.1 Anatomy of the distal part of the arm

In this project EMG recordings will be measured from the distal forearm of test subjects, in order to use EMG signals for control and test the effect of providing feedback during user training. Recordings will be recorded with a Myo armband (MYB) from Thalmic Labs, further described in section 2.3 on page 5. This section will provide information on the anatomy of the distal part of the arm and the general muscles involved in movements used in this project.
The human arm is the base and extender for our greatest tool: the hand. The human hand is a very versatile and dexterous tool, and the loss of that function is therefore a great loss in relation to functionality and independence. The hand gains its vast utilization by having 27 degrees of freedom (DOF). This in itself makes it very dexterous but it is the arm that moves the hand along seven DOFs, that enables the hand to use its dexterity.
Movement of limbs are caused by muscle contractions. The muscles contract when receiving nerve impulses from the central nervous system (CNS). [**Martini2012**]
The greater workings of muscle activation is described further in section 2.2 on page 4. This project will use six movements for control of a virtual interface and visual feedback. The movements are flexion and extension, ulnar and radial deviation of the wrist, and open and close hand. The movements are visualised on figure 2.1. These six movements cover three DOFs.

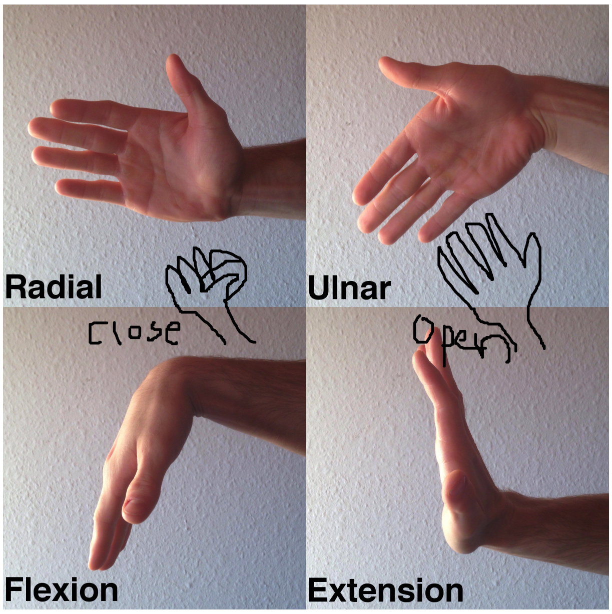

Figure 2.1: Flexion, extension, open, close, radial and ulnar deviation of the hand. **new picture**

Many muscles in the lower forearm are involved when performing hand gestures. Several muscles are actors in performing specific movements, and some of these are at times antagonistic muscles but will work together when performing other movements. The flexor carpi radialis and extensor carpi radialis brevis muscles are as an example antagonists in performing flexion and extension at the wrist, but are both involved when doing abduction of the wrist. [**Martini2012**] This can prove a problem when recording EMG signals from these muscles, since if based only on the recording there is no way of knowing which muscle and under which movement the signal is recorded from. However, this problem is overcome when doing EMG recordings of several muscles at the same time. As with the MYB, recordings are made in a circle all the way around one section of the forearm, providing a recording of several muscles at the same time. This enables a control system to evaluate individual muscle recordings in relation the recordings of other muscles, thus making correct classification of different hand gestures possible. [**Mendez2017**]

2.2 Recording Electromyography

This project will utilize the method of electromyography (EMG) to record the muscle activation of the lower arm muscles in relation to the gestures presented in. To develop theoretical background knowledge, a short introduction of the essentials of the signal and the technique of recording it will be presented.

Electromyography is the recording of muscle activity based on the amount of electrical stimulation. The amount of activity is found by measuring the electric potential, an action potential causing a muscle contraction. The process of planning and executing a voluntary movement starts at the motor cortex in the brain, where a signal is send, which propagates through the spinal cord to the lower motor neuron. As seen in figure 3.1 the path from alpha motor neuron through the axon to the motor endplates is what makes up a motor unit. The alpha motor neuron originates from the spinal cord along the axon to the muscle it controls. The axon branches out to multiple muscle fibers through motor endplates innervating the muscle fibers.

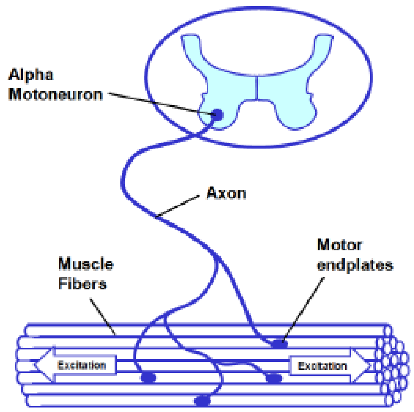

Figure 2.2: The figure describes the neural pathway from the alpha motor neuron to the innervated muscle fibers, making up a motor unit.[**Konrad2005**]

The essentials of understanding the application EMG is the excitation of muscle cells. The excitability of the muscle fibers play a crucial role in the making of a muscle contraction. The mechanisms of a contraction can be understood through a series of events. First the muscle cell membrane is at a resting potential between -80 to -90 mV, due to an equilibrium of NA^+ and K^+ through the intracellular and extracellular side of the membrane, maintained by an ion pump. The before mentioned alpha motor neuron reaches the motor endplates where a transmitter substance is released. The substance alters the membrane characteristics and allows a greater flow of Na^+ into the cell. This causes the a membrane depolarization, changing the membrane potential. If a threshold between -55 mV to -50 mV is reached excitation in the form of an action potential is formed, traveling in both directions of the muscle fiber, as seen on figure 3.1. The membrane potential is quickly restored with a great outflow of Na^+, resulting in a repolarization. The action potential from each of the activated muscle fibers summates spatially and temporally forming a motor unit action potential (MUAB). The spread of the MUAB over the muscle membrane is recorded with EMG. The number of recruited motor units is a way of controlling the force of a muscle contraction depending on the force needed. Like the recruitment of motor units, the frequency of activation can be modulated for generating a specific amount of force. A higher activation frequency leads to a higher generated force, but this also makes the muscle more prone to fatigue. The number of motor units innervating muscle fibers depend on the muscle characteristics and the purpose is serves. A low innervation ratio between motor units and muscle fibers make up the opportunity of fine motor tasks, while a low ratio is ideal for tasks demanding strength. Furthermore it is worth mentioning that the motor units are recruited in an asynchronous pattern. This further facilitates the possibility of smooth muscle movements. [**Cram2012**, **Martini2012**]

Recording EMG can be done either through the most often used surface EMG (sEMG) or by intra vascular EMG (iEMG). In IEMG a needle is inserted into the muscle measuring the MUAP directly on site. The more often used SEMG uses electrodes measuring the MUAP on the skin surface.[**Cram2012**]

2.3 Data acquisition

For a myoelectric prosthetic control system to be able to recognize hand movements it needs to be given prior information on how the movements looks like represented as a EMG-signal - this is also called training the control system. Thus, EMG data needs to be acquired from the user and used to train the control system. The following section describes which types of EMG acquisition techniques commonly are used.

As presented earlier in the source of the EMG signal is the motor unit action potentials. The energy generated in action potentials is of a very small size and is measured in microvolts. Very sensitive recording equipments is therefore key in doing electromyography. Essential is to consider the type of electrode intended to use. Electrodes come in various different sizes and shapes and are therefore very depended on the intended measurement site. Typically electrodes made of silver-impregnated plastic are used. They present desired characteristics by being disposable, relatively low price and by having low impedance with the skin. Most electrodes are covered with some adhesive compound in order for them to stick to the skin. These can either be 'dry' or covered with different types of gel, in order to reduce impedance and thereby noise, getting a more accurate EMG recording. Dry electrodes do not use gel, but instead rely on the skin to sweat and thereby decreasing the skin impedance. Dry electrodes should prove better to patients with sensitive skin. Different skin conditions may also effect the electrode-skin impedance. People with makeup, scale or much hair increases the impedance, why the site should be shaved or rinsed with an alcoholic wipe.[**Cram2012**] The following section will introduce the choice of acquisition device used in this project.

