AALBORG UNIVERSITY
STUDENT REPORT

Simultaneous and proportional control of reaching and grasping

P7 Master project - Autumn 2017

Group 17gr7404

AALBORG UNIVERSITY
STUDENT REPORT

7^{th} Semester, Master Project

School of Medicine and Health

Biomedical Engineering and Informatics

Fredrik Bajers Vej 7A

9220 Aalborg

Titel:
Simultaneous and proportional control of reaching and grasping

Theme:
Biomedical signals and information

Project period:
P7, Autumn 2017
01/08/2017 - 19/12/2017

Project group:
17gr7404

Collaborators:
Irene Uriarte
Martin Alexander Garenfeld
Oliver Thomsen Damsgaard
Simon Bruun

Supervisors:
Strahinja Dosen
Jakob Lund Dideriksen
Lotte N.S. Andreasen Struijk

Pages: 9000
Appendixes: maybe
Afsluttet: 19/12/2017

Abstract

Nulla in ipsum. Praesent eros nulla, congue vitae, euismod ut, commodo a, wisi. Pellentesque habitant morbi tristique senectus et netus et malesuada fames ac turpis egestas. Aenean nonummy magna non leo. Sed felis erat, ullamcorper in, dictum non, ultricies ut, lectus. Proin vel arcu a odio lobortis euismod. Vestibulum ante ipsum primis in faucibus orci luctus et ultrices posuere cubilia Curae; Proin ut est. Aliquam odio. Pellentesque massa turpis, cursus eu, euismod nec, tempor congue, nulla. Duis viverra gravida mauris. Cras tincidunt. Curabitur eros ligula, varius ut, pulvinar in, cursus faucibus, augue.

Preface

Morbi luctus, wisi viverra faucibus pretium, nibh est placerat odio, nec commodo wisi enim eget quam. Quisque libero justo, consectetuer a, feugiat vitae, porttitor eu, libero. Suspendisse sed mauris vitae elit sollicitudin malesuada. Maecenas ultricies eros sit amet ante. Ut venenatis velit. Maecenas sed mi eget dui varius euismod. Phasellus aliquet volutpat odio. Vestibulum ante ipsum primis in faucibus orci luctus et ultrices posuere cubilia Curae; Pellentesque sit amet pede ac sem eleifend consectetuer. Nullam elementum, urna vel imperdiet sodales, elit ipsum pharetra ligula, ac pretium ante justo a nulla. Curabitur tristique arcu eu metus. Vestibulum lectus. Proin mauris. Proin eu nunc eu urna hendrerit faucibus. Aliquam auctor, pede consequat laoreet varius, eros tellus scelerisque quam, pellentesque hendrerit ipsum dolor sed augue. Nulla nec lacus.

Contents

1 | Introduction

Upper limb prostheses have the purpose of fulfilling the costumers demand, which consists of cosmetic and functional support. The utmost wish for the consumer is to regain full appearance and function of the missing biological upper limb. The functionality is the most challenging aspects to fulfil. Two types of functional prostheses exist: body-powered and electrical, where the electrical has the highest functionality, and therefore ideally has a higher similarity to a biological upper limb. The most common electric prosthesis is the myoelectric prosthesis, where EMG signals are used as the control signal. [1].

In recent years the development of EMG controlled prosthetics have advanced considerably, due to an increased interest in the area along with a higher demand for better prosthetics and more precise control. [2] In the early years most EMG prosthetics functioned by only controlling one DOF by *on-off control*, mostly by linking antagonistic muscles to one DOF. This along with *mode switching* provided users a way to control more than one DOF, but never simultaneously. However, as demands would rise, more complex methods was introduced to the EMG scene, and proportional control was introduced with pattern recognition methods. This effectively enabled simultaneous control of more than one DOF, but gave rise to new problems; a wider range of control would give less accurate movements, and training the pattern recognition methods proved difficult, as the training could over-fit, causing extended use of the prosthetics to degrade in performance. [3] Applying regression as a new mapping method in proportional and simultaneous control of multiple DOF's has been shown to perform well and doing this with a low computation time. [4] In spite of the proportional and simultaneous control systems performing decently, a problem still occurs when the prostheses are to mimic daily life tasks outside the clinical training environment. [1] A study by Fougner et al. [5] has addressed the problem that most studies test their method on only one limb position. This proves a problem when it have been shown that muscles create muscle-synergies to perform movements, and so a change can be seen in recorded EMG signals from muscles when the arm is positioned in different positions. [5, 6, 7] In order to overcome this problem Fougner et al. [5] has suggested to combine recording of EMG signals with data from an accelerometer to provide upper limb position data, would be beneficial in increasing the accuracy of EMG controlled prosthetics. Even though the combination of EMG and IMUs has been proposed as a valid way to further improve upon EMG based prosthetics, and has in other research areas been acknowledged as a mean to acquire higher level of classification accuracy, is has only rarely been reported in studies. [8, 9, 1] A novel approach to improve upon these findings would be to include data from IMU, to the recordings of EMG, to the training of a regressor, as this to the authors knowledge only have been done with classification methods. It is possible to do proportional and simultaneous control of two DOFs in a lower-arm prosthesis, while having the arm in different positions, using simple/multiple linear regression on recorded surface EMG signals and inertial measurement units.

2 | Background

2.1 Anatomy of the lower arm

This project will focus on the lower arm as the Myo armband will be used extract information from this part of the body. The anatomy of the lower human arm will briefly be described in this section along with a description of relation between lower arm muscles and hand movements for selected gestures. The human arm is designed to give humans a manoeuvrability and dexterity to coordinate and execute complicated and precise hand and finger movements with ease. Each movement happens around an axis, and each axis denotes one degree of freedom (DOF). The arm posses six DOFs as shown in figure 2.1, where the DOF's of the hand is beeing ignored as they will not be relevant for the project.

