AALBORG UNIVERSITY
STUDENT REPORT

# The effect of limb position on myoelectric prosthetic control using linear regression

Biomedical Engineering & Infomatics, 1st semester - Autumn 2017

Project group: 17gr7404

**AALBORG UNIVERSITY**
STUDENT REPORT

**7$^{\text{th}}$ Semester, Masters Project**
**School of Medicine and Health**
**Biomedical Engineering and Informatics**
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**The effect of limb position on myoelectric prosthetic control using linear regression**

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**Abstract**

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## 0.1 Abstract

**Background:** Electromyography (EMG) is widely used as input to control scheme of myoelectric prosthetics. However, EMG signals change with limb position and thus lowers the accuracy in classification.Inclusion use of Inertial Measurement Units (IMU) has proved to raise the accuracy in pattern recognition methods. However, pattern recognition methods provides only control of one degree of freedom (DoF) at a time, and are computational costly. This study propose to use the combination of EMG recordings and accelerometer data in a linear regression model to overcome the slower reaction time of pattern recognition systems and to enable a simultaneous and proportional control scheme.

**Methods:** In this study recordings from four able-bodied subjects has been collected, performing four hand movements at the wrist in three different limb positions. The data is evaluated through principal component analysis (PCA) and processed/trained with a linear model to classify the hand movements. Eight regressors are trained for each test subject; four with and without using IMU data. The regressors are tested in a real-time visual environment on PC measuring time to complete a target-reaching task of eight targets. The performance of the regressors are compared between using the IMU data and not using IMU data to determine the effect of including IMU data.

**Results:**

**Conclusion:**

**Keywords:** surface electromyography, inertial measurement unit, simultaneous and proportional myoelectric control, regression, hand motion classification, hand prosthetic

# Preface

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# Contents

# 1 | Introduction

Upper limb prostheses have the purpose of fulfilling the users 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 lower arm prosthetics has 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 degree of freedom (DOF) by *on-off control*, mostly by linking antagonistic muscles to one DOF. This kind of prostheses change between states due to a switching impulse which cause a state machine to shift its present state. Usually a strong and fast muscle contraction from the users are employed to generate the switching signals. [3] This type of control provided users a way to control more than one DOF, but never simultaneously. The switch-control functioned on a cycle, so users would have to go through all the movements of the prosthesis to find the one they wanted to perform. However, as demands would rise, more complex methods was introduced to the EMG prosthetics scene. Classification methods effectively enabled users to use DOF's more freely because the switching was now replaced by direct recognition of different muscle contractions linked to specific prosthetic movements. This also effectively enabled proportional control of movements, but gave rise to new problems; a wider range of control would give less accurate movements, and training the classifiers proved difficult, as the training could over-fit, causing extended use of the prosthetics to degrade in performance. [4]

Introducing regression as a new mapping method in myoelectric prosthetics provided a way to enable both simultaneous and proportional control of multiple DOF's. Regression is able to provide a continuous value for each DOF based on the recorded EMG signal, while a classifier only decides upon a certain class. [5, 6]This means that classification can only translate a recorded EMG signal to one movement of the prosthetic at a time. It can do so proportionally but the handling still lacks natural control, since movements by able-bodied individuals very rarely only happen in one DOF at a time. Regression methods constantly provide a value, and since several regressors can be used at a time, several values can be used in the recognition of movements. This is what enables regression methods to perform simultaneous and proportionally.

Applying regression as a mapping method in proportional and simultaneous control of multiple DOF's has been shown to perform well in recognition of movements and doing so with a low computation time. [5] However, very few studies have tested the regressor performance in daily life tasks outside the clinical training environment. [1] A study by Fougner et al. [7] has addressed the problem that most studies test their method on only one limb position. This means that the actual performance of regression methods has not yet been properly addressed when recognizing movements where the arm is in positions that is normally a part of daily life tasks.

When recording EMG signals it has been shown that some muscles are activated based on joint angles, even though the muscles are not involved in the movement of that joint [7]. This provides a problem, but can be explained by muscle-synergies, which have been shown to exist between muscles [8]. These muscle-synergies are created by the Central Nervous System (CNS) and coordinated into activation of different muscles at varying times. This enables the CNS to control the muscle-synergies instead of controlling each muscle individually, to perform movements [9]. This means that muscles in the lower arm can be activated when muscles in the upper arm are activated, in a level that will be detectable in

EMG recordings, and enough to alter recognition of movements, when the arm is active in limb positions other than the one tested in a clinical environment.

In order to overcome the problem of muscles activating, when movements, other than those they are directly involved in, are performed, Fougner et al. [7] has suggested to combine recordings of EMG signals with inertial information(IMU) to provide limb position data. This could be beneficial in increasing the accuracy of EMG controlled prosthetics. Even though the combination of EMG and IMU data has been proposed as a valid way to improve the performance and accuracy of EMG based prosthetics, it has only been investigated in few studies. [10, 11, 1] To the authors knowledge the combination of EMG recordings and IMU data has only been done with classification methods. A novel approach to further investigate the usability of combining EMG and IMU is to build a regression based control scheme for myoelectric prosthetics. This would enable both proportional and simultaneous control of several DOF's, where the inclusion of IMU data should provide more information on limb position to counter the effect of muscle-synergies. This leads to the following hypothesis:

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 linear regression on recorded surface EMG signals and inertial measurement data.

