1 | Introduction

1.1 Introduction

Electromyography (EMG) is the recording and utilization of muscle generated electric potentials, widely used in control of functional prosthetics. The electric potentials recorded from the muscles are action potentials generated by the activation 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 several steps of amplification, filtering and feature extraction before they are used for control in a myoelectric prosthesis. [**Cram2012**, **Fougner2012**] For the actual control of the prosthetics several different methods for control schemes exist.

In recent years the research area of myoelectric prosthetics has been dominated by classification methods for control schemes. Classification attempt to classify similar patterns in EMG signals, between previously acquired data and new data [**Mendez2017**]. This approach for control have proved adequate when performing proportional and simultaneous movements in several degrees of freedom (DOF), but have lacked usability outside of clinical environments due to poor accuracy with change in limb position. This have resulted in a high rejection rate by users. However, recently regression methods have been gaining more interest as a control scheme for myoelectric prosthetics. Regression methods provide a continuous output value, contrary to classification which will provide a single class per movement [**Hahne2014**]. Regression methods have shown promising results of robust control while performing both proportional and simultaneous movements, while also having proved to effectively combat the effect of limb position changes [**Hwang2017**, **Hanhe2014**]. This shows potential for regression based control schemes to be more reliable when used for performing daily life tasks, outside clinical environments.

However, in studies the use of regression based control have been directly based off of the output of a trained regression model. This approach have shown robust control across different limb positions but lacks accurate control when performing delicate/precise movements or when only performing movement in one DOF. [cite til 7.semester projekt]. Many advancements have been made on system training to improve the systems and control schemes to best recognize the performed movements by the users. However, far fewer studies have investigated the effect of user training, improving the users ability to properly utilize the system. Here, an important consideration is that each user will have individual competences when initiating user training. Some might perform well form the beginning while others will show little to no success. [**Powell2013**] Powell et. al [**Powell2013**] 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 [**Powell2013**].

The significance of user training is not doubted, but an effective way to properly provide feedback to the user have yet to be developed. Fang et. al [**Fang2017**] 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 for user training, and an ability to quicken the learning for amputees who are unfamiliar with EMG controlled prosthetic use. [**Fang2017**] Other studies have also showed promising results using an LDA classifier during user training. Powell et. al [**Powell2014**] 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 prosthesis.

Ever increasingly advanced myoelectric prosthetics and control systems are being developed, a critical bottleneck still exist: the ability to properly control the prosthetic. 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. Thus system training has become exceedingly good at this task. However, the challenge for user training is for the user to be able to consistently produce distinguishable muscle pattern, and the better these muscle patterns the better the system will function. [**Powell2014**] 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.

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 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[1]. To develop theoretical background knowledge, a short introduction of the signals essentials and the technique of recording it will be presented.

Electromyography is the detection 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 2.1 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. The number of motor units innervating a muscle depend on its characteristics and the purpose is serves. Muscle control that demand high precision have a higher innervation than muscles used for more powerful contractions. The recruitment of motor units is another 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.[**Cram2012**, **Martini2012**]

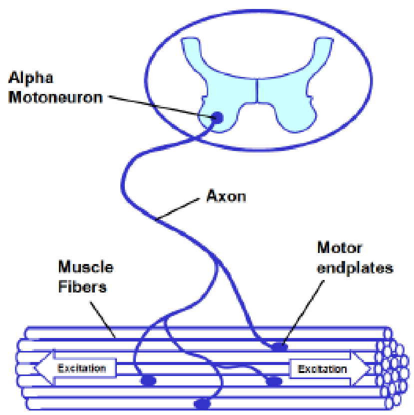

Figure 2.1: The figure describes the neural pathway from the alpha motor neuron to the innervated muscle fibers, making up a motor unit.[**Konrad2005**]

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 of -80 to -90 mV, due to an equilibrium of NA^+ and K^+ through the intracellular and extracellular side, 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 NA^+ into the cell. This causes the a membrane depolarization,

[1] FiXme Note: ref to anatomi

changing the membrane potential. If a threshold of approximately -55 mV to + 30 is reached action potential is formed traveling in both directions of the muscle fiber, as seen on figure 2.1. The membrane potential is quickly restored with a great outflow of NA^+, resulting in a repolarization. The generation of the motor unit action potential in the muscle via the shift from depolarization to repolarization is what with an EMG recording. The EMG recording represents the signal as a summation of motor unit action potentials over the muscle fiber membranes.[**Cram2012**, **Martini2012**]

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

2.2 Performance measures

In aiding the quantification of the two proposed test groups, a Fitts' law test will be used. A general Fitts' law incorporates five different performance metrics in the evaluation of movement.[**Kamavuako2014**, **Scheme2013**] The five metrics and their description can be found in table 2.2

Metric	*Description*
Throughput	Time-based metric that summarizes usability through the tradeoff of speed and accuracy
Efficiency	Distance-based metric that describes the path taken; a ratio of the optimal path to the target to the actual path taken
Overshoot	Fine control metric that describes the ability to stop on a target; the average number of times the target was exited after being acquired
Stopping Distance	Stopping metric that describes the ability to elicit and hold no motion; the total distance travelled during the 1 second dwell time
Completion Rate	Describes overall success; the percentage of tests completed within the allowed time

Figure 2.2: The table shows the metrics used in a generel Fitts' law test followed by a description of these.[**Scheme2013**]

Often the throughput (TP) is used by its own representing the tradeoff 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**]

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

where i is a specific movement condition and N is the total number of targets. 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**]

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

Put in figure of the GUI used for testing where we represent the number of targets and the distance to them. Them afterward also calculate the ID for our targets.