2.3.1 Myo armband

In this project the Myo armband(MYB) from Thalmic Labs will be used for EMG data acquisition. MYB is an electrode armband with eight dry stainless steel electrode-pairs around the inside of the armband, as depicted in figure 2.3. The advantage of dry electrodes is that they do not need to be disposed after usage as conventional gelled EMG-electrodes [**Cram2012**]. In addition, MYB can communicate cordless with a computer via a Bluetooth 4.0 unit [**Myoarmband2013**]. Thus, it is an easy and non-time-consuming device to use both during pilot-testing and for the final experiment. In the following section more information about the MYB will be given.

MYB records EMG data in a unitless 8-bit resolution. As usual when recording EMG the higher the performed contraction is, the higher the values in the output will be. To avoid interference from power lines a 50 Hz notch filter is implemented in the MYB. However, the MYB is not able to make any further filtering, therefore this will be implemented later during signal processing described further in section 3.3.1 on page 17. The MYB has a 200 Hz sample rate, and thus samples with a lower resolution than the EMG spectrum consists of, which is between 10-500 Hz [**Cram2012**]. Using MYB will likely result in an aliased EMG signal and confinement in using features representing the frequency information the signal. In section **??** on page **??**, different techniques to counter the negative effect of low-resolution EMG will be proposed for the implementation. Besides the EMG sensors the MYB can provide position and orientation information, using its three inertial measurement units consisting of a three axis gyroscope, a three axis magnetometer and a three axis accelerometer. This inertial information is sampled at 50 Hz. [**Myoarmband2013**] When initiating the wearing of the armband there is two calibration phases the user must follow before the armband is ready to use - the warm-up phase and the sync phase. During the warm-up phase the armband is ensuring as strong electrical connection with the muscles in the forearm as possible. This is mainly provided by light sweating on the skin under the electrodes, which improve the connection similar to electrode gel [**Cram2012**]. During the sync phase, the armband determines its orientation in space, position on and which arm it is placed on. The MYB works better when fitted tightly on the thickest part of the forearm. For users with smaller forearms a set of clips can be added for the armband to get a constrained grip. [**Myoarmband2013**]

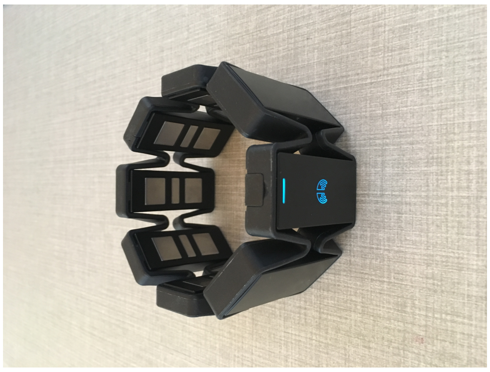

Figure 2.3: MYB from Thalmic Labs. The number on each channel indicates which channel corresponds to which column in the digital output, when acquiring data from MYB.

2.4 Data processing

In order to use the acquired EMG-signal in myoelectric prosthesis control, it first has to be processed, this is also refereed to as pre-processing. Since the acquisition and most processing is done in the MYB before Bluetooth transmission, further processing of the signal before use is kept at a minimum. In myoelectric prosthesis control features are extracted for use in control, instead of using the entire EMG-signal. Hereby the amount of information is reduced resulting in faster computational speed by reducing redundant information. The following two sections will briefly describe theory behind filtering and feature extraction in relation to this project.

2.4.1 Filtering

Filtering is a cornerstone in preparing an EMG-signal for any kind of use. The frequency spectrum of EMG is 10 Hz to 500 Hz and most electrodes has a working range of 0 Hz to 500 Hz [**DeLuca2010**]. According to the Nyquist theorem, to achieve a loss-less representation of the signal the sampling frequency must be at least twice the maximum frequency of interest of the original signal [**Pozzo2004**]. Besides sampling with twice the maximum frequency, EMG is sensitive to artifacts of movement and electrical interference. Due to these circumstances, filters are often implemented to remove these unwanted contributers [**DeLuca2010**]. General practice in filtering the EMG-signal will imply implementing a notch filter with very narrow width (49-51 Hz) or (59-61 Hz) depending on the power supply and with a very steep slope. The intend is to remove any electrical interference noise. In the low frequency spectrum several recommendations (5 Hz, 10 Hz and 20 Hz) has been made for optimal corner frequency of a high pass filter, to remove noise. A low pass filter is also introduced to remove any noise and unwanted signal above 500 Hz [**Cram2012**].

This project will utilize the MYB for data acquisition and as mentioned in section 2.3 on page 5 the MYB has a sample rate of 200 Hz. In relation to this paper a sampling frequency of at least twice the maximum of the recorded signal is not possible, since muscles of the forearm have a maximum frequency of 400-500 Hz [**Cram2012**]. This would require a sample rate of at least 1000 Hz, which cannot be achieved due to limitations in the MYB. The effect of the low sample rate of the MYB is aliasing in the recording, causing a frequency component not originally in the EMG signal. To account for this it would be resourceful to implement an anti-aliasing filter.

2.4.2 Feature extraction

The raw EMG-signal is not itself used for myoelectric prosthesis control, but features that are extracted from it. Thereby reducing the amount of redundant information limiting it to its most useful properties, resulting in faster computational speed. There are numerous feature components from an EMG signal which can be extracted either from the time-domain, frequency-domain, or time-frequency domain. Most used are features from the time- and frequency-domain. Time-domain features can be categorized in five different types based on their mathematical properties: energy information complexity information, frequency information, prediction modelling and time-dependency. Extracting features from the frequency-domain requires a frequency transformation, calculating the spectral properties of the recorded signal, which takes up longer processing time than simply using time-domain features. Time-domain features are often chosen based on their quick and easy implementation. They do not require any transformation before extraction and are calculated based on the raw EMG-signal. In addition, it is important not to choose redundant features for the classifier; features containing similar information. [**Phiny2012**]

Extracting features for real-time prosthesis control are done by taking segments of the continuous signal, called windows, and calculation are therefore done on these discriminated windows. This is done instead of using the instantaneous value due to the signals random nature. These windows are overlapped to create a dense information stream for extraction. The relationship between window and overlap length is significant, when trying to determine the best representation. The window length is a matter of getting enough samples to do the calculation, but to long a window will result in delays slowing the control. Overlapping the window is a way to faster acquire windows by reusing a determined last segment of the prior window. Smith et al. found that the optimal window length that enables best performance ranges from 150-250 ms, in a classification control scheme. [**Smith2014**]

2.5 Classification

For a myoelectric prosthesis to be able to distinguish between movements it needs to perform, a control scheme is needed to categorize the movements. The control scheme is trained by being given information about the EMG signal represented as the features extracted from the raw EMG. If the features between each movement are well separated the control scheme is able to recognize each distinct movement. For this purpose classification control schemes are commonly used. A classifier categorizes each movement as a class, and based on the input features it gives one class as output at a time. Using a classifier thus limits the user to only performing individual movements. However, if trained properly a classifier can reach a low error rate for the trained movements [**Scheme2013**]. A frequently used classification control scheme for myoelectric prosthetic control is the Linear Discriminant Analysis classifier(LDA) [**Scheme2013**, **Fang2017**, **Scheme2015**, **Englehart2003**]. The advantage of LDA is that whilst having a low computation time it still enables robust control. An assumption about the LDA is that the input needs to be Gaussian distributed [**Duda2000**], which the EMG probability properties has shown to adhere to [**Nazarpour2013**]. The following section provides further theoretical information about the LDA classifier.