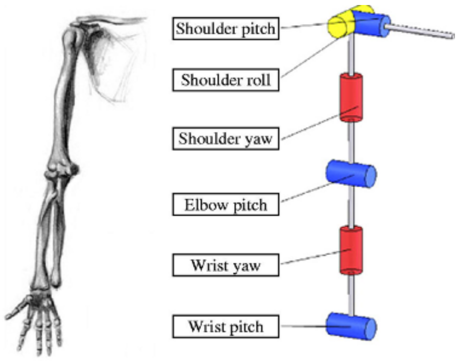


Figure 2.1: Visualisation on the arms six degrees of freedom. [10]

The number of DOFs is defined as the number of possible input parameters to a movable mechanism, where each input controls an independent movement in one axis. Several bodies can work together in relation to each other, but the total number of DOFs will be the number of possible independent movements that can be performed between the bodies. [11]

The great dexterity of the human arm is achieved through the use of several muscles which intertwine and make synergies to perform all the different gestures of the hand [12, 6]. Muscles in the lower arm is arranged in layers, having an outer, middle and inner layer. These muscles are used to rotate the forearm, flex and extend the hand at the wrist as well as performing ulnar and radial deviation. The muscles control extension and flexion of the fingers at each separate joint and the movements of the thumb, so that hand can be opened and closed. This enables movement in six DOFs of the arm and several more at the hand and fingers.

The aim for this project is to translate ulnar and radial deviation along with extension and flexion of the wrist via EMG signals to control a robotic arm. Therefore, only selected muscles will be relevant to further investigate. Muscles involved with radial and ulnar deviation includes several muscles in the arm. Most of these muscles extend throughout the whole forearm as most of them originates from the distal lateral surfaces of humerus or the proximal portions of radius and ulnar, and extends towards the wrist and fingers to fixate on the metacarpal bones in the wrist and through tendons fixate on the different phalanges bones of the fingers and thumb. The two most important muscles in radial/ulnar deviation are the flexor and extensor carpi ulnaris and radialis muscles.

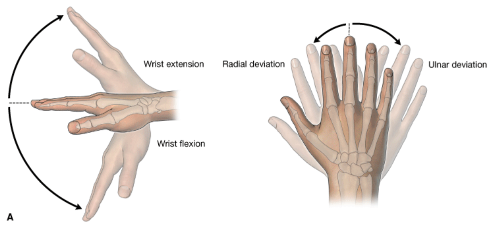


Figure 2.2: Flexion, extension and radial and ulnar deviation of the hand. Modified from [13]

Several more muscles in addition to those responsible for ulnar and radial deviation are involved with the flexion and extension of the wrist. Like the other muscles, the flexor and extensor muscles also extend through the whole forearm from the distal part of humerus and proximal parts of radius and ulnar to the metacarpal bones in the wrist. Many of these muscles are included in movements of both radial/ulnar deviation and flexion/extension, though flexion/extension have one muscle who is only used for flexion at the wrist, the palmaris longus muscle. This can be explained as more force is usually needed in flexion at the wrist than in extension or radial/ulnar deviation. The movements which will be performed in this project are depicted in figure 2.2.

Though several of the same muscles are included in both types of movement, studies have shown that it is possible to differentiate between recorded EMG signals form these muscles when performing radial/ulnar deviation and flexion/extension at the wrist. [4] In figure 2.3 the muscles in the forearm both involved with extension/flexion and radial/ulnar deviation is marked with boxes around the name of the muscles.

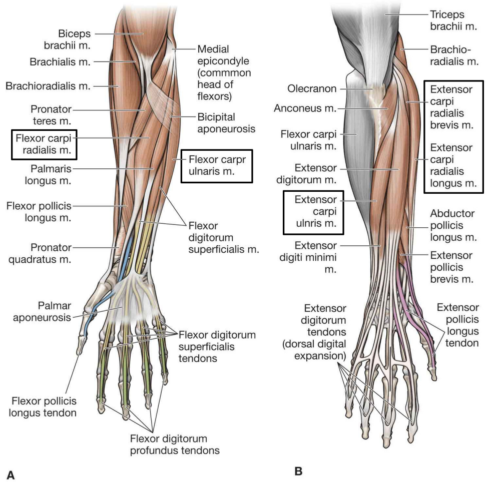


Figure 2.3: **A)** posterior view of the superficial muscle layer in a right arm. **B)** posterior view of the middle muscle layer in a left arm. The muscle names in the boxes are muscles which are included in both extension/flexion and ulnar/radial deviation at the wrist. Modified from [13]

2.2 Origin of electromyography

This project will use EMG to map the hand gestures mentioned in the previous section. In this section it will be described how the EMG signal is generated and which problems that can occur in detecting it.

The electric potential detected with electromyography is an action potential causing the muscle to contract. Certain mechanisms are involved for this to happen. The motor unit of the muscle needs to be activated alongside with its associated alpha motor system, which is the lower motor neuron, its axon, and the muscle fibres the motor unit innervates. The muscle fibre is an excitable cell with a resting potential of between -90mV and -70mV. A threshold of approximately -55mV needs to be reached for an action potential to be generated, this is visualised in figure 2.4. The sarcolemma, the membrane covering the muscle fibres, has sodium and potassium ion channels that maintains the resting potential, depolarize the muscle fibre if the threshold is exceeded or repolarize the muscle fibre. [14]

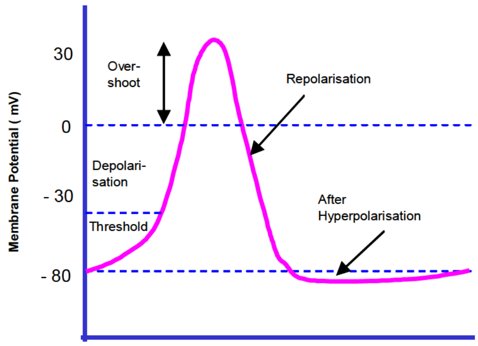


Figure 2.4: Illustration of the action potential exceeding the threshold for it to be generated and the following depolarization and repolarization. [15]

