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 as input in the control for a myoelectric prosthesis. [**Cram2012**, **Fougner2012**]

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 [**Hwang2017**]. 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. Pattern recognition/-Computer 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. [**Powell2014**]

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**]. Classification enables proportional and simultaneous control of movements in several degrees of freedom (DOF), but have lacked usability outside of clinical environments [**Scheme2010**]. This have resulted in a lack of commercial success [**Jiang2012**]. Recently regression methods have been gaining more interest as a newer 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 [**Hwang2017**, **Hahne2014**]. 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 off a trained regression model. This approach have shown robust control 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. Jiang et. al [**Jiang2012**] 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. [**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, and several different approaches has been investigated. 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 animated prosthesis. Pen et. al [**Pen2017**] provided a visual feedback of an arrow to be moved on a 2D plane. Pen 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. [**Pen2017**]

The general challenge of user training is for the user to be able to consistently produce distinguishable muscle patterns. [**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, but an effective way to properly provide feedback to the user have yet to be developed. Further studies should for now concentrate on developing different feedback methods which should later be compared to determine an ideal method. This study will seek to develop a new method of feedback during user training, by providing the users with the estimation uncertainty of the classification. To the authors knowledge, user feedback has not been provided with this method before. Initially the project will propose providing feedback via a bar chart each bar representing the estimated uncertainty of a classified movement.

The study will consist of steps of data acquisition, user training and an online test. The user will undergo user training followed by a targets reaching Fitts' Law test. The study will have a test and control group, where the control group will be trained without visual feedback during user training. Ad hoc statistic comparisons will be made between online tests and maybe some other things we have not entirely decided upon yet. /cite(we decide)

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 **??** on page **??**. 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) /citecounting. This in itself makes it very dexterous but it is the arm that moves the hand along seven DOFs, that really enables the hand to use its dexterity. [**strahinjaKursusSlides2018**]

Movement of limbs are caused by muscle contractions. The muscles contract when receiving nerve impulses from the central nervous system (CNS). The greater workings of muscle activation is described further in section **??** on page **??**. This project will use four movements for control of a virtual interface and visual feedback. The movements are flexion and extension of the wrist, and ulnar and radial deviation. The movements are visualised on figure 2.1. These four movements cover two DOFs.

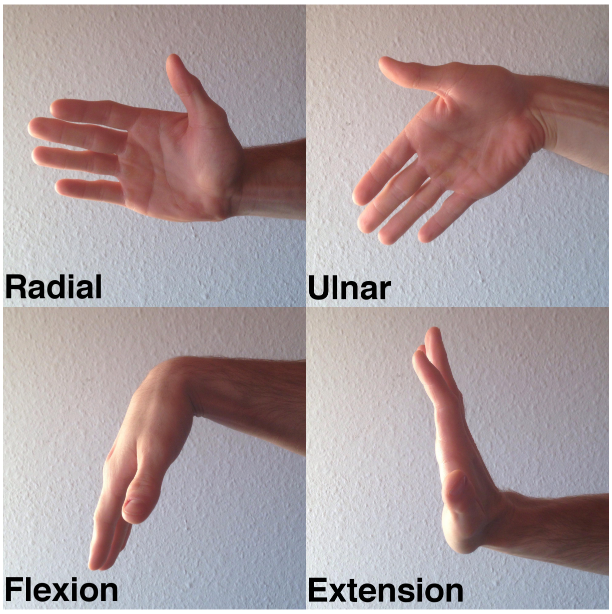

Figure 2.1: Flexion, extension and radial and ulnar deviation of the hand. **same picture used on 7. semester. should we make new picture or cite ourselves**

Looking closer at the anatomy and arrangement of the muscles involved in performing these four movements, several of the muscles are active during movements in both DOFs. As noted on figure 2.2 a total of five muscles in the distal part of the forearm are activated during both flexion/extension and ulnar/radial deviation at the wrist. However, according to [**Mendez2017**] et. al the MYB has no problem correctly classifying different hand gestures, even when the active muscles are anatomically overlapping.