2.5.1 Linear Discriminant Analysis

LDA is a supervised classification method used to separate classes of data by linear decision boundaries. Each decision boundary is a hyperplane from which the shortest distance to each class feature value and class mean is maximized for each class. A decision boundary is defined as a linear combination of the feature values x and is given as [**Duda2000**]:

$$g(x) = w^t x + w_0 \tag{2.1}$$

where w is a weight vector deciding the orientation of $g(x)$, and w_0 is a bias deciding the position of the hyperplane in relation to the origin. If $w_0 > 0$ the origin is on the positive side of the decision boundary, and if $w_0 < 0$ the origin is on the negative side. In the case of $w_0 = 0$ the decision boundary passes through origin. The distance from origin to the boundary is given as $\frac{w_0}{||w||}$. The position of the decision boundary is necessary to know to when separating features into regions. [**Duda2000**]

In a two category case the decision rule for deciding classes is to decide class w_1 if $g(x) > 0$ and class w_2 if $g(x) < 0$. $g(x) = 0$ then defines the decision boundary that separates the features into two decision regions R_1 for w_1 and R_2 for w_2. The normal vector w is orthogonal to any vector on the hyperplane, which is used to calculate the distance r from feature values (x) to the decision boundary [**Duda2000**]:

$$r = \frac{g(x)}{||w||} \tag{2.2}$$

The distance from origin and boundary to feature value (x) is needed to decide in which region the feature value belongs. [**Duda2000**] These distances are illustrated in figure 2.4.

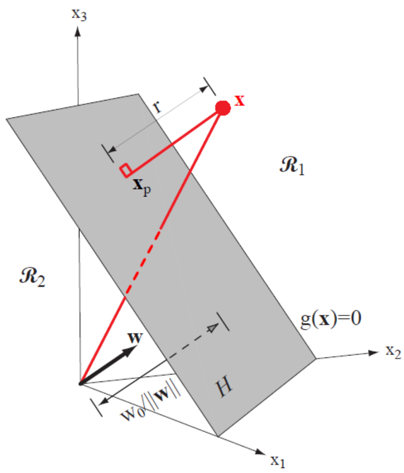

Figure 2.4: A geometric illustration of the linear decision boundary $g(x)$ that separates the feature space into two decision regions R_1 and R_2. x is the feature value, and x_p is the point on the decision boundary in which x is orthogonal projected on vector w. The distances from origin and boundary to feature value x is marked red. [**Duda2000**]

When feature values are to be classified into more than two classes more decision boundaries are needed. This is a multicategory case in which c numbers of boundaries are defined. When defining linear boundaries in this case any number can be chosen, but to minimize ambiguous decision regions the boundaries are defined by [**Duda2000**]:

$$g_i(x) = w^t x_i + w_{i0} \qquad i = 1, ..., c, \tag{2.3}$$

This equation follows the notation of the two-category case, with the addition of i numbers of boundaries, feature values and biases. This type of classifier is called a linear machine, dividing the feature space into c regions. A liner machine will be adopted as classification method in this project. Regions R_i and R_j, that are connected is divided by a boundary hyperplane H_{ij} defined by [**Duda2000**]:

$$g_i(x) = g_j(x) \tag{2.4}$$

Often regions are contiguous and will have a single boundary to separate several regions. [**Duda2000**] Illustrations of this case can be seen on figure 2.5.

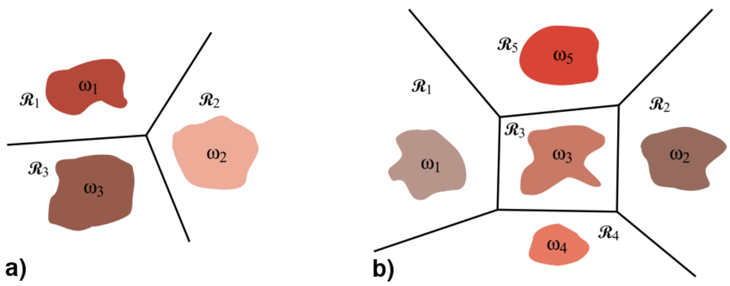

Figure 2.5: A three class (a) and five class (b) case each respectively separated by one decision boundary linear machine. [**Duda2000**]

When the decision boundaries $g_i(w)$ have been calculated as in equation (2.3), the input feature values can be decided upon which class they belong to by calculating the distance to the decision boundary as in equation (2.2).

2.5.2 Classification confidence scores

An additional reason for using LDA as control scheme is because it enables the calculation of confidence scores for the classes, which will be used in section **??** on page **??** to improve the prosthesis control. Based on the classification of feature values by the linear machine, confidence scores for the classes can be evaluated by computing the posterior probability of each class. Calculating the posterior probability is possible by knowing the likelihood $P(x|w_j)$ and the prior probability $P(w)$. The posterior probability for a class is a value between 0 and 1, and is calculated as follows:

$$P(w_j|x) = \frac{P(x|w_j)P(w)}{P(x)} \tag{2.5}$$

where w_j represents a class and x represents a feature value. The posterior probability is given as the product of the class conditional probability, $P(x|w_j)$ and the prior probability $P(w)$ divided by a normalization term $P(x)$ that guaranties that the posterior probabilities for all classes sums to one. $P(x|w_j)$ is the probability of obtaining a feature value when selecting samples randomly from a class. $P(w)$ is the probability of a sample from a specific class appears in its correct class, before it have actually appeared. Summation of posterior probabilities for all classes will equal 1.

2.6 Linear regression methods

The output from the LDA classifier only decides on which movement that is performed, and not at which contraction level the muscles used in the given movement are performing. Thus, the prosthesis can not perform any movement. In statistics linear regression is often used to determine relations between variables. This notion can also be applied for myoelectric prosthetic control. While classification only provides an output on which class is recognized, a linear regression model provides a continuous output value based on the input value. If the regression model is fitted with information on different contraction levels for a given movement, control proportional to the contraction level will be achieved [**Hwang2017**, **Bruun2017**, **Hahne2014**]. In the overall control scheme the classifier can then be used to decide which movement is performed, and a regression model can decide at which contraction level the movement is performed at. Similarly as with the classifier, regressors needs to be trained based on data acquired from the user, where the features extracted from the raw EMG signal is used as input. This procedure is described in the following section.

Different models of linear regression exist to account for different uses. When utilizing regression methods it must be considered which type of input variables are used and what type of relation these variables might have. The appropriate regression must then be applied. Simple linear regression approximate a relation between one dependent variable Y and one independent variable X [**Zar2009**]:

$$Y = \alpha + \beta X + \epsilon \tag{2.6}$$

where Y is the control output for the prosthesis, X is the feature extracted from the EMG signal, β is the regression coefficient in the sampled population, ϵ is the error, and α is the predicted value of Y at $X = 0$. This model can be expanded to estimate relations between one dependent variable and several independent variables. This is called multivariate regression and expands on the equation of simple linear regression (equation (2.6)) [**Zar2009**]:

$$\hat{Y} = \alpha + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_i X_i + \epsilon_i \tag{2.7}$$

where i in this project corresponds to the number of channels in the MYB [**Zar2009**]. Since this regression model approximates the relation between several independent variables and one dependent variable, this model can be used as a control scheme in myoelectric prosthetics, and . Here the channel-recordings of muscle activity can be considered independent variables, and used to estimate one control output, which would be the dependent variable. [**Bruun2017**]

2.7 Validating Performance

Measuring the performance of achieved prosthesis control cannot be seen as a trivial task, and different approaches can be used. The achieved performance can be measured by affixing a prosthesis on to the test subject and validate performance hereby. Often, like the current project, the subjects do not consist of actual amputees but instead healthy subject. In these cases the performance validation is done by implementing a virtual test environment where the subjects is to control an object on the computer screen by performing movements. The following section will further elude the procedures of such a virtual test for validating prosthetic control.