# 2 | Background

## 2.1 Anatomy of the lower arm

This project will focus on the lower arm as the Myo armband will be used to 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 DOF. The arm has seven DOF's, where the arm is defined as distal to the shoulder joint and proximal to the hand. This means DOF's of the hands and fingers and translation of the shoulder are not included. Thus the DOF's included in this study are at the shoulder; abduction and adduction, flexion and extension, medial and lateral rotation. Extension and flexion at the elbow. Pronation and supination of the lower arm and at the wrist; extension and flexion, radial and ulnar deviation.

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. [12]

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 [9, 13]. 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.

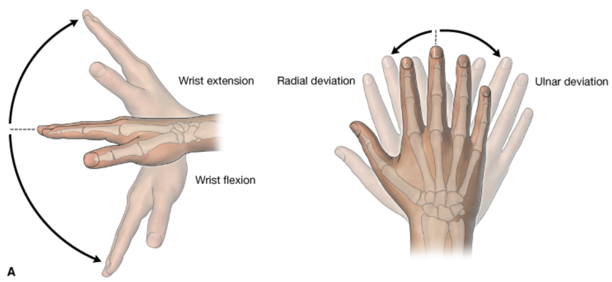



**Figure 2.1:** Flexion, extension and radial and ulnar deviation of the hand. Modified from [14]

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 2.1.

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. [5] In figure 2.2 the muscles in the forearm both involved with extension/flexion and radial/ulnar deviation is marked with boxes around the name of the muscles.

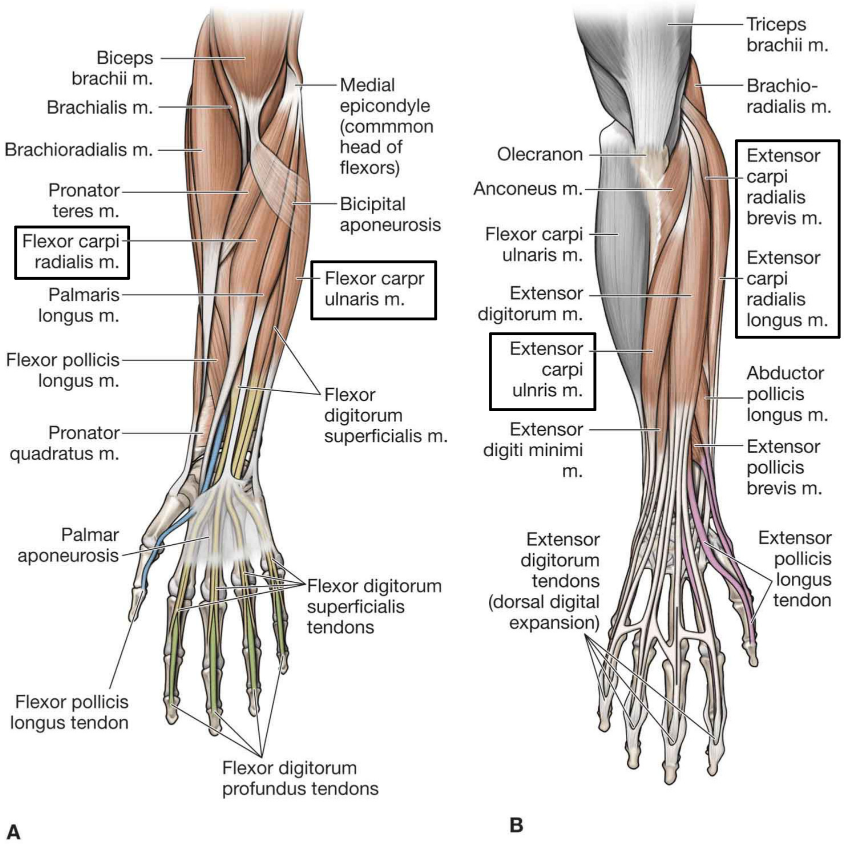



**Figure 2.2:** **A)** posterior view of the superficial muscle layer in a right arm. **B)** posterior view of the middle muscle layer in a left arm. The muscle names in the boxes are muscles which are included in both extension/flexion and ulnar/radial deviation at the wrist. Modified from [14]

## 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.

The electric potential detected with electromyography is an action potential causing the muscle to contract. Certain mechanisms are involved for this to happen.

As depicted in figure 2.3 the alpha motor neuron originates from the spinal cord along an axon to the muscle it controls. From the axon it branches out to lower motor neurons which attach to muscles fibres via motor endplates. All the muscle fibres connected to the lower motor neuron are what makes up one motor unit.