The lower motor axon is branching out so that it can attach to the muscle fibre at the motor end-plate and create neuromuscular synapses. The action potential traveling down the axon reaches the synapses and releases Acetylcholine (ACh). ACh raises the permeability of the cell membrane where sodium ions influx and causes the membrane to depolarize. Calcium ions are released and binds with troponin and exposes the active sites on the thin filaments which allows the muscle to contract. The action potential travels along the whole muscle fibre through t-tubuluses, as depicted in figure 2.5. This happens in both directions from the motor end-plate to the tendentious attachment. When the peak of the depolarization of about 30mV is reached a rapid efflux of potassium ions causes the muscle fibre to repolarize and reach its resting potential again. [14]

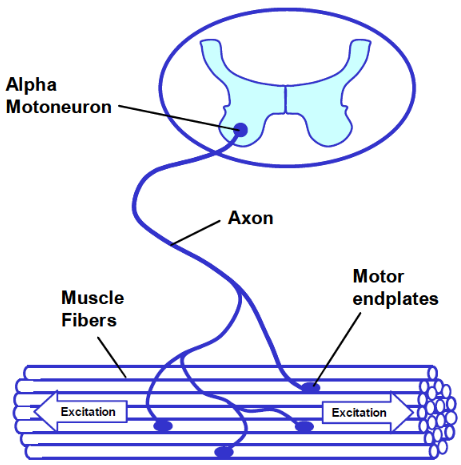


Figure 2.5: Illustration of the action potential exciting the muscle fibre, which causes the release of calcium ions and the muscle to contract. [15]

Depending on the force that needs to be applied for a given task more or less motor units are activated and therefore more or less muscle fibres are contracted. The bigger the force the more motor units are activated. Furthermore, the number muscle fibres per motor unit varies between muscles in the human anatomy. The finer the movement the higher the innervation, e.g. the lower arm muscles has a higher innervation than those in the quadriceps. [14]

2.3 Electromyography acquisition

The following section will contain an explanation of the main component of acquiring EMG signals using surface electrodes.

When acquiring EMG signals the electrodes act as a transducer by converting the differences in ion distribution on the skin surface caused by ion exchange under muscle activity, into an electric current. Surface electrodes used to aquire EMG signals comes both with and without gel covered surfaces, where the the Myo armband employs dry electrodes. Using dry electrodes will often be more practical in use, while the gel covered electrodes will aquire more exact readings of the signals. [16, 14]

The most commonly used electrodes for EMG are made of disposable silver-impregnated plastic, and in order to keep the electric potential on the skin surface stable and reduce impedance between the surfaces, they are often covered in a silver chloride gel. Using dry electrodes will result in a higher surface impedance, which means that the signal contains more noise compared to a gel covered electrode. However, when using dry electrodes the skin will itself provide a “gel” by sweating which will increase readings and decrease the impedance. [14]

2.4 Instrumentation

The following section will contain a presentation of the Myo armband from Thalmic Labs, which will be used for data acquisition in this study and an explanation of acquiring EMG signals using surface electrodes.

2.4.1 Myo armband

The Myo armband is a device developed by Thalmic Labs capable of identifying hand gestures and arm movements in order to interact and control different electronic devices. The system can be used with software provided by Thalmic Labs to control a limited range of devices using the data from the armband. The Myo armband is illustrated in figure 2.6.

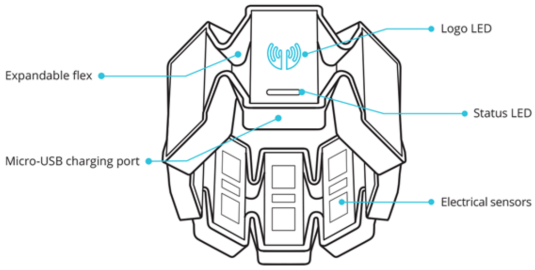


Figure 2.6: Main components of the Myo armband. **SOURCE**

The Myo armband has eight medical grade stainless steel surface EMG sensors. These electrodes are dry and therefore not covered in silver chloride gel to reduce impedance between the electrode and skin. However, it has been shown by Mendez et al. [17] that the EMG recorded with the Myo armband is a suitable acquisition system for mapping hand gestures compared to conventional EMG acquisition. The only mapping method used in that study was linear discriminant analysis, and it is noted that other mapping methods should be investigated to further validate the quality of mapping the EMG obtained by the Myo armband.

In addition, it has a nine axis inertial measurement unit (IMU) which enable the detection of arm movement. An IMU is an electronic device that provides information concerning position and orientation for navigation and stabilization purposes. The IMU's in the Myo armband is a three axis accelerometer, a three axis gyroscope and a three axis magnetometer. The accelerometer measures the physical acceleration experienced by an object, where the object in this case is the body part where the Myo armband is placed. The gyroscope has the property of measuring angluar velocity, giving the ability to measure the speed at which movements happen at. The magnetometer has the property of a compass, measuring the earth's magnetic field. This enables the armband to provide data on orientation.

The Myo armband is capable of pulling sEMG data at a sample rate of 200Hz while the IMU data is pulled at a sample rate of 50Hz. The Myo armband communicates through Bluetooth 4.0 to a PC.