2.7.1 Modified Fitt's Law

Fitt's law task is a common way resorted to when quantifying movements, first proposed by Paul M. Fitts in 1954 [**Fitts1954**]. Originally, the only output of a Fitts' law task was the throughput, as given by equation (3.7). A modified Fitts' law task designed for a virtual 2D and 3D target acquisition task has later been used by [**Kamavuako2014**] and [**Scheme2013**] respectively. Here, four additional metrics were added in an online task, where a virtual computer cursor was used to represent the control output [**Kamavuako2014**, **Scheme2013**]. The four additional metrics were made by [**Poulton2013**] and [**Simon2011**]. While the throughput measure from the conventional Fitt's law task is usable, it does not cover all aspects of the control required to complete a task. The four measures were added to quantitatively assess performance of naturalness, spontaneity, and compensatory motions during use. The five proposed performance measures in assessing myoelectric control are [**Scheme2013a**]:

Throughput (TP) which represents the trade-off between speed and accuracy. TP uses the relationship of time taken to reach a certain target in seconds (MT) and the index of difficulty (ID). This forms: [**Scheme2013**, **Fitts1954**]

$$TP = \frac{1}{N}\sum_{i=1}^{N}\frac{ID_i}{MT_i} \tag{2.8}$$

where i is a specific movement and N is the total number of movements. ID relates to the target distance D and width W. The ID for each task, from the origin to a specific target of a certain size is calculated using [**Scheme2013**, **Fitts1954**]:

$$ID = log_2(\frac{D}{W} + 1) \tag{2.9}$$

Path Efficiency (PE) describes the quality of control by making a measure of the straightness of the cursor's path to the target, by making a ratio of the actual path distance versus the optimal path distance. This tests the users ability to continuously control the cursor position. Following the optimal path will result in a PE of 100%. PE is calculated as follows [**Poulton2013**, **Scheme2013**]:

$$PE = \frac{Optimal\ Distance}{Actual\ Distance} \tag{2.10}$$

Overshoot (OS) is the number of times the cursor enters and then leaves the target before the dwell time inside the target is reached, across all target in the task, divided by the total number of targets. Overshoot tests the users ability to control the velocity of the cursor accurately. A perfect score of zero is reached if the cursor dwells within the target boundaries on the first try for all targets, and is calculated as the following [**Poulton2013**, **Scheme2013**]:

$$OS = \frac{Total\ Number\ of\ Overshoots}{Total\ Number\ of\ Targets} \tag{2.11}$$

Stopping Distance SD describes the users ability to rest and thereby perform no movement. The SD measure is the distance moved during the dwell time across all targets, and is given as [**Scheme2013**]:

$$SD = \sum_{i=1}^{N} (Distance\ Inside\ Target)_i \tag{2.12}$$

, where i is a reached target and N is the total number of reached targets.

Completion Rate CR describes the percentage of targets reached within the total allowed time. This gives a general idea of the user's performance, and is calculated as [**Scheme2013**, **Simon2011**]:

$$CR = \frac{Number\ of\ Reached\ Targets}{Total\ Number\ of\ Targets} \tag{2.13}$$

2.8 Statistical analysis

When evaluating the scores obtained in the performance test a statistical analysis is used. For this project a Friedman's test will be utilized due to a small sample population, and because it is assumed that the probability distribution of the performance scores is unknown [**Zar2009**]. Friedman's test is commonly used to test if different treatments have similar or different effects in a subject population. In the case of this project it is used to test whether performance in prosthesis control is similar or different across sessions in a subject population and if performance scores differ or bear resemblance between two subject populations. In the following section, theory on how the Friedman's test is calculated will be presented.

2.8.1 Friedman's test

The aim for the Friedman's test is to calculate the Friedman's F value to compare it with its corresponding critical F value to finally decide if the null-hypothesis or an alternative hypothesis should be accepted. The null-hypothesis expresses a relationship between measurements(the means of measurements are equal) and the alternative hypothesis expresses no relationship between measurements(the means od measurements are unequal). When testing a subject population of a given number of measurements the measurements must first be arranged in columns, where each column corresponds to a certain measurement, and each row corresponds to one subject; this row is also called a block. Each block must then be ranked separately, where the smallest number is ranked 1. If numbers in a row are equal they get the mean of the rank they would have received. The sum R of each column is then calculated, and the number of measurements k and number of subjects n are used to calculate the Friedman's F value in the following equation [**Zar2009**]:

$$F = \left[\frac{12}{n \cdot k \cdot (k+1)}\right] \sum_{i=1}^{k} R_i^2 - 3 \cdot n(k+1) \tag{2.14}$$

The critical value of F is then determined by looking in a table of critical values for Friedman's test using the values for k, n and a significance level α. α needs to be chosen when looking up the critical values, where a level of 0.05 typically is selected; it is not excessively high to seize too many type 1

errors(rejecting a true null hypothesis) and not excessively low to seize too many type 2 errors(retaining a false null hypothesis). The F value and critical F value are then compared in order to decide whether to retain or reject the null-hypothesis. If the calculated F value is larger than the critical F value the null-hypothesis is rejected and vice versa. [**Zar2009**]
Another method of deciding on which hypothesis to be accepted is to evaluate the probability value (p-value), which can be returned by using statistical software. A significance level of 0.05 is again usually chosen. If the p-value is under 0.05 the null-hypothesis is rejected and vice versa. [**Zar2009**]

When comparing multiple groups of measurements the incident of rejecting a true null-hypothesis increase, and thus ignoring type 1 errors between pairs of means in the measurement groups. Several methods exist to counteract this multiple comparison problem. In this project the Bonferroni correction will be utilized for this purpose.

2.8.2 Bonferroni correction

A total number of $\frac{k(k-1)}{2}$ pairs can be coupled in multiple comparison testing, thus a total number of $\frac{k(k-1)}{2}$ hypotheses can be defined. The Bonferroni correction counteracts the incorrectly rejection of a null-hypothesis by lowering the significance level for each tested hypothesis by a scale m, where m is the total number of hypotheses. Thus, the new significance level tested for each individual hypothesis is $\frac{\alpha}{m}$. The Bonferroni correction then rejects the null-hypothesis when $p - value < \frac{\alpha}{m}$.