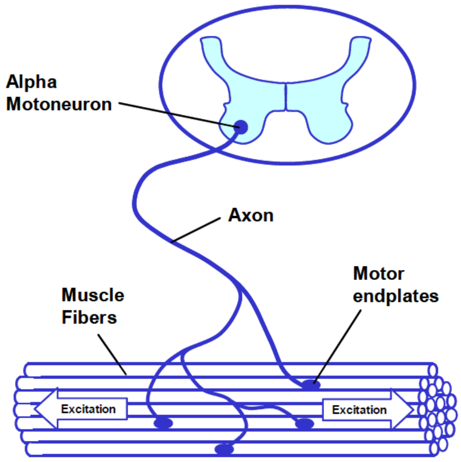



**Figure 2.3:** Illustration of the action potential exciting the muscle fibre, which causes the release of calcium ions and the muscle to contract. [15]

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. [16]

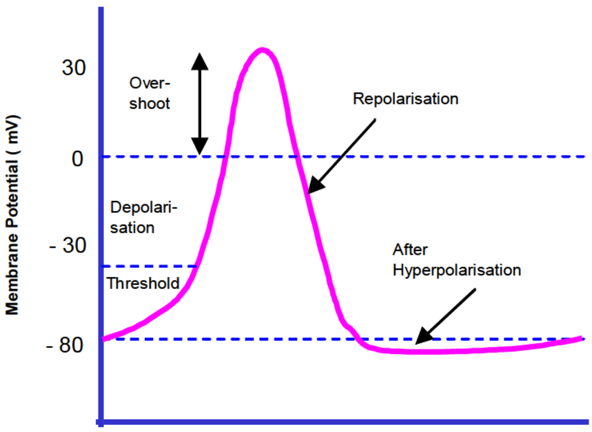



**Figure 2.4:** Illustration of the action potential exceeding the threshold for it to be generated and the following depolarization and repolarization. [15]

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 travelling 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. This creates a new action potential that travels along the whole muscle fibre along the sarcolemma. This happens in both directions from the motor end-plate to the tendinous 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. This is the action potential which is recorded with EMG. [16]

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 of 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 have a higher innervation than those in the quadriceps. [16]

### 2.2.1 Recording of electromyography

Recording of EMG can be done either at the skin surface (sEMG) or intra muscular (iEMG). sEMG is performed using electrodes placed on the skin while iEMG is done using needle electrodes inserted into the muscle, but sEMG is far more commonly used as it is non-invasive and easy to use. [16]

When acquiring sEMG signals the electrodes act as a transducer by converting the recorded action potentials from the muscles 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. [17, 16]

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 decrease the skin impedance. [16]

## 2.3 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.

### 2.3.1 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 2.5.

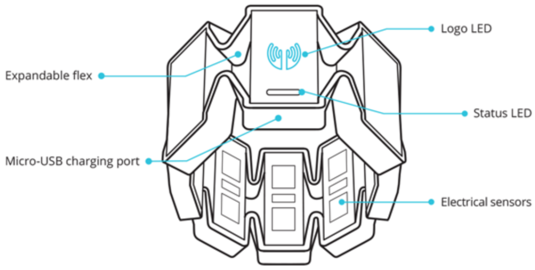



**Figure 2.5:** Main components of the Myo armband. **SOURCE**

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. [18] 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. The Myo armband is sampling sEMG data at a sample rate of 200 Hz. A low sample rate could result in problems of aliasing later on in the data processing, since the range of the sEMG signal is 10-500 Hz. [16]

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 comprises 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. The magnetometer has the property of a compass, measuring the earth's magnetic field. This enables the armband to provide data on orientation. IMU data is sampled at a sample rate of 50 Hz. The Myo armband communicates through Bluetooth 4.0 to a computer.

## 2.4 Preprocessing of EMG

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

As mentioned in section 2.3 on page 6 sEMG is in a 10-500 Hz range. Thus it is recommended to implement a bandpass filter from 10 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. [16]

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 [16].

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 built in gain as well which determines the final strength of the signal, and both of these features are implemented in order to maximize the SNR.

### 2.4.1 Feature extraction

Following preprocessing of the recorded EMG signal, features can be extracted and used to map different hand gestures. Features are extracted from the signal to represent the signal using fewer data samples. This is also called dimension reduction and result in faster computation times. 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] Different features are visualized in figure 2.6.

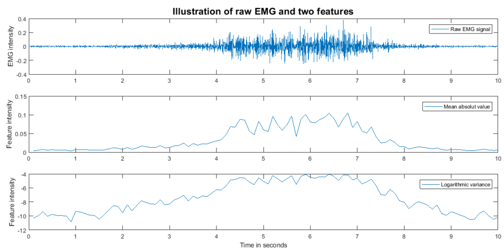



**Figure 2.6:** Above a raw EMG signal. Below are different features extracted from the EMG signal presented.

## 2.5 Regression methods

Regression methods are widely used in 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.