2.4.2 Surface electromyography

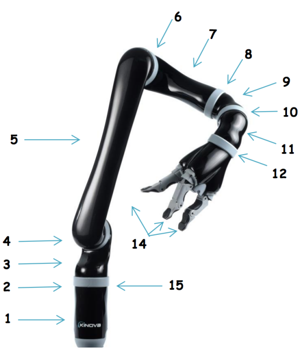
Surface EMG is a means of obtaining recordings from muscle activity at the skin. This procedure can also be done using needle electrodes inserted into the muscle, but sEMG is far more commonly used as it is non-invasive and easy to use. [14]

When acquiring sEMG signals the electrodes act as a transducer by converting the recorded action potentials from the muscles, as explained in section 2.2 on site 4, into an electric current. Surface electrodes used to acquire EMG signals comes both with and without gel covered surfaces, where the use of dry electrodes will often be more practical in use, while the gel covered electrodes will acquire more exact readings of the signals. [16, 14]

The most commonly used electrodes for EMG are made of disposable silver-impregnated plastic, and in order to keep the electric potential on the skin surface stable and reduce impedance between the surfaces, they are often covered in a silver chloride gel. Using dry electrodes will result in a higher surface impedance, which means that the signal contains more noise compared to a gel covered electrode. However, when using dry electrodes the skin will itself provide a "gel" by sweating which will increase readings and decrease the impedance. [14]

2.5 JACO2 robotic arm

In this section a briefly description of the JACO^2 robotic arm will be given. It is a 6 DOF robotic arm with a three fingered hand, as shown in 2.7, developed by Kinova Robotics. It is lightweight ($4.4kg$), which makes this machine specially usable in assistive and collaborative applications. It is designed to help people with upper body disabilities in order to gain more autonomy in ordinary daily tasks [18].



PART ID	NAME
1	Controller
2	Actuator #1
3	Shoulder
4	Actuator #2
5	Arm
6	Actuator #3
7	Forearm
8	Actuator #4
9	Wrist #1
10	Actuator #5
11	Wrist #2
12	Actuator #6
13	Gripper
14	Fingers
15	Plastic Ring

Figure 2.7: 6 DOF JACO^2 robotic arm from Kinova Robotics. [18]

The JACO^2 is a serial manipulator, which means that this kind of robotic arm is designed as a series of links connected by motor-actuated joints that extend from a base to an end-effector. Any movement in a joint affects all the following joints and links in the chain. The arm can by default be controlled with the help of a joystick, but it can be programmed in C++ to be controlled by other means, using the software development kit (SDK) provided by the manufacturer [18].

2.6 Preprocessing of EMG

Before recorded EMG signals can be utilized in control of prosthetics, the signals must be processed. This section will feature information on preprocessing of the signal with filtering and noise reduction, following with feature extraction.

Surface EMG is emitted up to 500 Hz and depending on the area of the EMG acquisition, it is recommended to implement a bandpass filter from 25 to 500 Hz in order to avoid low frequency movement artifacts in the recorded signal. A downside to this bandwidth is that fatigued muscles will fire at a lower rate, which means the performance of the system will be affected when the subject gets tired. [14]

In order to achieve a higher signal to noise ratio (SNR) it is common practice to perform preprocessing of the signalThe raw EMG signals has to be preprocessed due to them being sensible to noise elements from the surroundings, since the range of the signal is in the order of millivolts to microvolts. To acquire a high SNR, the input impedance of the amplifier has to be between 10 and 100 times the impedance at the skin-electrode interface [14].

Differential amplification is used in EMG in order to amplify the original signal and remove common signals from two or more electrodes, in order to avoid common noise from more electrodes in the amplified signal. The amplifier must have a build in gain as well which determines the final strength of the signal, and both of these features are implemented in order to avoid the SNR. Basic filtering should be implemented in order to avoid electrical noise. The filtering should include a bandpass filter with a bandwidth chosen depending on where the EMG is performed. The low-pass filtering will ensure avoiding aliasing in the signal, because is will filter out frequencies higher than the used samplings frequency. The high-pass filter will filter out movement artifact, and thus lowering the baseline. [14]

2.6.1 Feature extraction

Following preprocessing of the recorded EMG signal, features can be extracted and used to map different hand gestures. When analyzing EMG signals there will be three different signal components to be extracted, which are the frequency and time domains, as well as the time-scale representation. Frequency domain features require a Fourier transformation of the signal, which requires more processing than the direct extraction of time domain features. [19]

The time domain features are extracted directly from the EMG signal, and these feature extraction methods are often used both for research and practices since they often require very little processing compared to frequency domain features. Time domain features are mainly focused on the amplitude of the signal, which means they have a disadvantage if the signal differs in amplitude due to muscle fatigue. [19]

Based on the study af Hahne et al. [4], we will choose logarithmic variance as the feature to be extracted from the recorded EMG signal. Hahne et al. finds that the cross-validation performance improves significantly with the use of linear regression combined with logarithmic variance, compared to combining the linear regression with variance or RMS. [4].

2.7 Regression methods

Regression methods are widely used is statistics as a method to determine relationship between variables. It can be used to extract relations to predict future developments or tendencies in a given data set. It is also a commonly used method to evaluate EMG signals to determine different parameters.

The most basic form of regression is linear regression, which is a test for linear dependency between two variables. In simple linear regression it is investigated how one, dependent variable, is related to another, independent variable. The term *simple* denotes that only two variables are being considered simultaneously. The equation for simple linear regression is: [20]

$$Y_i = \alpha + \beta X_i + \epsilon_i \tag{2.1}$$

In equation (2.1) Y is the dependent variable, X is the independent variable, β is the regression coefficient in the sampled population, and α is the predicted value of Y at $X = 0$. ϵ is the error, since the goal of regression is to find an approximation of Y on some function of X, thus there will always be some error.