3 | Methods

3.1 Study Design

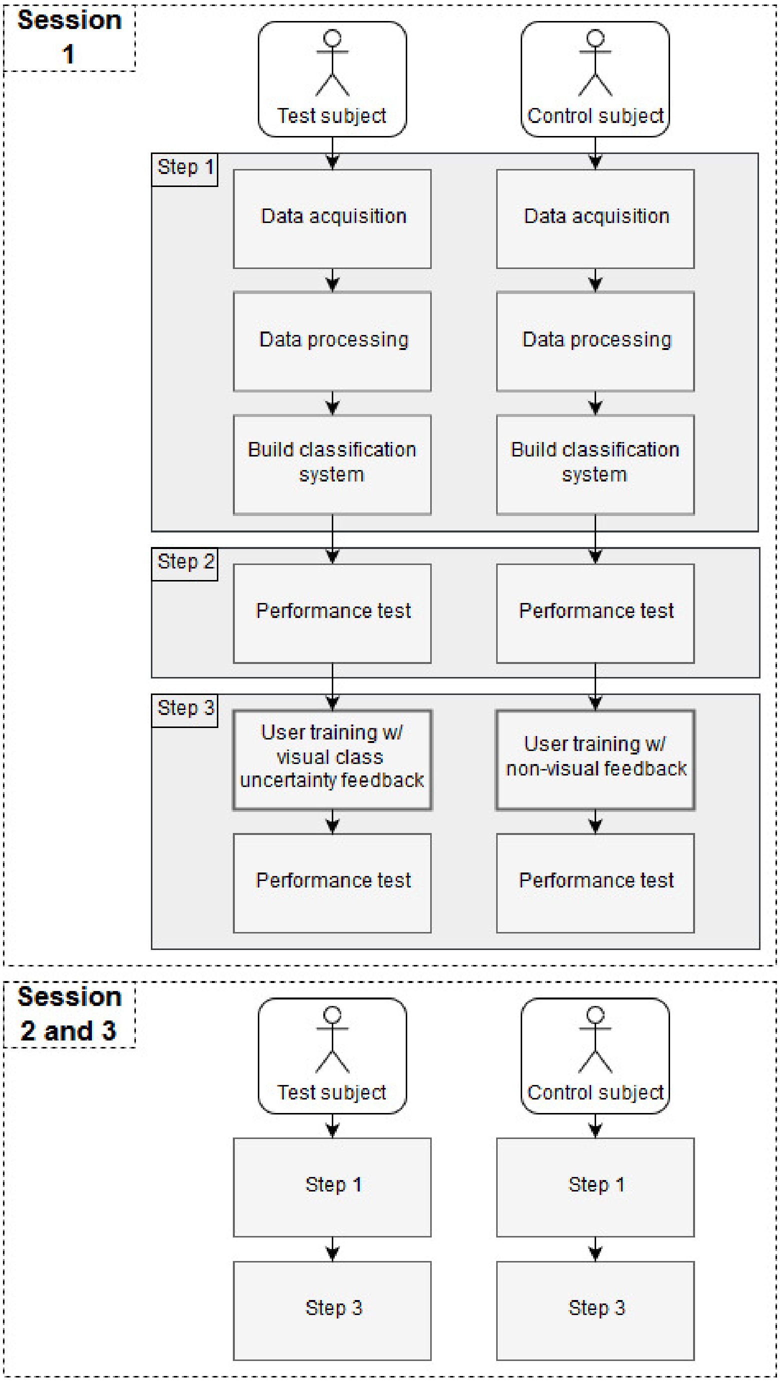

Figure 3.1: Ttext

3.2 Data Acquisition

This section will clarify the method of acquiring data in this paper/report.

For data acquisition the MYB will be used to record EMG signals from muscles in the lower forearm described in section 2.1 on page 3. The recordings will be made on test subjects instructed to perform six different hand gestures as introduced in the protokol, section 3.4 on page 19.

For acquiring data a Graphical User Interface (GUI) has been designed using MATLAB. In the GUI it is possible to change settings for different types of recordings. The first type of recording are of a baseline. This recording is made in order to be able to remove signal artefacts. The second recording type is Maximum Voluntary Contraction (MVC) which is a 15 second recording of the subjects maximum contraction in one gesture that can be kept constant for 15 seconds. The third type of recording is of EMG signals used in data processing. The recordings of EMG signals are based on fractions of the MVC which can be set using a slider in the GUI. As stated in the protokol, section 3.4 on page 19, three contraction levels will be used: 20%, 40% and 60%. The level of contraction defines the height of the plateau of a trapezoid trajectory which will be plotted in a window in the GUI. When doing EMG recordings the subjects must perform the instructed gesture to control the height of a cursor in the trapezoid plot to best match the trajectory of the trapezoid. The subject only controls the height of the cursor as the cursor will automatically move forward along the x-axis in relation with time. The recording time is 15 seconds, with 2.5 seconds on the trajectory incline and decline and 5 seconds on the plateau. This approach provides data on a performed gesture in both the transition and steady state phase, at the specified contraction level. A illustration of the GUI is shown if figure 3.2 during acquisition of EMG data. During recordings the investigators will evaluate if the subject followed the trajectory well enough, and following the data acquisition for a subject a Principal Component Analysis (PCA) will be used to evaluate if the acquired data are applicable. The PCA evaluation is further described in section **??** on page **??** If the data is not usable a new recording will be made.

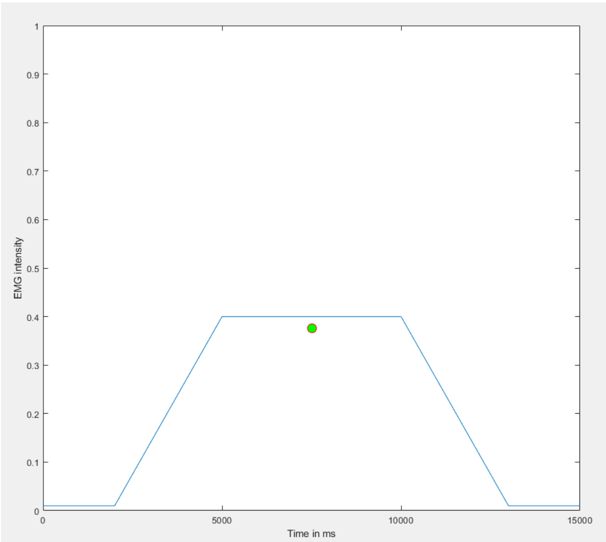

Figure 3.2: The implemented GUI in MATLAB, during data acquisition.

3.3 Data processing

The following two sections will cover the implementation of the filter used to prepare the EMG-signal and the extraction of features to represent the signal. Choices behind implemented methods builds on background knowsedge acquired in section 2.4 on page 6.

3.3.1 Filtering of signal

As earlier mentioned in section 2.4.1 on page 6, due to the MYB specifications limiting the sample rate to 200 Hz and movement artefact's in the low-frequency spectrum, it would be resourceful to implement a bandpass filter to avoid a biased signal. In the interest of representing the signal with its true properties a second order Butterworth bandpass filter has been implemented with cut-off frequencies of 10 Hz and 90 Hz. A filter steeper than second order was deselected due to a chosen trade-off between filter performance and computational performance, which is of great importance when doing real-time control. Below in figure 3.3 is the result of implementing the bandpass filter shown. The unfiltered signal shows frequency components in low-frequency spectrum around 0-10 Hz and indicating frequency components above above 100 Hz. Both ends of the spectrum has been dampened limiting impact of artefact's and possible aliasing. Furthermore is the presence of the build-in 50 Hz notch filter elucidated as explained in section 2.3 on page 5.

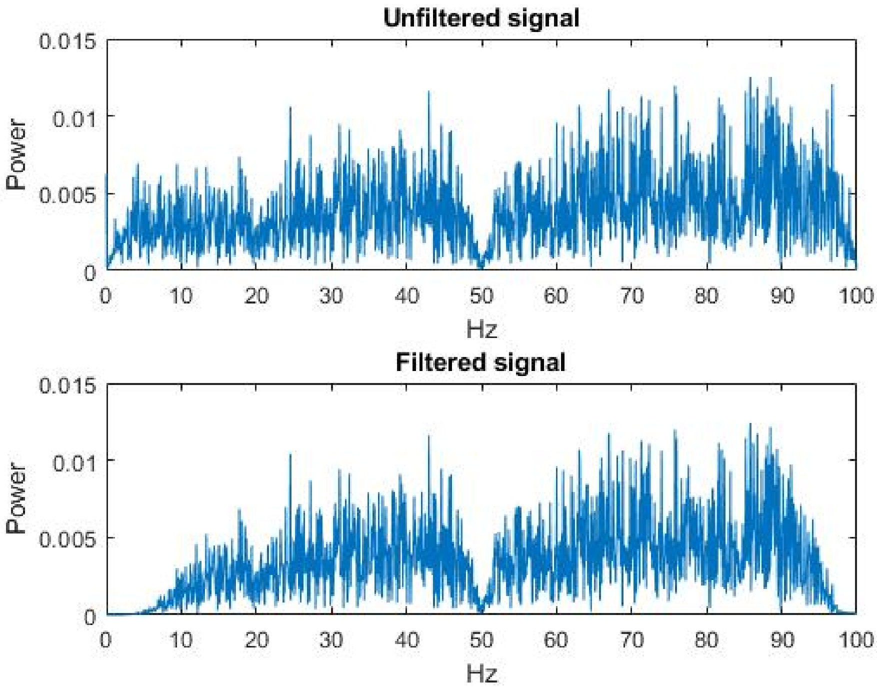

Figure 3.3: Output showing the difference before an after implementing the bandpass filter. The unfiltered signal shows frequency components in low-frequency spectrum around 0-10 Hz and indicating frequency components above above 100 Hz.