2.3 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 H from which the minimum distance from the classes it separates is maximized, and the distance from the means of the classes are maximized. A decision boundary is defined as a linear combination of the feature values x and is given as:

$$g(x) = w^t x + w_0 \tag{2.3}$$

where w is a weight vector deciding the orientation of H, and w_0 is a bias deciding the position of the hyperplane in relation to the origin. In a two category case the decision rule for deciding class w_1 or w_2 is: decide w_1 if $g(x) > 0$ and 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 R_2 for w_2. w is normal (orthogonal) to any vector on H, which can be used to calculate the distance r from feature values to the decision boundary:

$$r = \frac{g(x)}{||w||} \tag{2.4}$$

From origin the distance is given as $\frac{w_0}{||w||}$, where if $w_0 > 0$ the origin is on the positive side of the decision surface, and if $w_0 < 0$ the origin is on the negative side. In the case of $w_0 = 0$ the decision surface passes through origin. In figure **??** a geometric illustration of the linear discriminant function and its properties is depicted.

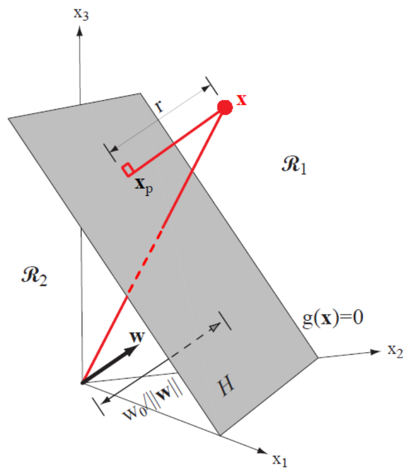

Figure 2.3: A geometric illustration of the linear decision surface $g(x)$ that separates the feature space into two decision regions R_1 and R_2. [**Duda2000**]

In a multicategory case c decision boundaries are defined. The approach for defining the decision boundaries is given as:

$$g_i(x) = w^t x_i + w_{i0} \qquad i = 1, ..., c, \tag{2.5}$$

where x is assigned to w_i if $g_i(x) > g_i(x)$ for all $j \neq i$. This type of classifier is called a linear machine, and will be adopted as classification method in this project.

3 | Methods

3.0.1 System Design

The feedback of the test part of the system will consist of a compass plot, where the output will be based on either the regression based control scheme alone or a combined model with classification included as well.

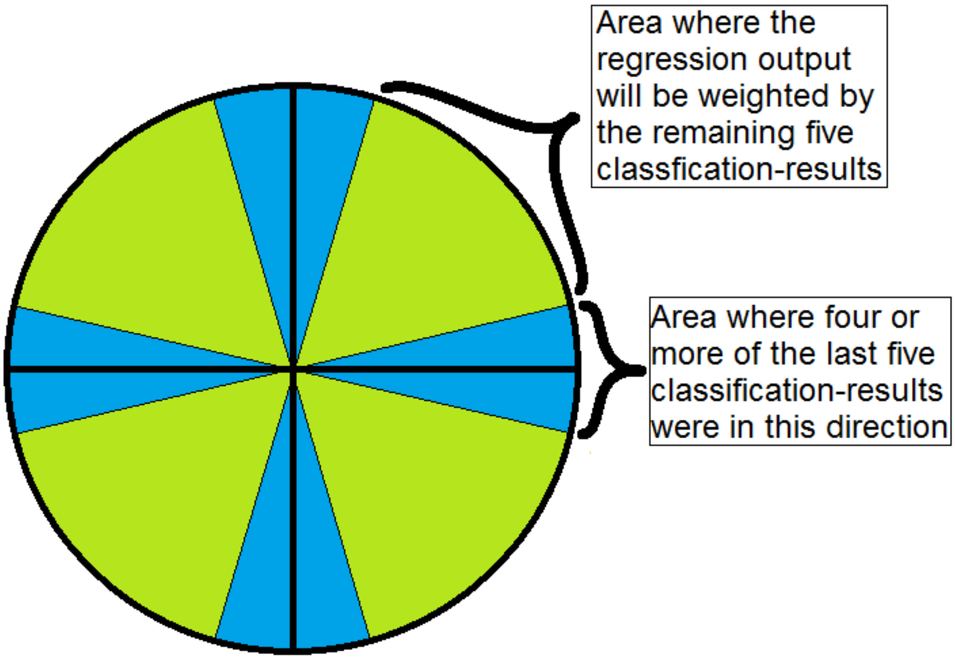

Figure 3.1: Suggestion on the areas where multiple DOF's (green) and a single DOF (blue) will be activated in the compass plot inside the GUI with a control scheme based on both classification and regression