Performing simple linear regression finds the correlation between the tested variables, and is expressed by the correlation coefficient. This coefficient describes how the two variables relate to each other by how the development of one variable is dependent on the the other. Thus a positive correlation represent that a change in one variable will resolve in a similar change in the other variable as well. On the contrary, a negative correlation imply that change in one variable will resolve in an opposite change in the other variable. If no correlation is present between the two variables no change in either variable will resolve in change in the other, and it can therefore be determined that the two variables has no relation to each other. [20] The simple correlation coefficient is calculated as: [20]

$$r = \frac{\sum xy}{\sqrt{\sum x^2 \sum y^2}} \tag{2.2}$$

Furthermore a coefficient of determination can be calculated to express how much of the variability of the dependent variable is accounted for when regressing upon the independent variable. This coefficient is denoted r^2 and can be calculated by simply squaring the correlation coefficient (r). The higher the correlation the closer to 1 the r^2 value will be. Both r and r^2 can be used to determine the strength of the relationship between the two tested variables. [20]

2.8 Ik-State-of-the-Art

For a prosthetic user a good performing prosthesis must perform hand gestures as well in an elevated limb position as in a seated position to be able to support the user in daily tasks, e.g. taking a cup from a cupboard and pouring water into the cup. However, changes in the EMG occurs when performing the same hand gestures in different limb positions [5, 6]. These signal alternations can occur for different reasons. Changing limb position can make muscles move under the skin, relative to the placement of the EMG electrodes, resolving in change of the signal source. Muscle contractions in them selves can also make changes to the recorded EMG due to change in the microscopic structure of the muscles caused by overlap of thick and thin filaments. [21] Other findings have shown that the activity of certain muscles' is depending on angles of joints besides those primarily actuating the contraction of these muscles. [5] Thus, the effect of limb position must be seen as an important aspect to take into consideration in the mapping of hand gestures to control a prosthesis for the user to receive a good performing support device. In 2010, Scheme et al. investigated the effect of different limb positions on pattern recognition based control. They tested eight different limb positions and processed the data using time-domain feature extraction and linear discriminant analysis. Here they found that for each limb position the classification using both EMG and accelerometer data, clearly outperformed using only EMG data. Thus, it might be insufficient to only train the control scheme in one position and expect it to translate to multiple positions. [22] Several studies have tried to address the problem of limb position and changes in classification accuracy in EMG controlled prosthetics, using pattern recognition.

Fougner et al. combined EMG recordings and accelerometer data when classifying movements in five different arm positions during eight different hand gestures. Using pattern recognition they found a reduction in classification error from 18% to 5% when using both EMG and accelerometer data. [5] Jiang et al. used EMG data and recordings of 3D markers places on able-bodied and amputated subjects' arms when performing different hand movements in three different arm positions. They found a decrease in classification error when using training data across different arm positions. They also concluded that the limb position does have a significant effect on the estimation performance for both subject groups, but that results cannot be translated between able-bodied and amputees. [23] Krasoulis et al. used linear discriminant analysis to analyse recordings from 22 subjects (20 able-bodied, 2 amputees) performing 40 different movements at the wrist, hand and fingers. The recordings included EMG data along with accelerometer, gyroscope and magnetometer data. They found a significant increase in classification accuracy by 22.6% when using both EMG and IMU data. [24]

Based on previous studies it can be determined that a combination of EMG and IMU's can be used to achieve higher classification accuracy when classifying different hand movements in different limb positions. Thus, this project will focus on the mapping of different hand gestures while having the arm in different positions. As a novel approach this project will also investigate the possibility of using regression methods instead of recognitions methods.

3 | Methods

3.1 Data Acquisition

The following section will include a description on how the data for the study have been acquired and processed. All data processing, along with GUI design and implementation, will be done in Matlab.

To acquire data a training GUI has been designed and implemented in Matlab. The GUI has been designed to fulfil the specific needs for this project. An illustration of the GUI can be seen in figure 3.1.

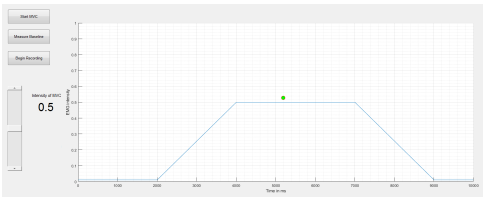


Figure 3.1: WE GONNA NEED A NEW PIC OF THE GUI HERE The training GUI implemented with Matlab GUI development environment. Control buttons to calculate MVC and perform MVC fraction recordings are placed on the left side. The trapezoid plot with the green dot controlled by the input EMG signal from the subject is shown on the right. The fraction of the MVC can be defined by the slider located under the control buttons.

The functions of the GUI consists of a baseline measurement button, a MVC measurement button, a data recording button and a fraction of MVC intensity slider. The baseline measurement is acquired for the purpose of being subtracted from the signal, in order to remove the signal artefacts that are present. At the baseline acquisition the subject is resting the lower arm in the given limb position. The MVC is calculated as a mean of the maximum values in each of the eight channels, and is set as a normalized reference point of 1. The MVC is a contraction at the intensity of which the subject can withhold for 15 seconds. The data recording contains the raw data of a given fraction of the MVC. The fraction is decided by setting the slider to the wanted fraction value, before the recording is started. The slider sets the fraction value so the plateau of the trapeze is at the set value. The trapeze depicts an initial resting phase of two seconds with the intensity of 0, a transition phase of two seconds with an ascending slope until the plateau phase is reached, which has a three second duration, and then a final descending transition phase of two seconds and resting phase of one second. Initialization of the recording will show a green dot, which moves with time in relation to the normalized intensity. The green dot is calculated as the mean of the input EMG signal in a 200 ms window with a 100 ms overlap. From this acquired data features will be extracted and used to train regressors for each of the subjects for each of the hand gestures performed.

3.1.1 Validation of data

After features has been extracted from the data, the feature data is validated through Principal Component Analysis (PCA) to determine the quality of the recorded data in the sense of identify outliers and examining whether the data from the different hand gestures are distinguishable. Thus, the PCA will only be used as a qualitative tool to validate the data. PCA is an analysis tool used to express a set of correlated variables into non-correlated components, such that the dataset can be expressed using less variables, however more defining variables for the given data set. These variables are called the principal components. Each PC is orthogonal on the former, meaning that they each define the largest variance in an axis, different from axes described by other components. PCA also provides knowledge on which components are the most defining for the data set, so only the most important can be considered. When performing PCA it provides the coefficients of the principal components (PCC), which can be visualised in a plot. This plotting of the coefficients are what is used to evaluate the quality of the feature data. A threshold of 90% for preserved information is used.