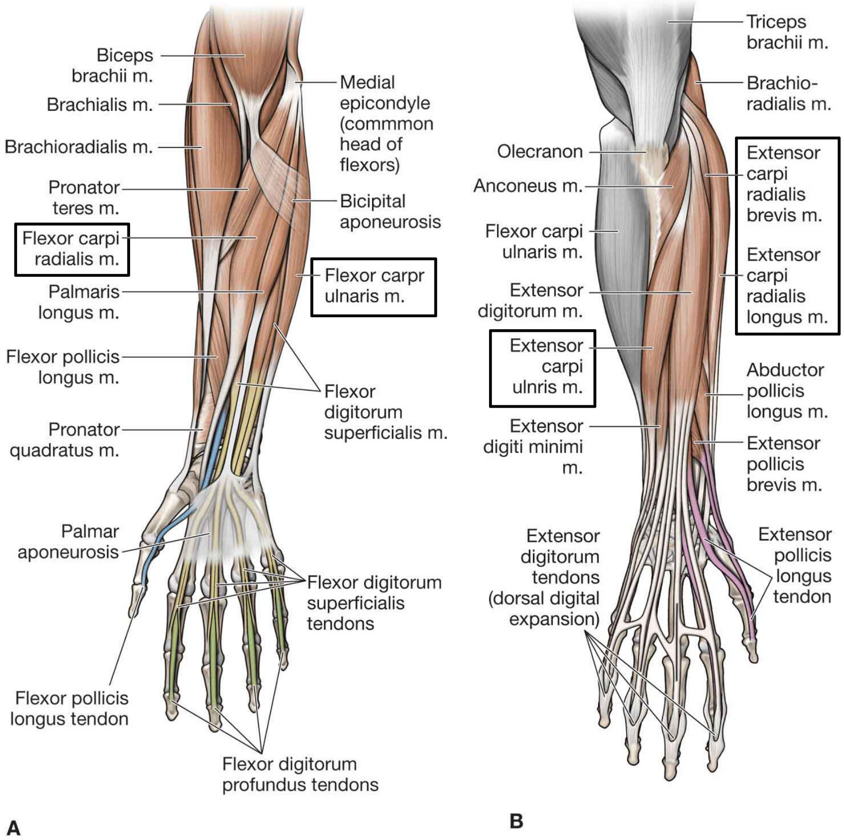

Figure 2.2: A) anterior view of lower muscles. **B)** posterior view of lower muscles. The boxed names are of muscles included in both flexion/extension and ulnar/radial deviation. [**7semesterprojekt**]

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 2.3 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.[**Cram2012**, **Martini2012**]

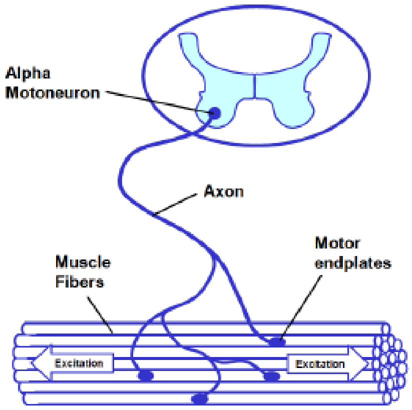

Figure 2.3: The figure describes the neural pathway from the alpha motor neuron to the innervated muscle fibers, making up a motor unit.[**Konrad2005**]

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 2.3. 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.[**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**]

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.[**Cram2012**]

2.3 Myo armband overview

The Myo armband from Thalmic Labs will be used for EMG data acquisition. It contains 8 dry stainless steel electrode-pairs around the inside of the armband, as depicted in figure 2.4. The recorded EMG is unitless and in 8-bit resolution, and therefore not represented in volts as EMG normally is. But as usual EMG the higher the performed contraction is, the higher the integer values in the output will be. To avoid interference from the power lines a 50 Hz notch filter is implemented in the Myo armband. The Myo armband is not able to make any further filtering, and will thus be implemented digitally later in the signal processing. The Myo armband pulls the data with a 200 Hz sample rate. Besides the EMG sensors the Myo armband contains a nine axis inertial measurement unit consisting of three axis gyroscope, three axis magnetometer and three axis accelerometer. This inertial information is pulled at a 50 Hz sample rate. The inertial measurement units gives information about the orientation, position and movement of the user's arm. [**Myoarmband2013**]

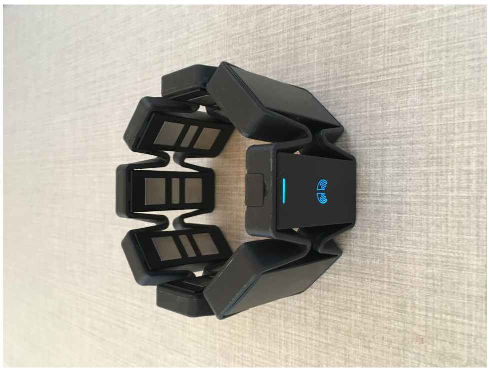

Figure 2.4: Myo armband from Thalmic Labs.