When testing the combination of regression and classification, the system will be designed with the regression result as the main output while the classification results will be used as weights to determine if the subject intends to perform a single movement or a combination of multiple movements. The system will perform a single movement if four of the previous five classification outputs were the same movement. This means that there will be a certain area where the output will be in a single direction, as shown with blue on figure 3.1. Combining the two types of control should give the user a possibility to activate a single DOF proportional movement without being extremely precise.

In cases where the subject intends to activate multiple DOF's at the same time in the green areas of figure 3.1, the previous five classification results will be used to weight the regression outputs. An example of this could be three extensions and two radial deviations within the five most recent classifier results, where the extension regression output will be weighted with $\frac{3}{5}$ and the radial deviation will have a weight of $\frac{2}{5}$. This implementation should give the subject a possibility of activating multiple DOF's proportionally at the same time.

The output of the regression based control scheme will be translated directly to the compass plot, where it will be used to reach targets in the test. This means that the subjects will have to be more precise when trying to activate a single DOF, as there are no areas where the classifier will force the output to be a single DOF.

3.1 Study protocol

Title of project

Using estimation uncertainty to improve prosthesis control

Detail on investigators

All investigators are currently 8th. semester students, studying at Aalborg University.

Purpose and background

Commercially available prosthesis have yet to adopt the use of pattern recognition methods in their control scheme. Mainly, this is due to the disadvantages exploited in "ref til introduction om problemer måske?". A control scheme that reduce these disadvantages are therefore sought through the combination of regression and classification based methods. The overall aim is to develop a novel control scheme for myoelectric prosthetic devices. Hereby it is sought to clarify if a combined regression and classification control scheme yields higher subject performance in a Fitts' Law test compared to a method only using regression.

Research question/hypothesis

The use of a Fitts's Law test will show a significant improvement in subject prosthesis control with a combined regression and classification control scheme compared to a method using only regression.

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 one session divided into two sub-sessions with an estimated total duration of 2-3 hours.

Inclusion criteria

The subject needs to be:

- able bodied.
- between 18 and 35 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 is divided into two sessions: 1) training data acquisition, user training and performance test and 2) new training data acquisition and performance test. During the training data acquisition EMG data will be recorded from the subject with an EMG-electrode armband (Myoband from Thalmic Labs) when performing four different wrist movements(flexion, extension, radial deviation and ulnar deviation) as illustrated in figure **??**. The data is subsequently used to fit a classification model used in the myoelectric control scheme for the following user training and performance test. Before the performance test the user is given a training period to get familiar with wrist movements used in the performance test. During the performance test the subject will perform a target-reaching task in a cartesian coordinate system of reaching a number of targets using wrist movements, where each axis represent a one of four wrist movements, as seen in figure figure **??**. The aim for the subject is to reach as many targets as quickly as possible. The subject will perform the target-reaching task twice - one in each session. The subject are divided into two groups: a test group and a control group. As the study is single-blinded the subject will not be informed which group he/she belongs to.

Chronology of session 1):

1. Apply Myoband on dominant forearm at the thickest part.
2. Synchronize Myoband 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 30 resting period to avoid fatigue.
4. Perform 15 seconds contractions of respectively 20%, 40% 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 a precise as possible. The trapezoidal trajectory consists of two five second transition phases and one five second plateau phase as illustrated in figure figure **??**. Between each trial the subject will be given a 15 seconds resting period to avoid muscle fatigue.
5. Repeat step 3-4 until training data from all four wrist movements has been recorded.
6. The subject will train the four wrist movements. Each movement will be performed 10 times, where each single movement consists of a five second movement with increased intensity. To improve the precision of movements the subject will receive visual feedback consisting of the probability the movement to belong to based on the classifier. The ideal probability during the training is a 100% probability of belonging to the trained movement and a 0% probability of belonging to the remaining movements.
7. The subject will perform a target-reaching task. The subject will control an arrow originated from origo in a cartesian coordinate system representing the features extracted from the EMG data, where the length represent the intensity and direction depicts the movement performed. To reach a target the subject must dwell the head of the arrow within the target for 0.5 seconds. If this is achieved the target will disappear. The target will similarly disappear if the subject fails to achieve this within 15 seconds. When an outer target disappears a target centred in origo appears and the subject must reach this before a new outer target appears. This procedure is continued until no

more targets are shown. After finishing the performance test the subject will be given a 2 minutes resting period.

Chronology of session 2):

1. Perform step 3-5 from session 1.
2. Perform step 7 from session 1.