PCA is performed for each movement in each limb position and plotted in a three dimensional space. If the PCC's of a movement has significant outliers, or the points are clustered, it will be identified shortly after the feature extraction, and a new recording session for the test subject can be executed to prevent inaccurate training of regressors and time delays. If the data is of high quality, meaning the data points are easily distinguishable from each other, it can be used further on to train the regressors.

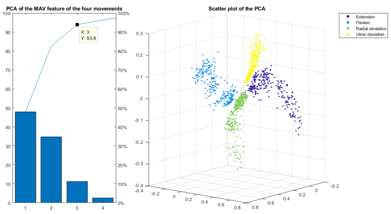


Figure 3.2: Plot of PCA. To the left the first four principal components are visualised. The first three principal components account for describing 93.8% of the data set. On the right the PCC's are plotted for each movement. The clusters for each movement are distinguishable from each other and have no noteworthy outliers, so the data is considered of high quality.

In figure 3.2 an example of a PCA performed on feature data from one test subject is shown. The left plot of the principal components describe the importance of each identified components, and how much of the variance in the data that is described. Using only the first three components, 93.8% of the full dataset can be described. Only these principal components are used in the plot to the right in figure 3.2. Here it can be seen that the clusters are easily distinguishable and have no remarkable outliers. Therefore the data is considered good and can be used in the training of the regressors.

3.2 Accuracy of regressors

To measure the accuracy of the regressors the Root Mean Squared Error(RMSE) is calculated. RMSE is a measure to examine how much the regressors disagrees with the actual data. RMSE a calculation of the standard deviation of the residuals, which is the difference between the estimated values and the actual values. The RMSE is calculated as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{N}} \tag{3.1}$$

Where N is the length of the signal, y_i is the i^th variable of the actual data and $\hat{y}_i$ is the i^th output of the regressor. The RMSE will be done for the regressor for each movement.

3.3 Feature extraction

In this section it will be explained which features that are extracted from the EMG data, and which features that behaves more linearly.

A commonly used feature in control of prosthetics is the Mean Absolute Value (MAV). The equation of MAV is as follows:

$$MAV = \frac{1}{N}\sum_{i=1}^{N}|x_i| \tag{3.2}$$

As the equation and name indicates MAV is the average of the absolute values of the EMG signal, where N is the length of the signal, and x_i is the signal of i samples. MAV expresses the amplitude of the signal and will be use as a feature in this project.

According to a study by [4] the logarithmic variance $log(\sigma^2)$ behaves more linearly than features similar to the mean absolute (root means squared). This linear property might yield a better estimation in the recognition of the hand gestures since linear regression is used to as the mapping tool of the hand gestures. The logarithmic variance is calculated as in equation (3.3):

$$log(\sigma^2) = log(\frac{\sum_{i=1}^{N}(x_i - \mu)^2}{N}) \tag{3.3}$$

N expresses the length of the signal, x_i is the i^th sample of the signal and μ is the mean.

The logarithmic variance calculates the logarithm of the variance, which is the sum of the squared deviation of a variable from its mean. Thus, how spread the signal is from its average. In the study by [4], it is found that the variance behaves non-linearly. Taking the logarithm of the variance linearises the variance, which is the reason for the logarithmic variance to be extracted as a feature in this project.

3.4 Test GUI

As a means to express the movement recognition of the trained regressors, a test GUI has been implemented to confirm that the regressors are trained accordingly and translate to a specific direction. Furthermore, the test GUI serves as a digital way to test the system before moving on the controlling the JACO robotic arm.

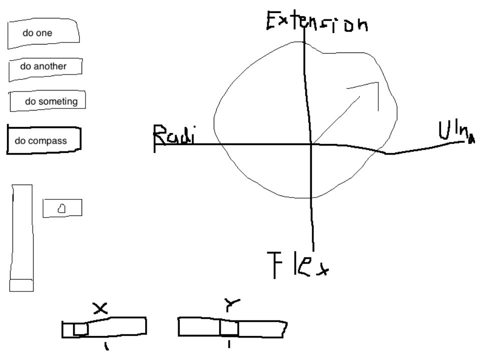


Figure 3.3: The compass plot shows the movement and intensity of the EMG, as recognised by the regressor, by arrow direction and length. The test GUI is implemented in the same GUI as the training GUI and will change the plot type once the correct button is pressed.

As seen in figure 3.3 the test GUI consists of a compass-like plot with captions for the four movements in four different direction. The compass-plot will illustrate the performed movement by an arrow pointing in the direction of the movement with the intensity of the movement shown as the length of the arrow. The compass-plot have been made so the directions are intuitive in relation to performed movements of the hand, with the palm of the hand facing down as starting point. This is not necessary according to Ison et al. [3], as non-intuitive control schemes are not a barrier in learning proper control of prosthetics. The control scheme might change when adapting to system for control of the JACO robotic arm. Sensitivity sliders are implemented in the GUI to enable fine tuning of the intensity to make valid plotting of the arrow in the (X,Y) directions, in case the regressor values are too small to make a proper plot. The compass plot will continuously update to plot the direction of the movement and intensity.

3.5 Fitts' Law

Fitts' Law will be used to quantify the versatility of the regressors. Fitts' Law is a predictive model describing the relation that the time it takes to do a rapid movement to reach a target area, is dependent on the distance to the target area, and the size of the target area. The law demonstrates that the information of any human motor tasks, is finite and only limited by the capabilities of the control system. The control exhibit a negative correlation between speed and accuracy. [25] Fitts' Law calculates an *Index of Difficulty* (ID) by equation (3.4)

$$ID = log_2 * (\frac{2D}{W}) \tag{3.4}$$

Where ID is Index of Difficulty, D is distance to targes, W is width of target area. To calculate the performance of the human interacting with the control system, the *throughput* (TP) was introduced. IP is calculated by equation (3.5).

$$TP = \frac{ID}{MT} \tag{3.5}$$

where ID is Index of Difficulty, MT is movement time. MT is the time it would take a subject to move a pointer from origin to the target area.