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 forming as strong electrical connection with the muscles in the forearm as possible, and during the sync phase, the armband is figuring out its orientation in space, position on the arm, and on which arm it is placed. Th Myo armband works better when fitted tightly on the thickest part of the forearm. For users with small forearms a set of clips can be added to the armband to get a constrained grip. [**Myoarmband2013**]

2.3.1 Feature extraction

Before using the recorded EMG-signal for any myoelectric prosthesis control, features are often extracted from the original signal and used for control instead. 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 as a time-frequency domain. Most used are features from the time- and frequency-domain. Extracting features to the frequency-domain requires some sort of frequency analysis, showing the spectral properties of the recorded signal, which takes up longer processing time than simply using the direct time–domain. Time-domain features are often chosen base on their quick and easy implementation. They do not require any transformation before extraction and are calculated based on the raw EMG-signal.[**Phiny2012**]

2.4 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 2.5

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 2.5: 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.

2.5 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 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.

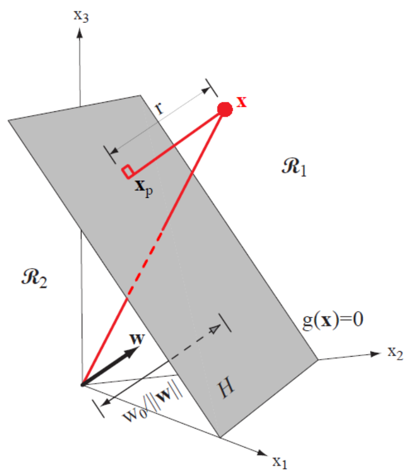

Figure 2.6: A geometric illustration of the linear decision surface $g(x)$ that separates the feature space into two decision regions R_1 and R_2. [**Duda2000**]

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.

2.5.1 Generalized discriminant function

2.5.2 Gradient descend/minimum criterion function

2.5.3 Classification scores

Evaluating the certainty that a feature value belongs to a given class can be done by computing the posterior probability of each class. The posterior probability is a value between 0 and 1, and is calculated as follows:

$$P(w_j|x) = \frac{P(x|w_j)P(w)}{P(x)} \tag{2.6}$$

, 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 $P(w)$ 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 likelihood that a sample from a class appears compared to the other class before it actually has appeared.

3 | Methods

3.1 Feature extraction

To obtain the best possible classification, four different features have been extracted from the time-domain (TD) using their respective extraction methods. The features are Mean Absolute Value, Zero crossings, Slope Sign Changes and Waveform length. These will from now on be referred to as MAV, ZC, SSC and WL respectively. This set of features is chosen based on their extensive popularity when used for classification purposes and effect in real-time myoelectric control schemes, along with showing fast computational speeds.[**Hudgins1993**, **Kamavuako2016**, **Scheme2010**]

MAV is an estimate of the mean absolute value of the signal, $\bar{X}_i$. i is the chosen segment where N is the number of samples in i. MAV is derived from,

$$\bar{X}_i = 1/N \sum_{k=1}^{X} |x_k| \quad for\ i = 1...I \tag{3.1}$$

where x_k is the k^{th} sample in i and I being the total number segments.

ZC Finder lige ud af om de skal bruges

SSC Samme her

WL provides information on the waveform complexity in each segment by calculating the cumulative length of the waveform over time. The length is defined as,

$$l_0 = \sum_{k-1}^{N} |\triangle x_k| \tag{3.2}$$

where $\triangle x_k = x_k - x_{k-1}$, which is the difference in consecutive sample voltage values).

representation af hver feature

[**Hudgins1993**]

3.2 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.