1 | Introduction

1.1 Introduction

Electromyography (EMG) is the recording of muscle generated electric potentials, widely used in control of functional prosthetics. The electric potentials recorded from the muscles are action potentials generated before the inception of a muscle contraction. The contraction force a muscle produce is related to the intensity of an EMG recording. The recorded EMG signals are processed through steps of amplification, filtering and feature extraction before they are used as input in the control for a myoelectric prosthesis. [1, 2]

Ever increasingly advanced myoelectric prosthetics and control systems are being developed. Despite the efforts a critical bottleneck still exist: the ability to properly control the advanced prosthetic [3]. In relation to pattern recognition methods the overall challenge lies in the ability for the system to be able to recognizing the muscle patterns produced by the user. Control systems have become exceedingly good at correctly estimating muscle patterns. However, there still exist a challenge for the users to be able to consistently produce distinguishable muscle patterns, and the better these muscle patterns the better the system will function. [4]

In recent years the research area of myoelectric prosthetics has been dominated by classification methods for control schemes. Classification attempts to classify similar patterns in EMG signals, between previously acquired data and new data [5]. Classification enables proportional control of trained movements in several degrees of freedom (DOF), but but only a single movement a time. The classification control scheme has lacked usability outside of clinical environments [6], which has resulted in scarce commercial success [7].

Many advancements have been made on system training to improve the systems and control schemes to best recognize the performed movements by the users. Jiang et. al [7] determine that a change of focus in the myoelectric prosthetics research area should be made. Perhaps as a result of a too single-minded approach in the research community, compared to system training, far fewer studies have investigated the effect of user training. Improving the users ability to properly utilize the system is the goal of user training. Here, an important consideration is that each user will have individual competences when initiating user training. Some might perform well from the beginning while others will show little to no success. [8] Powell et. al [8] conclude that in order for amputees to understand the significance of producing consistent and distinguishable muscle patterns, the need for user training is important. User training can help amputees to gain the skill of controlling pattern recognition based prosthetics and to later adopt the use of one such prosthesis [8].

The significance of user training is not doubted, and several different approaches has been investigated. Fang et. al [9] evaluated the progress of the human learning ability in a pattern recognition based control scheme when providing classifier-feedback during user training. Here, a clustering-feedback method based on Principal Component Analysis (PCA) was used to provide users with real-time visual feedback, to guide users to correctly perform movements based on the recorded EMG signals. The visual feedback consisted of a map with dots representing centroids of classes. Through control based on an Linear Discriminant Analysis (LDA) classifier, users could match the control input to these centroids to best perform a movement to be classified correctly. The study showed great improvements in performance after user training, and an ability to quicken the learning for amputees who are unfamiliar with EMG controlled prosthetic use. [9] Other studies have also showed promising results using an LDA classifier during user training. Powell et. al [4] demonstrated an increase in movement completion percentage from 70.8% to 99.0%, a decrease in movement completion time from 1.47 to 1.13, as well as a significant improvement in classifier accuracy from 77.5% to 94.4%, for users undergoing user training for a two week period. This study provided feedback through a virtual animated prosthesis. Pan et. al [10] provided a visual feedback of an arrow to be moved on a 2D plane. Pan et. al also tested the effect of stimulating the subjects brain with transcranial direct current stimulation (tDCS). The study concluded that tDCS together with user training provided significantly better results than user training alone. [10]

The general challenge of user training is for the user to be able to consistently produce distinguishable muscle patterns. [4] Therefore further research in user training could provide a vital leap towards more precise classification using current methods, as well as a faster user adaptation of myoelectric controlled prosthetics, but an effective way to properly provide feedback to the user have yet to be developed. This study will seek to develop a new method of feedback during user training, by providing the users with the confidence scores of a LDA classifier as used in [11] for a confidence-based rejection system control scheme, and the level of contraction of the performed movement as proposed in [12]. To the authors knowledge, these feedback parameters have not yet been provided in a combination in user training for myoelectric prosthesis users.

The remainder of this paper will be structured in "x numbers" of sections. Section 2 will further describe the experimental setup, subject management and experimental protocol. Section 3 will describe the methods used to do something with the control off and the user training thing we do. Section 4 present the result, discussion and conclusion.

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). [13]

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.