Fitts' Law will be implemented into the test GUI described in section 3.4 on site 16, where it will test the control systems ability to correctly convey the test subjects task of reaching points in the compass-plot.

4 | Results

no

Bibliography

[1] Ning Jiang et al. "Myoelectric Control of Artificial Limbs: Is There a Need to Change Focus?" In: *IEEE Signal Processing Magazine* 29.5 (2012), pp. 150–152. ISSN: 1053-5888. DOI: 10.1109/msp.2012.2203480.

[2] Anders Fougner et al. "Control of upper limb prostheses: Terminology and proportional myoelectric controla review". In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 20.5 (2012). ISSN: 15344320. DOI: 10.1109/TNSRE.2012.2196711.

[3] M Ison et al. "High-density electromyography and motor skill learning for robust long-term control of a 7-DoF robot arm". In: *IEEE Transactions on . . .* 24.4 (2016). URL: http://ieeexplore.ieee.org/abstract/document/7073629/.

[4] J. M. Hahne et al. "Linear and Nonlinear Regression Techniques for Simultaneous and Proportional Myoelectric Control". In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 22.2 (2014). ISSN: 1534-4320. DOI: 10.1109/TNSRE.2014.2305520. URL: http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=6742730.

[5] Anders Fougner et al. "Resolving the limb position effect in myoelectric pattern recognition". In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 19 (2011). ISSN: 15344320. DOI: 10.1109/TNSRE.2011.2163529.

[6] A. D'Avella et al. "Control of Fast-Reaching Movements by Muscle Synergy Combinations". In: *Journal of Neuroscience* 26.30 (2006). ISSN: 0270-6474. DOI: 10.1523/JNEUROSCI.0830-06.2006. URL: http://www.jneurosci.org/cgi/doi/10.1523/JNEUROSCI.0830-06.2006.

[7] Aymar de Rugy, Gerald E. Loeb, and Timothy J. Carroll. "Are muscle synergies useful for neural control?" In: *Frontiers in Computational Neuroscience* 7 (2013). ISSN: 1662-5188. DOI: 10.3389/fncom.2013.00019. URL: http://journal.frontiersin.org/article/10.3389/fncom.2013.00019/abstract.

[8] Serge H Roy and M Samuel Cheng. "A Combined sEMG and Accelerometer System for Monitoring Functional Activity in Stroke". In: *Vital And Health Statistics. Series 20 Data From The National Vitalstatistics System Vital Health Stat 20 Data Natl Vital Sta* 17.6 (2010). DOI: 10.1109/TNSRE.2009.2036615.A.

[9] U. Imtiaz et al. "Application of wireless inertial measurement units and EMG sensors for studying deglutition - Preliminary results". In: *Conference proceedings : ... Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual Conference* 2014 (2014), pp. 5381–5384. ISSN: 1557170X. DOI: 10.1109/EMBC.2014.6944842.

[10] Arslan Ahmed et al. *Design and Implementation of Robotic Arm that Copies the Human Arm.* 2017. URL: https://www.researchgate.net/figure/319619198%7B%5C_%7Dfig4%7B%5C_%7DFigure-21-7-DOF-of-Human-Arm (visited on 11/09/2017).

[11] John J Dicker, Gordon R Pennock, and Joseph E Shigley. "THEORY OF MACHINES Third Edition". In: (2003).

[12] Ning Jiang, Kevin B. Englehart, and Philip A. Parker. "Extracting simultaneous and proportional neural control information for multiple-dof prostheses from the surface electromyographic signal". In: *IEEE Transactions on Biomedical Engineering* 56.4 (2009). ISSN: 00189294. DOI: 10.1109/TBME.2008.2007967.

[13] Zezo. "The Forearm, Wrist, and Hand". In: *Musclesceletal Key*. 2016. Chap. 18. URL: https://musculoskeletalkey.com/the-forearm-wrist-and-hand-3/.

[14] Jeffrey R. Cram. *Cram's Introduction to Surface EMG*. Eleanor Cr. 2012. ISBN: 9780801026935. DOI: 10.1016/S0167-8922(09)70001-X. arXiv: arXiv:1011.1669v3.

[15] Peter Konrad. *The ABC of EMG*. 2005, pp. 1–60. ISBN: 0977162214. DOI: 10.1016/j.jacc.2008.05.066. URL: http://demotu.org/aulas/controle/ABCofEMG.pdf.

[16] S. Lee and John Kruse. "Biopotential Electrode Sensors in ECG/EEG/EMG Systems". In: *Motorcontrol.Analog.Com* (2008). URL: http://motorcontrol.analog.com/static/imported-files/tech%7B%5C_%7Ddocs/ECG-EEG-EMG%7B%5C_%7DFINAL.pdf.

[17] I Mendez et al. "Evaluation of the Myo Armband for the Classification of hand motions". In: (2017), pp. 1211–1214.

[18] KINOVA Robotics. *Assistive Robotics*. 2017. URL: http://www.kinovarobotics.com/assistive-robotics/products/robot-arms/ (visited on 10/20/2017).

[19] Angkoon Phinyomark, Pornchai Phukpattaranont, and Chusak Limsakul. "Feature reduction and selection for EMG signal classification". In: *Expert Systems with Applications* 39 (2012). ISSN: 09574174. DOI: 10.1016/j.eswa.2012.01.102. URL: http://dx.doi.org/10.1016/j.eswa.2012.01.102.

[20] Zar Jerrold H. *Biostastical Analysis*. 5th ed. Pearson, 2009. ISBN: 978-0321656865.