Based on the principle of simple linear regression, multivariate linear regression are used in cases where more that two variables should be investigated. Multivariate linear regression are used when two or more variables are expected to have a linear correlation to a dependent variable. Multivariate linear regression expand on the equation for simple linear regression, where more independent variables $X_i$ are added to the equation: [20]

$$\hat{Y} = \alpha + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_i X_i + \epsilon_i \tag{2.1}$$

Where $Y$ is the dependent variable, $X_i$ are the independent variables, $\beta_i$ is the regression coefficient in the sampled population, and $\alpha$ is the predicted value of $Y$ at $X = 0$. $\epsilon$ 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. When three variables are present in the equation, the visual representation of the regression is in the 3rd dimension, and will no longer be presented as a line in 2D, but as a plane in 3D. Having more than three variables will resolve in a regression in the $m$-dimension, where $m$ is the number of variables. This plane of regression is called the hyperplane. However, regression is not a perfect fit to every sample point, and thus the equation for three or more variables is only complete when the error is also calculated, denotes as $\epsilon$.

There exist no limit to the number of variables which can be tested, however there should always be at least two observations more than the number of variables, so that $n \geq m + 2$. Otherwise multivariate regression is not possible. [20]

Regression methods finds correlation between tested variables which is expressed by a correlation coefficient. The 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]

## 2.6 Overview of previous research

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 [7, 13]. 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 themselves 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 EMG signals can be detected from muscles in situations where the muscles would not be considered to be active. As an example, the muscles in the lower arm would not be considered to be active during flexion of the elbow, because it is the biceps located in the upper arm which is responsible for flexing the elbow, however activity can be measured with EMG from the muscles in the lower arm during the movement. Fougner et al. [7] have reported that the activity of certain muscles' is depending on angles of joints besides those primarily actuating the contraction of these muscles. 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. [22] investigated the effect of different limb positions on classification based control. They tested eight different limb positions and processed the data using time-domain feature extraction and linear discriminant analysis. They thought it might be insufficient to only train the control scheme in one position and expect it to translate to multiple positions, and thus they found that for each limb position the classification using both EMG and accelerometer data, clearly outperformed using only EMG data. [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. [7] 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. In the study [24] no information on limb positions are reported, but the authors of this report assume are in a forward position, based on the study Krasoulis et al. reference. 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.

However, it has not been investigated before how changing limb position affects the control when using regression. Therefore, the aim of the present study is to investigate if IMU data can be used to compensate for the limb position effect when using a regression-based control method for use in EMG prosthetics.

This leads to the following hypothesis:

Combining EMG data and IMU data can minimize the limb position effect when using regression as control system.

# 3 | Methods

## 3.1 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 3.1. The order of the execution of the movements will be the same for each subject.

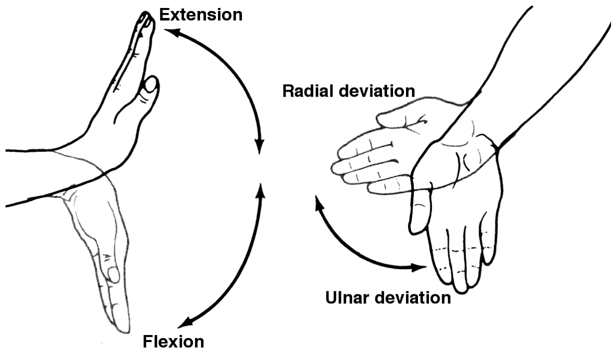



**Figure 3.1:** Flexion, extension, radial and ulnar deviation of the hand. Modified from [25]

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 **??**.