3.3.2 Feature extraction

In section 2.4.2 on page 7 it was stated that when extracting features for real-time prosthesis control, features are extracted form segments of the signal called windows. This projects will for the feature extraction utilize a window size of 200 ms and a 50 % overlap for all channels. This thereby gives the possibility of calculating and updating the feature values ten times a second.

The features chosen to represent the information of movements contained in the signal is primarily based on recommendations from [**Donavan2017**] where they found the optimal features for a real-time classification control scheme using the MYB. Donavan et al. used so called space domain features along with the MYB and got a five percent higher accuracy than by using the well known Hudgins time domain features. A total of seven features, Mean Absolute Value (MAV), Mean Mean Absolute Value (MMAV), Scaled Mean Absolute Value (SMAV), Correlation Coefficient (CC), Mean Absolute Difference Normalized (MADN), Mean Absolute Difference Raw (MADR) and Scaled Mean Absolute Difference Raw (SMADR) were derived and the following section will explain the extraction of each. This project will use SMAV, CC, MADN and SMADR for the final classification to reduce redundancy, but all seven will be explained because some features are a combination of others. [**Donavan2017**] Furthermore it has been chosen to extract the time domain feature of waveform length (WL) to represent frequency related information of the signal. The extraction of this feature will lastly be explained as well.

MAV is a feature that primarily is affected by the force produces when making a contraction. MAV is extracted for each window and calculated for each of the i^{th} channel. The extraction is expressed as

$$MAV_i = \frac{\sum_{n=1}^{ws} |x_i[n]|}{ws} \tag{3.1}$$

ws is the window size, the number of raw data points in that exact window. $x_i[n]$ is the n^{th} raw data points from one i^{th}.

The averaged MAV across all channels is called MMAV and is used to remove dependency of movement intensity. MMAV is calculated by using the MAV of all channels for the current window, and is done as following

$$MMAV = \frac{\sum_{i=1}^{8} MAV_i}{8} \tag{3.2}$$

MMAV can be used to scale the MAV feature making up the SMAV feature. This feature should represent a non-dimensional relationship between channels. SMAV is simply calculated as

$$SMAV_i = \frac{MAV_i}{MMAV} \tag{3.3}$$

As each of the eight MYB sensors are located around the arm, the pick up signals from a mixture of sources. Also individual sources may affect multiple sensors depending on their size. Due to this a source measured by multiple sensors will effect their acquired signal correlation. An idea is therefore to calculate the correlation coefficient between each channel and its neighboring channel.

$$CC_i = \frac{\sum_{n=1}^{ws} X_i[n]X_{i+1}[n]}{\sum_{n=1}^{ws} X_i[n]^2} = \frac{\sum_{n=1}^{ws} X_i[n]X_{i+1}[n]}{ws} \tag{3.4}$$

$X_i[n]$ is the n^{th} data point from channel i. When calculating CC the data from window is normalized by subtracting its mean value from each raw data point, and afterwards divided by their standard deviation.

Calculating CC can prove rather demanding computatinaly due to the series og multiplication operations. Therefore Donavan et al. proposed introducing a MAD-based feature of lower computational complexity which still characterizes the spatial relationship between channels. The MAD feature feature is normalized in the same way as CC making up the MADN feature calculated as

$$MADN_i = \frac{\sum_{n=1}^{ws} |X_i[n] - X_{i+1}[n]|}{\sum_{n=1}^{ws} X_i[n]^2} = \frac{\sum_{n=1}^{ws} |X_i[n] - X_{i+1}[n]|}{ws} \tag{3.5}$$

If the normalization of the signal proves too demanding the feature can be calculated without the normalization. This makes up the MADR feature

$$MADR_i = \frac{\sum_{n=1}^{ws} |X_i[n] - X_{i+1}[n]|}{ws} \tag{3.6}$$

As the SMAV feature the MAD feature can be scaled by MMAV to remove movement intensity dependency. SMADR is calculated for each channel by

$$SMADR_i = \frac{MADR_i}{MMAV} \tag{3.7}$$

As stated in the beginning some of these features introduce redundancy, subsequently the features of SMAV, CC, MADN and SMADR are the ones used for classification. [**Donavan2017**]

To further improve the decision foundation of the classifier it was proposed to include the time domain feature of WL calculated by

$$WL_i = \sum_{n=1}^{N-1} |x_{i+1}[n] - x_i[n]| \tag{3.8}$$

WL is a measure of the signal complexity by calculating the cumulative length for each channel [**Phiny2012**].

3.4 Experiment protocol for test subjects

Title of the project
Using confidence levels of movement recognition in user training to improve prosthesis control

Details on investigators
All investigators are 2th semester biomedical engineering master students at Aalborg University.

Background and purpose
Electromyography (EMG) is widely used for controlling functional lower arm prosthetics for transradial

amputees. The ideal purpose of a functional prosthesis is to behave as functional as possible compared to a biological arm. Functional prosthetics that rely on pattern recognition-based control are becoming exceedingly good in performance in a clinical environment, due to highly optimized system control. However, still only one commercially available pattern recognition-based prosthesis exist. Users reject these functional prosthetics usually due to functionality issues when utilizing them in daily life tasks outside the clinical environment. Many improvements have been made in the area of system control, but another approach of improving the prosthetic control is by training the user. User training has only been explored moderately in the research literature, thus, techniques to improve the user's ability to control a prosthesis are yet untouched. This experiment will focus on training the user to improve prosthetic control on a fixed pattern recognition-based control system. The novel approach in this study is to provide the user with information on how well the system recognizes the performed movement during user training.

Research hypothesis
Exposing subjects to user training, in which confidence levels of movement recognition is used as feedback, will show improvement in performance in a classification-based myoelectric prosthetic control scheme.

Ethical considerations
The investigators do not foresee any obstacles of ethical nature during the proceedings of this experiment. No test subjects will be exposed to any physical interventions besides being asked to wear the Myo armband. No part of this experiment should put the subject in danger.

Session time
The experiment consist of three sessions, which are spread over three consecutive days; one session per day. Each session is estimated to have a total duration of 30-60 minutes.

Inclusion criteria
The subject needs to be:

- able bodied.
- between 18 and 60 years of age.
- able to understand and speak Danish and/or English.
- assessed by the investigators to understand and perform the instructions given during the experiment.

Exclusion criteria
The subject must not have:

- diseases that might influence subject performance.

Experiment procedure

The experiment consists of three sessions containing different steps as illustrated on figure 3.4. The concept and chronology of each step is described below the illustration.

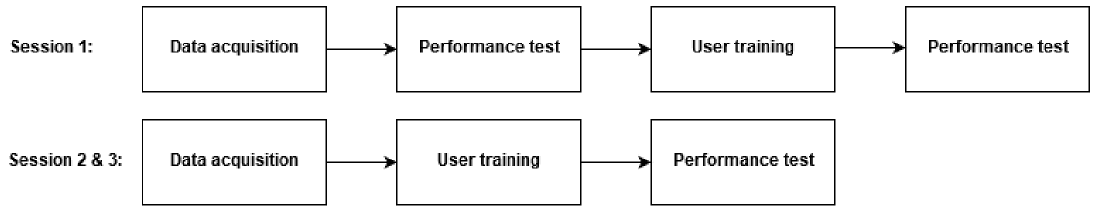

Figure 3.4: Pipeline for the three sessions in the experiment and what steps each session contains.