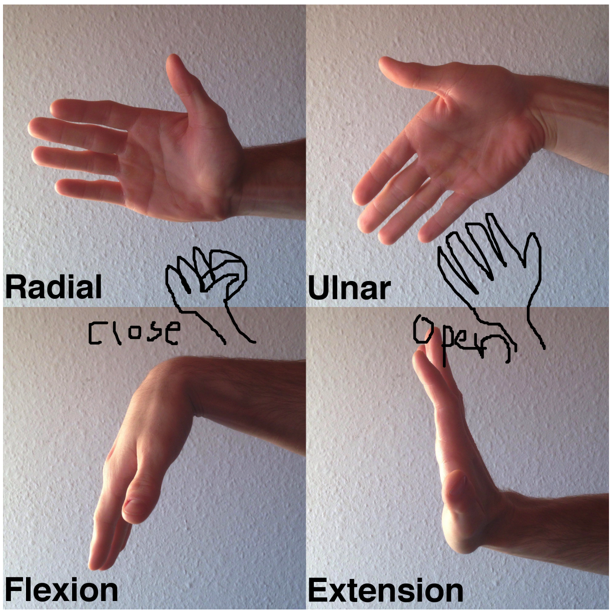

Figure 2.1: Flexion, extension, open, close, radial and ulnar deviation of the hand. **new picture**

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. [13] 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. [5]

2.2 Recording Electromyography

This project will utilize the method of electromyography (EMG) to record the muscle activation of the lower arm 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 neurological/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, and propagates through the spinal cord to the lower motor neuron. As seen in figure 2.2 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. The number of motor units innervating a muscle depend on the muscle characteristics and the purpose is serves. Muscle movement demanding high precision have a higher innervation of motor units than muscles used for more powerful movements. 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.[1, 13]

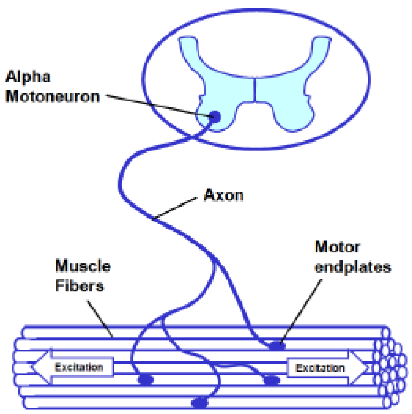

Figure 2.2: The figure describes the neural pathway from the alpha motor neuron to the innervated muscle fibers, making up a motor unit.[14]

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 2.2. The membrane potential is quickly restored with a great outflow of Na^{+}, resulting in a repolarization. The spread of the motor unit action potential (MUAB) over the muscle membrane is recorded with EMG. The EMG recording represents the signal as a summation of motor unit action potentials over the muscle fiber membranes.[1, 13]

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.[1]

As presented earlier in the source of sEMG 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 varies different sizes and shapes and are therefore very depended on the intended measurement site. Typically are electrodes made of silver-impregnated plastic 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 form 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 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.[1]

2.3 Myo armband overview

The Myo armband (MYB) from Thalmic Labs will be used for EMG data acquisition. It contains eight dry stainless steel electrode-pairs around the inside of the armband, as depicted in figure 2.3. The recorded EMG is unitless in an 8-bit resolution. As usual when recording EMG the higher the performed contraction is, the higher the float 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, thus this will be implemented later during signal processing described further in section **??** on page **??**. The MYB has a 200 Hz sample rate, and thus a lower resolution than the EMG spectrum [1]. 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. [15]

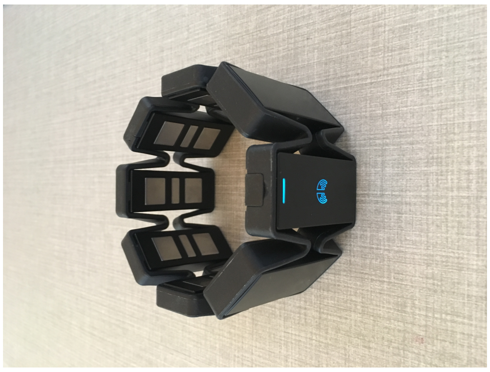

Figure 2.3: MYB from Thalmic Labs. The number on each channel indicates which channel corresponds to which column in the digital output, when acquiring data from MYB.

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 a 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 [1]. 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. [15]

2.3.1 Feature extraction

The raw EMG-signal itself is not used for myoelectric prosthesis control, but features that are extracted it. 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 four different types based on their mathematical properties: energy and complexity, frequency information, prediction modeling and time-dependency. Extracting features from the frequency-domain requires a frequency transformation, showing 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. It is important not to choose redundant features for the classifier; features containing similar information. [16]

2.4 Performance Metrics

Measuring the performance of achieved prosthesis control cannot be seen as a trivial task, and different approaches can be used. Fitt's law task is a common way resorted to when quantifying movements, first proposed by Paul M. Fitts in 1954 [17]. Originally, the only output of a Fitts' law task was the throughput, as given by equation (2.1). A Modified Fitts' law task designed for a virtual 2D and 3D target acquisition task has later been used by [18] and [11] respectively. Here, four additional metrics were added in an online task, where a virtual computer cursor was used to represent the control output [18, 11]. The four additional metrics were made by [19] and [20]. 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 [21]:

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: [11, 17]

$$TP = \frac{1}{N}\sum_{i=1}^{N}\frac{ID_i}{MT_i} \tag{2.1}$$

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 [11, 17]:

$$ID = log_2(\frac{D}{W} + 1) \tag{2.2}$$

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 [19, 11]:

$$PE = \frac{Optimal\ Distance}{Actual\ Distance} \tag{2.3}$$

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 [19, 11]:

$$OS = \frac{Total\ Number\ of\ Overshoots}{Total\ Number\ of\ Targets} \tag{2.4}$$

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 [11]:

$$SD = \sum_{i=1}^{N}(Distance\ Inside\ Target)_i \tag{2.5}$$

, 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 [11, 20]:

$$CR = \frac{Number\ of\ Reached\ Targets}{Total\ Number\ of\ Targets} \tag{2.6}$$

2.5 Linear Discriminant Analysis

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 [22]:

$$g(x) = w^t x + w_0 \tag{2.7}$$

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. [22]

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 [22]:

$$r = \frac{g(x)}{||w||} \tag{2.8}$$

The distance from origin and boundary to feature value (x) is needed to decide in which region the feature value belongs. [22] These distances are illustrated in figure 2.4.

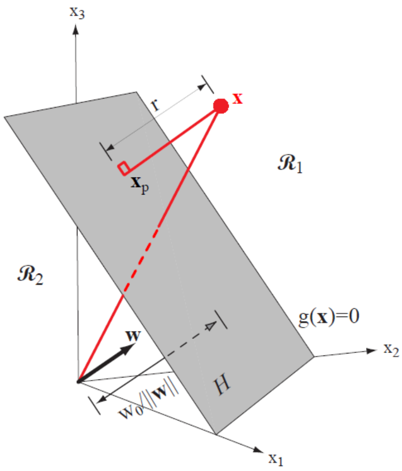

Figure 2.4: A geometric illustration of the linear decision boundary $g(x)$ that separates the feature space into two decision regions R_1 and R_2. x is the feature value, and x_p is the point on the decision boundary in which x is orthogonal projected on vector w. The distances from origin and boundary to feature value x is marked red. [22]

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 [22]:

$$g_i(x) = w^t x_i + w_{i0} \qquad i = 1, ..., c, \tag{2.9}$$

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 [22]:

$$g_i(x) = g_j(x) \tag{2.10}$$

Often regions are contiguous and will have a single boundary to separate several regions. [22] Illustrations of this case can be seen on figure 2.5.

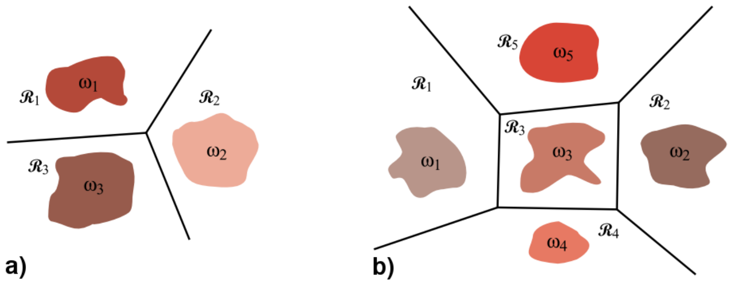

Figure 2.5: A three class (a) and five class (b) case each respectively separated by one decision boundary linear machine. [22]

When the decision boundaries $g_i(w)$ have been calculated as in equation (2.9), the input feature values can be decided upon which class they belong to by calculating the distance to the decision boundary as in equation (2.8).

2.5.1 Classification probability scores

Based on the classification of feature values by the linear machine, certainties 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 is a value between 0 and 1, and is calculated as follows:

$$P(w_j|x) = \frac{P(x|w_j)P(w)}{P(x)} \tag{2.11}$$

, 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 probabilties for all classes will equal 1.

2.6 Linear regression methods

The use of linear regression is often used in statistics to determine relations between variables. Regressions methods also has its use in control schemes of myoelectric prosthetics [3, 23, 24]. The difference between classification and regression is that classification attempt to classify similar patterns in recordings, between previously acquired data and new data, while regression methods provide a continuous output value based on the input value [5, 24].

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 and one independent variable [25]:

$$Y = \alpha + \beta X + \epsilon \tag{2.12}$$

, where Y is the dependent variable, X is the independent variable, 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 (2.12)) [25]:

$$\hat{Y} = \alpha + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_i X_i + \epsilon_i \tag{2.13}$$

, where i is the number of independent variables [25]. 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. Here several channel-recordings of muscle activity can be considered independent variables, and used to estimate one control output, which would be the dependent variable. [23]

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