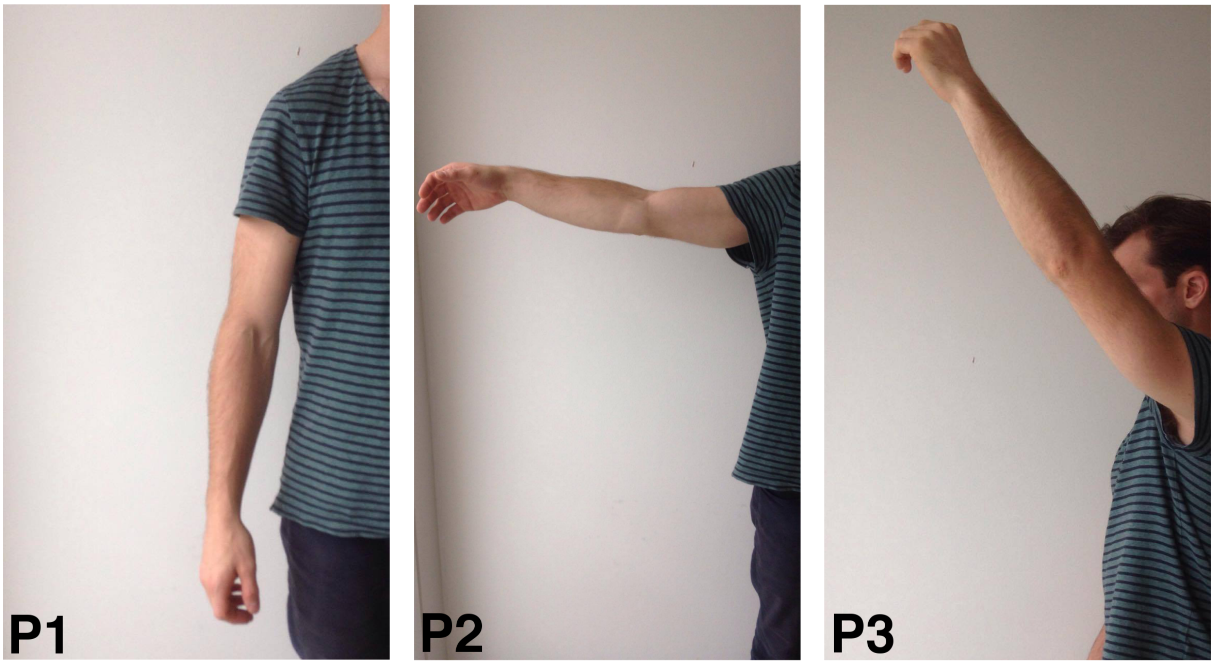



**Figure 3.2:** The limb positions consist of: 1) Relaxed arm hanging at the side of the torso, 2) straight arm reaching horizontally away from the torso and 3) straight arm reaching up 45 degrees from vertical.

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.

## 3.2 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, were done in Matlab.

As described in section 3.1 on page 11, data is acquired from subjects through a series of movements in different limb positions at varying forces of muscle contraction. EMG data is recorded at the skin surface for each movement at different contraction levels in each limb position. Inertial measurements are also recorded during each movement.

To acquire data a training Graphical User Interface (GUI) has been designed and implemented in Matlab. The GUI has been designed to fulfil the specific needs for this project.

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. Acquiring data for a subject consists of a sequence of steps. First a 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. Second MVC is recorded by the subject performing contraction of an intensity it can withhold for 15 seconds. 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. Then the

**Table 3.1:** My caption

| | Limb 1 | Limb 2 | Limb 3 |
|---|---|---|---|
| Baseline | | | |
| MVC ulnar | | | |
| 30% ulnar | | | |
| 50% ulnar | | | |
| 80% ulnar | | | |
| MVC radial | | | |
| 30% radial | | | |
| 50% radial | | | |
| 80% radial | | | |
| MVC flex. | | | |
| 30% flex. | | | |
| 50% flex. | | | |
| 80% flex. | | | |
| MVC ext. | | | |
| 30% ext. | | | |
| 50% ext. | | | |
| 80% ext. | | | |

subject goes through three phases of performing the wrist movements at different contraction levels. The levels are set to 30%, 50% and 80%. To ensure the subjects are performing contraction at the desired level the fraction of MVC is calculated and used to plot a trapezoid in the training GUI. During the recording a green dot will skip along the x-axis of trapezoid plot and the subject must then control the height of the green dot along the y-axis, by contracting the muscles accordingly. An illustration of the GUI can be seen in figure 3.3.

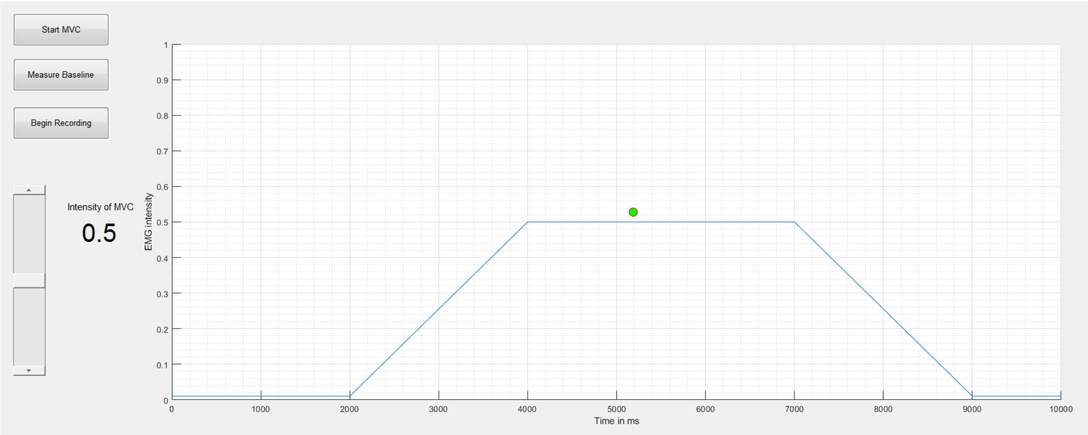



**Figure 3.3:** The training GUI implemented with Matlab GUI development environment. Control buttons to calculate MVC and perform MVC fraction recordings are placed on the left side. The trapezoid plot with the green dot controlled by the input EMG signal from the subject is shown on the right. The fraction of the MVC can be defined by the slider located under the control buttons.

For the project only data acquired from the steady state of the signal, meaning the plateau of the trapeze, will be used in data processing. Although the steady state only contains a short temporal structure of the patterns involved in the contraction of the muscle [26], studies has shown that it is possible to achieve online continuous control using steady-state EMG signals. A study by Englehart et al. [27] demonstrated that steady-state data classified more precisely than transient state data. This could be due to the fact that a larger amount of meaningful data is contained in this muscle contraction phase [28].