Data acquisition
For the myoelectric control system to be able to identify a performed movement as the movement that is actually performed, it needs information about how the movement looks when represented as a EMG signal. Thus, EMG data needs to be acquired from the forearm of the subject meanwhile the subject performs the movements that is used in the experiment, see figure 3.9 on the last page. This data is fed to the control system for it to be able to recognize each movement. In this experiment EMG data will be acquired from the subject with an EMG-electrode armband: Myo armband (MYB) from Thalmic Labs. The chronology of this step is as follows:

1. Apply MYB on dominant forearm at the thickest part.
2. Synchronize MYB by performing wrist extension until three distinct vibrations are felt.
3. Perform 15 seconds of maximum voluntary contraction (MVC) of instructed movement. Following the MVC the subject will be given a 15 seconds resting period to avoid muscle fatigue.
4. Perform three 15 seconds contraction trails of respectively 40%, 50% and 60% of MVC. During these contractions the subject will control a green marker representing the EMG signal and try to follow a trapezoidal trajectory as precise as possible. The trapezoidal trajectory consists of two five second transition phases and one five second plateau phase. Between each trial the subject will be given a 10 seconds resting period to avoid muscle fatigue.
5. Repeat step 3-4 until training data from all four wrist movements has been recorded.

An illustration of the interface used for data acquisition is shown in figure 3.5.

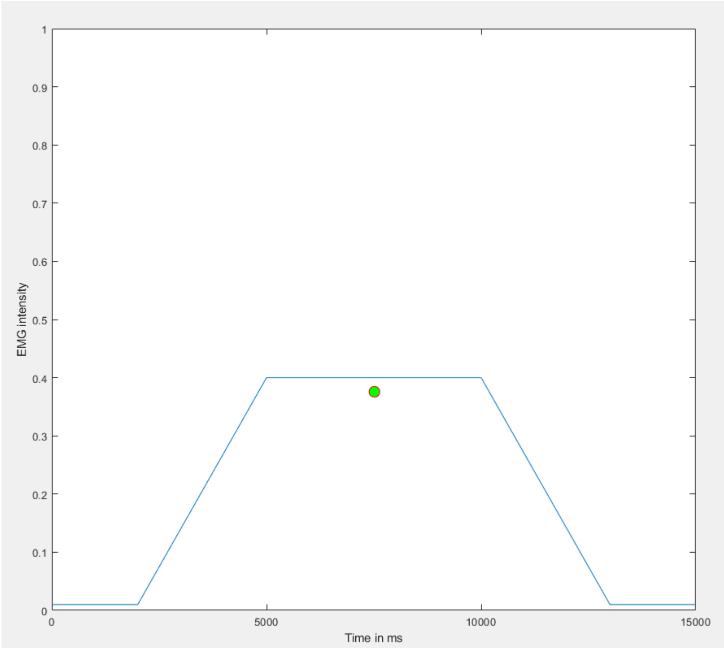

Figure 3.5: Illustration of the data acquisition interface showing the trapezoidal trajectory and the green marker representing the EMG signal.

User training

The purpose of user training is for the subject to train the movements used in the performance test. During the user training the subject will train one movement at a time in different contraction levels. When training a movement, visual feedback in form of confidence levels on how well the control system recognizes movements, is shown in percentage in a bar plot. In addition, the level of contraction is shown in a text box above the bar plot. When performing the instructed movement at the instructed level of contraction the background colour of the text box will appear green; if it is outside the instructed level it appears red. The aim for the subject is to reach and withhold the instructed contraction level with 100 % recognition certainty for each movement. The chronology of this step is as follows:

1. Perform extension at 15-25 % contraction level for 20 seconds followed by 10 seconds rest.
2. Perform flexion at 15-25 % contraction level for 20 seconds followed by 10 seconds rest.
3. Perform radial deviation at 15-25 % contraction level for 20 seconds followed by 10 seconds rest.
4. Perform ulnar deviation at 15-25 % contraction level for 20 seconds followed by 10 seconds rest.
5. Perform closed hand movement at 15-25 % contraction level for 20 seconds followed by 10 seconds rest.
6. Perform opened hand movement at 15-25 % contraction level for 20 seconds followed by 10 seconds rest.
7. Repeat step 1-6 at 35-45 % contraction level.
8. Repeat step 1-6 at 55-65 % contraction level.
9. Repeat step 1-6 at 75-85 % contraction level.

An illustration of the interface used for user training is shown in figure 3.6.

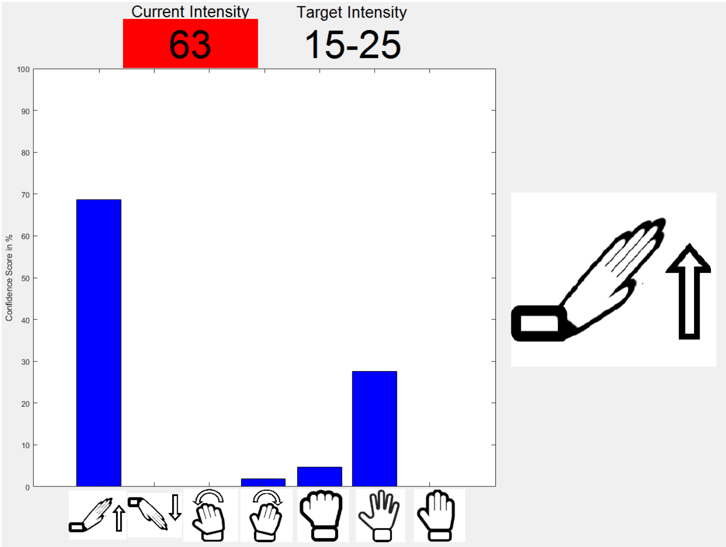

Figure 3.6: Illustration of the user training interface showing the bar plot indicating the confidence level of movement recognition and the text box indicating contraction level. The picture on the right side of the bar plot indicates which movement needs to be performed.

User Training

The purpose of user training is for the subject to train the movements used in the performance test. During the user training the subject will train one movement at a time in different contraction levels. When training a movement, visual feedback on which movement the control system recognizes, is shown in percentage in a bar plot. In addition, the level of contraction is shown in a text box above the bar plot. When performing the instructed movement at the instructed level of contraction the background colour of the text box will appear green; if it is outside the instructed level it appears red. The aim for the subject is to reach and withhold the instructed contraction level with 100 % recognition certainty for each movement. The chronology of this step is as follows:

1. Perform extension at 15-25 % contraction level for 20 seconds followed by 10 seconds rest.
2. Perform flexion at 15-25 % contraction level for 20 seconds followed by 10 seconds rest.
3. Perform radial deviation at 15-25 % contraction level for 20 seconds followed by 10 seconds rest.
4. Perform ulnar deviation at 15-25 % contraction level for 20 seconds followed by 10 seconds rest.
5. Perform closed hand movement at 15-25 % contraction level for 20 seconds followed by 10 seconds rest.
6. Perform opened hand movement at 15-25 % contraction level for 20 seconds followed by 10 seconds rest.
7. Repeat step 1-6 at 35-45 % contraction level.
8. Repeat step 1-6 at 55-65 % contraction level.
9. Repeat step 1-6 at 75-85 % contraction level.

An illustration of the interface used for user training is shown in figure 3.7.

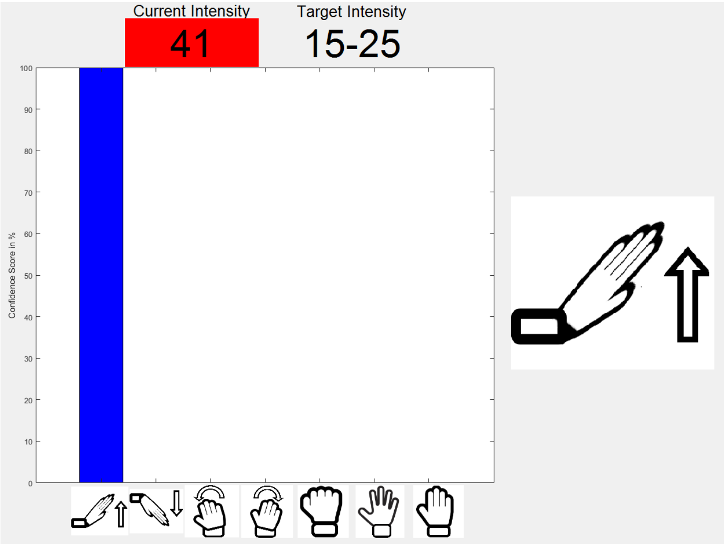

Figure 3.7: Illustration of the user training interface showing the bar plot indicating which movement is being recognized and the text box indicating contraction level. The picture on the right side of the bar plot indicates which movement needs to be performed.