[21] Frederic H. Martini, Judi L. Nath, and Edwin F. Bartholomew. *Fundametals of Anatomy&Physiology*. 2012. ISBN: 9788578110796. DOI: 10.1017/CBO9781107415324.004. arXiv: arXiv:1011.1669v3.

[22] E. Scheme et al. "Examining the adverse effects of limb position on pattern recognition based myoelectric control". In: *2010 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBC'10* (2010), pp. 6337–6340. ISSN: 1557-170X. DOI: 10.1109/IEMBS.2010.5627638.

[23] Ning Jiang et al. "Effect of arm position on the prediction of kinematics from EMG in amputees". In: *Medical and Biological Engineering and Computing* 51.1-2 (2013), pp. 143–151. ISSN: 01400118. DOI: 10.1007/s11517-012-0979-4.

[24] Agamemnon Krasoulis et al. "Improved prosthetic hand control with concurrent use of myoelectric and inertial measurements". In: *Journal of NeuroEngineering and Rehabilitation* 14.1 (2017). ISSN: 1743-0003. DOI: 10.1186/s12984-017-0284-4. URL: http://jneuroengrehab.biomedcentral.com/articles/10.1186/s12984-017-0284-4.

[25] Ernest N. Kamavuako, Erik J. Scheme, and Kevin B. Englehart. "On the usability of intramuscular EMG for prosthetic control: A Fitts' Law approach". In: *Journal of Electromyography and Kinesiology* 24.5 (2014), pp. 770–777. ISSN: 18735711. DOI: 10.1016/j.jelekin.2014.06.009. URL: http://dx.doi.org/10.1016/j.jelekin.2014.06.009.

[26] Nancy Hamilton Ph.D., Wendi Weimar Ph.D., and Kathryn Luttgens Ph.D. "Kinosiology: Scientific Basic of Human Motion". In: *Kinosiology*. 12th ed. The McGraw Hill Companies, 2008. Chap. 6. ISBN: 978-0-07-802254-8.

.1 Training data acquistion protocol

The inclusion criteria for the subjects is that they must be healthy and able-bodied. The subjects will perform four different hand gestures: ulnar deviation, radial deviation, flexion and extension of the wrist, as shown in figure 1. The order of the execution of the movements will be the same for each subject.

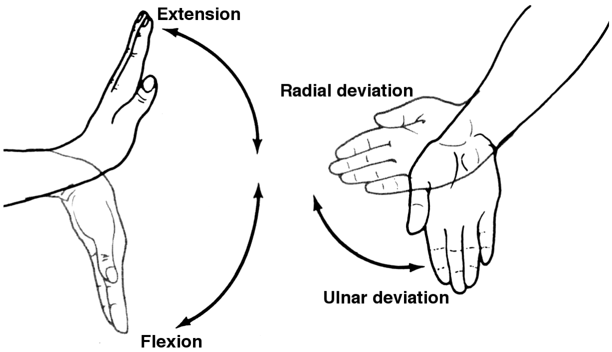


Figure 1: Flexion, extension, radial and ulnar deviation of the hand. Modified from [26]

At first the subject will have the baseline measured. The subject will have a relaxed forearm and hold the wrist in a neutral position. Afterwards each hand gesture will be performed as a fraction of the maximum voluntary contraction (MVC) set as 30% , 50% and 80%. The subjects will therefore initially be performing a MVC measure to be used as a reference measurement before the fraction of the MVC measures can be performed. The subjects will rest two minutes after the MVC measurement to avoid fatigue. This is done for each hand gesture.

The acquisition of the fraction of the MVC of each hand gesture will consist of four chronological phases: a relaxed phase, a transition phase, a plateau phase and a relaxed phase, which will be depicted as a trapeze in a plot. The EMG of the subject will be depicted as a small circle in the plot, and the subject must follow the shape of the trapeze with the circle as best as possible. The recording of one fraction of MVC of one hand gesture will take ten seconds, where the phase with the highest contraction is four seconds. This procedure will be performed in three different limb positions, illustrated in the figure figure 2.

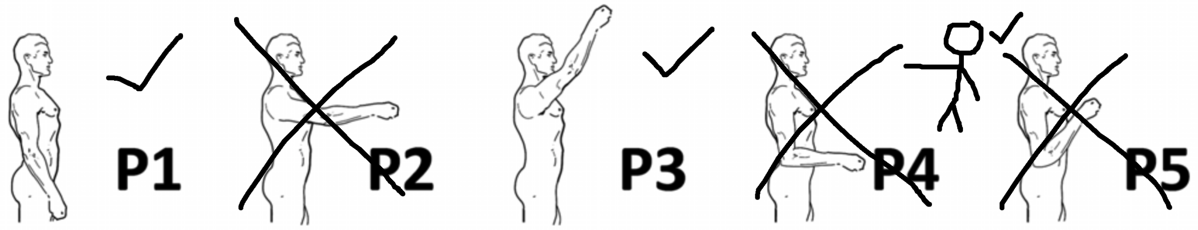


Figure 2: The limb positions consist of: 1) Relaxed arm hanging at the side of the torso, 2) straight arm reaching horizontally away from the torso and 3) straight arm reaching up 45 degrees from vertical.

The subject will be given a relaxation period between trials in order to avoid shoulder fatigue. Due to the fact that the hand gestures only consists of wrist movements, the subject must not move the fingers during the data acquisition. The subjects will be in a standing position during the data acquisition procedure. Below is a table of the order at which each hand gesture will be performed, at which intensity and at which limb position. The table functions as a checklist for acquiring the training data.

Table 1: My caption

	Limb 1	Limb 2	Limb 3
Baseline			
MVC ulnar			
25% ulnar			
50% ulnar			
75% ulnar			
MVC radial			
25% radial			
50% radial			
75% radial			
MVC flex.			
25% flex.			
50% flex.			
75% flex.			
MVC ext.			
25% ext.			
50% ext.			
75% ext.			