Data acquisition will begin by recording of the baseline in the limb position and the MVC of the movement to be tested. 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 50% overlap. (100 ms). Meanwhile IMU data for the orientation of the arm is being recorded and saved for later use. From this acquired data features will be extracted and used to train a regression model (a regressor) for each of the subjects for each of the hand gestures performed.

## 3.3 Feature extraction

In this section it will be explained which features that are extracted from the EMG data.

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

$$MAV = \frac{1}{N}\sum_{i=1}^{N}|x_i| \tag{3.1}$$

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 sample window, and $x_i$ is the $i^th$ sample of the signal. MAV expresses the amplitude of the signal and posses linear properties. It will be use as a feature in this project.

According to a study by [5], the variance of a signal has exponential properties, but taking the logarithm of it ($log(\sigma^2)$), makes it have linear properties 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 (LogVar) is calculated as in equation (3.2):

$$log(\sigma^2) = log(\frac{\sum_{i=1}^{N}(x_i - \mu)^2}{N}) \tag{3.2}$$

$N$ is the length of the sample window, $x_i$ is the $i^th$ sample of the signal and $\mu$ 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 [5], it is found that the variance behaves non-linearly. Taking the logarithm of the variance linearises the feature. This along with the MAV feature, which also show linear properties which is the reason these two features will be used in this project, since linear regression will be applied as control scheme.

### 3.3.1 Separability 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, to identify outliers and examining whether the data from the different hand gestures are distinguishable. Thus, the PCA is 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 in a reduced dimensionality hyperspace using less variables, however more defining variables for the given data set. These variables are called the principal components. Each principal component 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 dataset, where the first vectors in the hyperspace being the ones with highest variance, so only the most important can be considered.

When performing PCA it provides the most defining values of the data. The most defining values are determined by a 90% threshold for the principal components. This means that only the principal components who account for describing the first 90% of the data will be included in further work. The data described by the used principal components can be visualised in a three dimensional plot. In the setting of this project it can be used to determine the separability of the data and thus the quality of the data. If the data proves to be distinguishable it will be clustered in clouds separate from each other. If the data clouds are mixed and overlaps, the data is not separable and thus of poor quality.

PCA is performed for each movement in each limb position and plotted in a three dimensional space. The result of the PCA will determine the quality of the recorded data. If there exist significant outliers a new recording session for the test subject can be executed to prevent inaccurate training of regressors and time delays. If the data is clustered and easily distinguishable from each other, it can be used further on to train the regressors.

## 3.4 Regression model

Once the preprocessing and the feature extraction of the EMG data has been done, regression will be used as described in section 2.5 on page 8. The implementation follows multivariate linear regression as shown in equation (2.1). As mentioned in section 3.2 on page 12 one regressor will be trained for each subject for each of the hand gestures performed.

For each subject the extracted feature data from the eight sEMG channels will be mapped to estimate a movement. Because multivariate regression is used there will be an estimated output for each of the input variables (each of the eight channels). These outputs are expressed by one hyperplane, which is the output for the regressor. Each subject will then have four regressors trained, one for each movement. To train the regressors an input matrix will be constructed. This matrix will contain all the extracted features from all eight channels, for all recorded movements, for all intensities, in all three limb positions. The matrix will be structured into segments, where each segment contains data from one movement. One segment will be structured as shown in equation (3.3), with the feature data of a movement during 30% contraction in one limb position first, followed by 30% contraction for the same movement in the second limb position, and so on. This is true for all contraction intensities (30%, 50%, 80%).

$$\begin{bmatrix} Flex30Down_{1,1}, Flex30Down_{1,2} \cdots Flex30Down_{1,8} \\ \vdots \qquad\qquad \ddots \qquad\qquad \vdots \\ Flex30Down_{n,1}, Flex30Down_{n,2} \cdots Flex30Down_{n,8} \\ Flex30Side_{o,1}, Flex30Side_{o,2} \cdots Flex30Side_{o,8} \\ \vdots \qquad\qquad \ddots \qquad\qquad \vdots \\ Flex30Side_{p,1}, Flex30Side_{p,2} \cdots Flex30Side_{p,8} \\ Flex30Up_{q,1}, Flex30Up_{q,2} \cdots Flex30Up_{q,8} \\ \vdots \qquad\qquad \ddots \qquad\qquad \vdots \\ Flex30Up_{r,1}, Flex30Up_{r,2} \cdots Flex30Up_{r,8} \\ Flex50Down_{s,1}, Flex50Down_{s,2} \cdots Flex50Down_{s,8} \\ \vdots \qquad\qquad \ddots \qquad\qquad \vdots \\ \vdots \qquad\qquad \ddots \qquad\qquad \vdots \\ Flex80Up_{t,1}, Flex80Up_{t,2} \cdots Flex80Up_{t,8} \end{bmatrix} \tag{3.3}$$