Performance test

The purpose of the performance test is to assess the subject's ability to control a prosthesis. Instead of doing a test with a real prosthesis a virtual alternative has been developed for this experiment. The prosthesis is represented as a red circular cursor with a black dot inside in a Cartesian coordinate system, which the subject can move as well as expand and shrink in size by performing the trained movement. The following bullets describe which movement corresponds to which action in the coordinate system:

- Extension moves the cursor right.
- Flexion moves the cursor left.
- Radial deviation moves the cursor up.
- Ulnar deviation moves the cursor down.
- Closed hand shrinks the cursor.
- Opened hand expands the cursor.
- Rest keeps the cursor still.

The performance test consists of a target reaching test, where the subject must reach 16 targets of different sizes and locations. A target consists of a circle with a smaller circle inside. Only one target will be visible at a time. For the subject to reach a target and make a new appear, the subject must center the black dot of the cursor in the small circle of the target and expand/shrink the cursor to fit the size of outer circle of the target. The cursor will appear green, when located at the correct position. The subject must dwell the cursor in a target for 1 seconds for it to be reached. When the cursor has dwelled for 1 second, it will appear blue for 1 second to indicate that the target has been reached. If this is not done within 15 seconds a new target will appear. The aim for the subject is to reach as many target as possible as quickly as possible. The subject is only able to perform one movement at a time, as trained in the user training. Thus, no simultaneously performed movements will be recognized by the control system. The chronology of this step is as follows:

1. Reach the visible target.
2. Repeat step 1 until all targets have been shown.

An illustration of the interface used for the performance test is shown in figure 3.8.

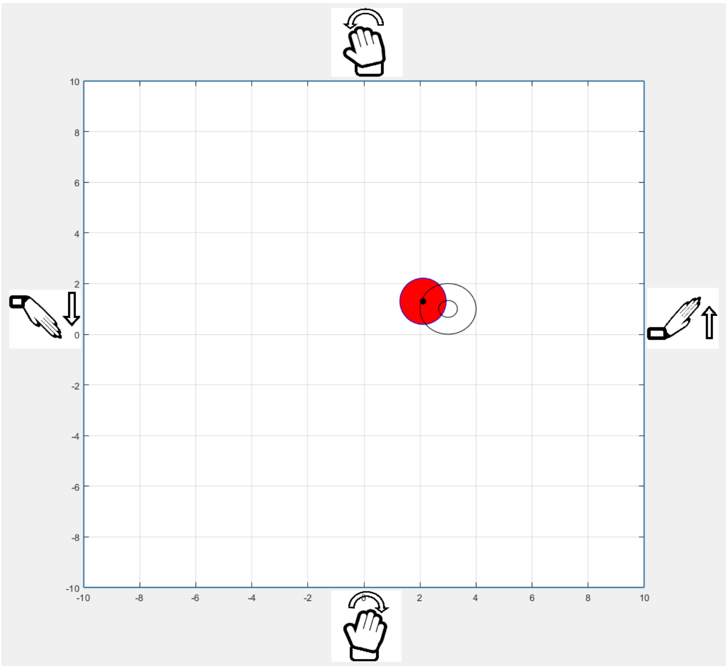

Figure 3.8: Illustration of the performance test interface showing a target and the cursor representing the prosthesis output. The pictures on the axes indicate which movement must be performed to move the cursor in a certain direction.

Movements used in the experiment

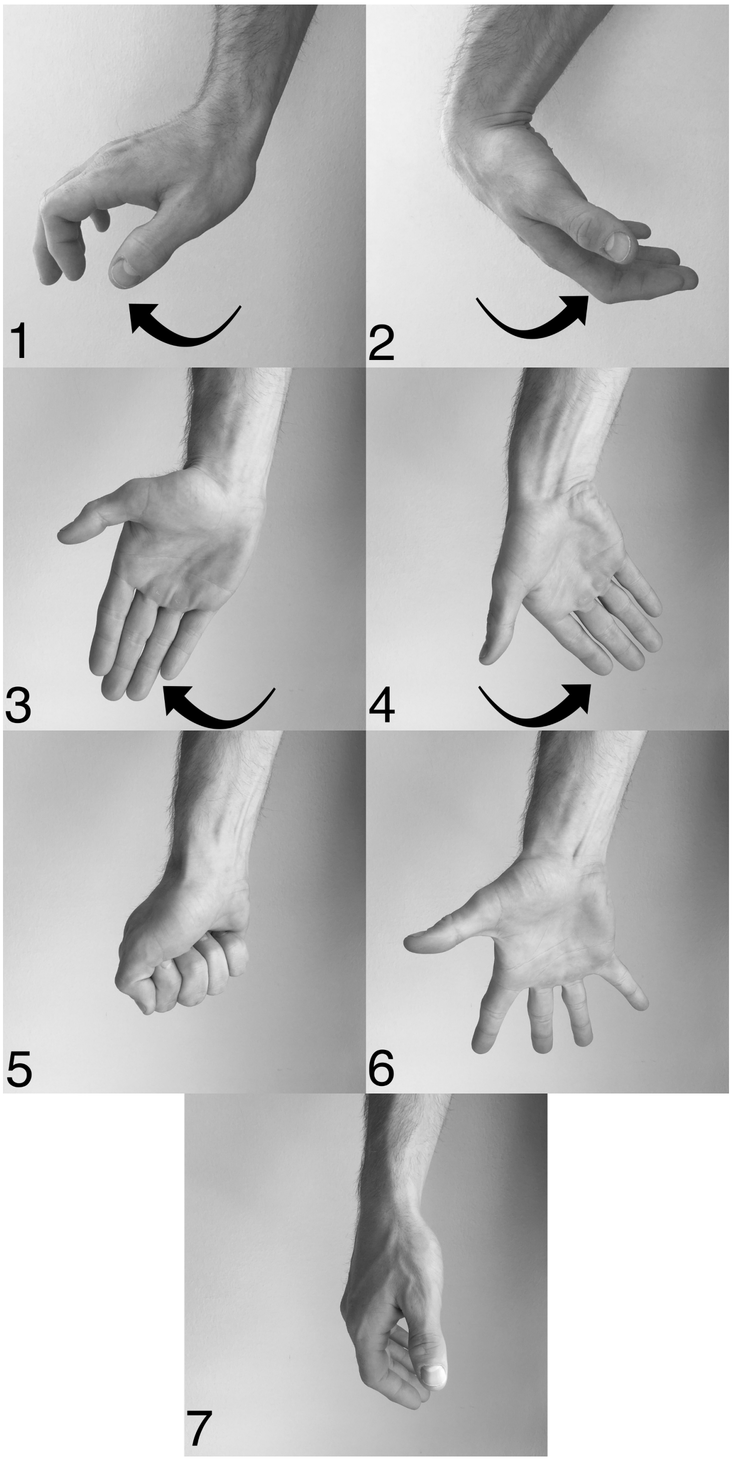

Figure 3.9: Illustration of the movements used in the experiment. 1: extension, 2: flexion, 3: radial deviation, 4: ulnar deviation, 5: closed hand, 6: opened hand and 7: rest.

4 | Results

5 | Discussion

6 | Conclusion