The input matrix will then consist of four segments, one for each movement in all three limb positions, as shown in equation (3.4):

$$\begin{bmatrix} Flex_{1,1}, Flex_{1,2} \cdots Flex_{1,8} \\ \vdots \quad \ddots \quad \vdots \\ Flex_{n,1}, Flex_{n,2} \cdots Flex_{n,8} \\ Exte_{o,1}, Exte_{o,2} \cdots Exte_{o,8} \\ \vdots \quad \ddots \quad \vdots \\ Exte_{p,1}, Exte_{p,2} \cdots Exte_{p,8} \\ Radi_{q,1}, Radi_{q,2} \cdots Radi_{q,8} \\ \vdots \quad \ddots \quad \vdots \\ Radi_{r,1}, Radi_{r,2} \cdots Radi_{r,8} \\ Ulna_{s,1}, Ulna_{s,2} \cdots Ulna_{s,8} \\ \vdots \quad \ddots \quad \vdots \\ Ulna_{t,1}, Ulna_{t,2} \cdots Ulna_{t,8} \end{bmatrix} \tag{3.4}$$

This matrix equation (3.4) including the baseline recordings, will be set as input to the training of the regressor. The output for training the regressors are set to the desired values for the performed movement. The desired values are the mean of the data from all eight channels when the subject traced the trapezoid during data acquisition, as shown on figure 3.3 in section 3.2 on page 12. The data is scaled in relation to the MVC for the subject and are structured in a vector with segments of data for each movement similar to that of the matrix equation (3.4) containing the feature data. When training a regressor for a movement, the desired values for the segments in the output vector corresponding to the movements that are not being trained, are augmented with zeros. This ensures that the trained regressor will estimate zero when recognising movements other than the one movement it is trained to recognise.

The regressor is implemented through the Matlab function *fitlm*, which use the input matrix and estimator vector to calculate the slope and intercept of the regressor, according to equation (2.1) in section 2.5 on page 8. This procedure is done for each movement, which yields four regressors trained to recognize one movement each. This procedure is done individually for MAV and LogVar, to compare the accuracy and performance between the two features.

When implementing the IMU data three extra columns are added to the input matrix, because the accelerometer provides a three axis output during recordings. The Mean Value (MV) is extracted from the accelerometer data. New regressors are trained for each subject similar to the described procedure, including the IMU data and is compared to the regressors trained with only the EMG feature data.

## 3.5 Accuracy of regressors

This section will cover the test used to determine the accuracy of the trained regressors. Both methods are performed on the regressors trained with only EMG data and when IMU data is combined with the EMG data.

### 3.5.1 Superimposition

To examine how well the regressors fit the actual data, the output of the regressors build for each feature is superimposed on the actual data. It can then be shown how the regressors perform at which intensities and which movements, and whether other regression methods should be considered to obtain a lower error.

### 3.5.2 Root Mean Square Error

To measure the accuracy of the regressors the Root Mean Square Error(RMSE) is calculated. RMSE is a measure to examine how much the regressors disagrees with the actual data. RMSE is 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:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y_i - \hat{y_i})^2}{N}} \tag{3.5}$$

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 of each movement.

To express that the regressors do not over- or under-fit the input data, the RMSE of new test data must be lower than or equal to the data used to train the regressors. The best results for RMSE is as close to zero as possible.

# 4 | Results

## 4.1 Separability of data

PCA is performed on all feature data from each test subject for both MAV and logarithmic variance features. As described in section 3.3.1 on page 15 the PCA is only used as a tool to qualitatively evaluate the data. In figure 4.1 a PCA is shown from one test subject, performed with the MAV feature.

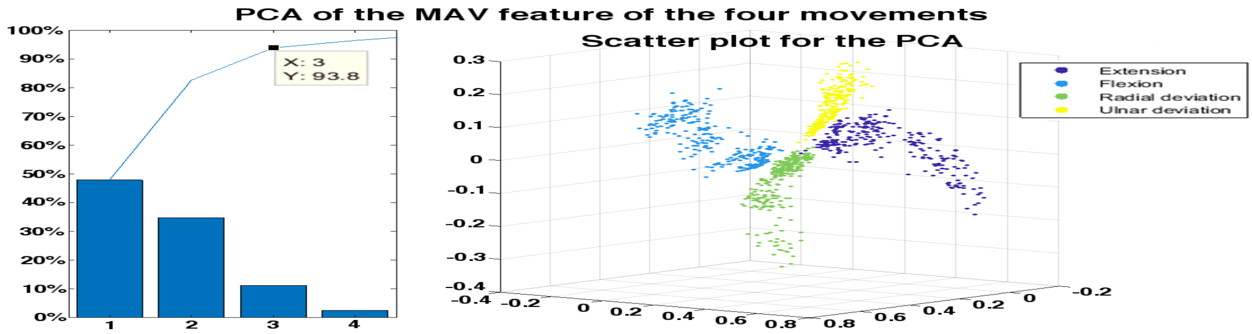



**Figure 4.1:** Plot of PCA of MAV feature. To the left are the amount of data that the first four principal components describe expressed in percentage. The first three principal components account for describing 93.8% of the data set. On the right are the data described by the first three principal components 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.

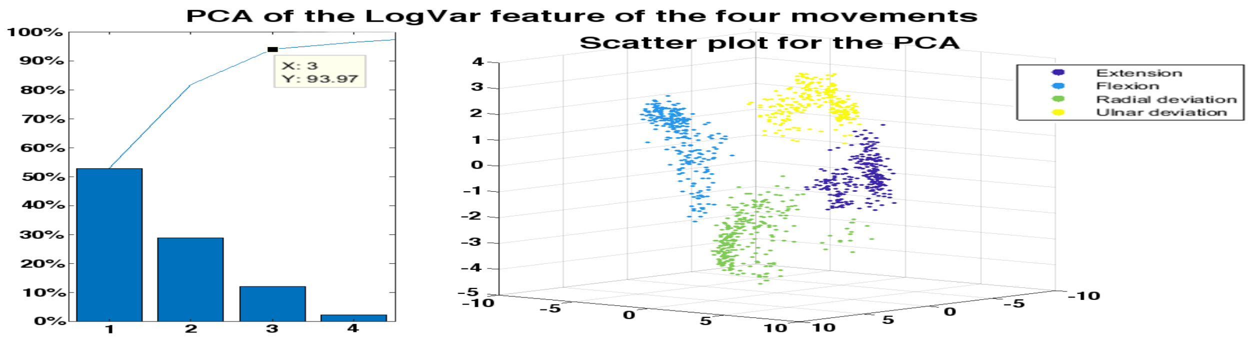



**Figure 4.2:** Plot of PCA of logarithmic variance feature. The first three principal components account for describing 93.97% of the data set. Here the clusters for each movement are also distinguishable from each other and have no noteworthy outliers, so the data is considered of high quality.

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. For the MAV feature depicted in figure 4.1, 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 both figures. The same is the case for the PCA of logarithmic variance shown in figure 4.2, where the first three PC's account for describing 93.97% og the data. In both PCA's 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.

## 4.2 Regression accuracy

This section includes an examination of the accuracy of the regressors. This will be examined through superimposition of the regressor outputs on the estimated data, and through RMSE plots. To evaluate how the regressors perform with new data, a test with new data of 50 % of the MVC of all movements in all limb positions will be fed the regressor and the above examination of accuracy will be performed.

The plot in figure 4.3 depicts the actual data superimposed on the estimated data from the regressors trained with the LogVar features.

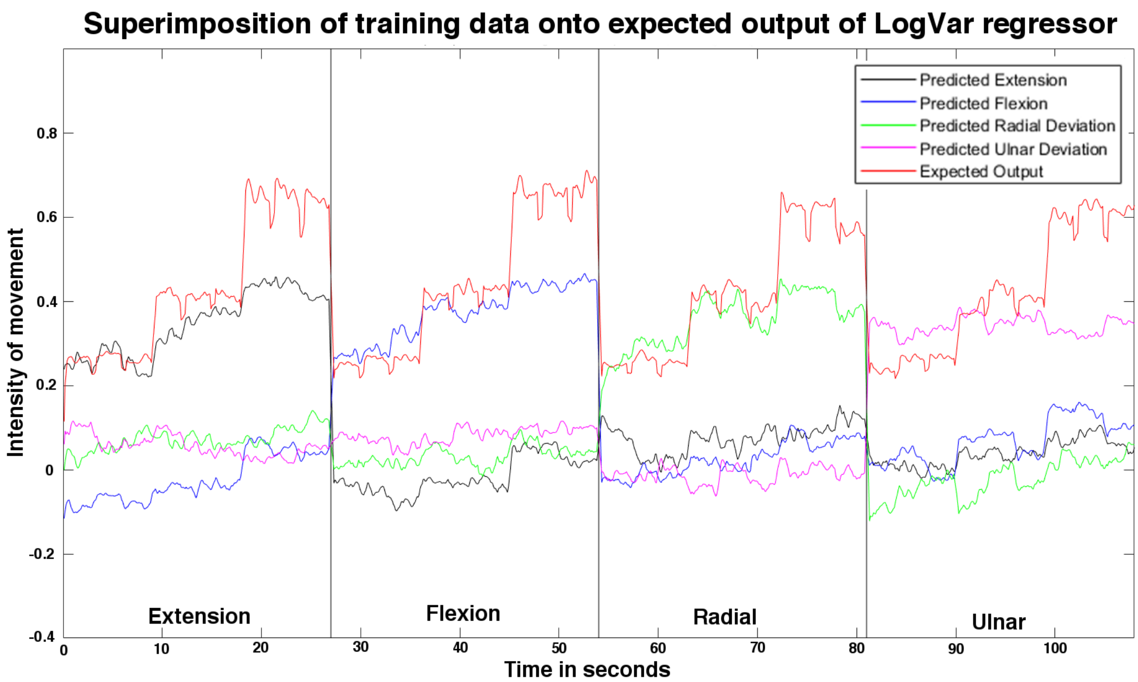



**Figure 4.3:** Plot of the actual data, red plot, superimposed on the output of the regressors trained with the LogVar features. The plot is divided into four segments, where each segment shows a different movement performed. Each segment has the same sample size.

The plot in figure 4.4 depicts the actual data superimposed on the estimated data from the regressors trained with the MAV features.

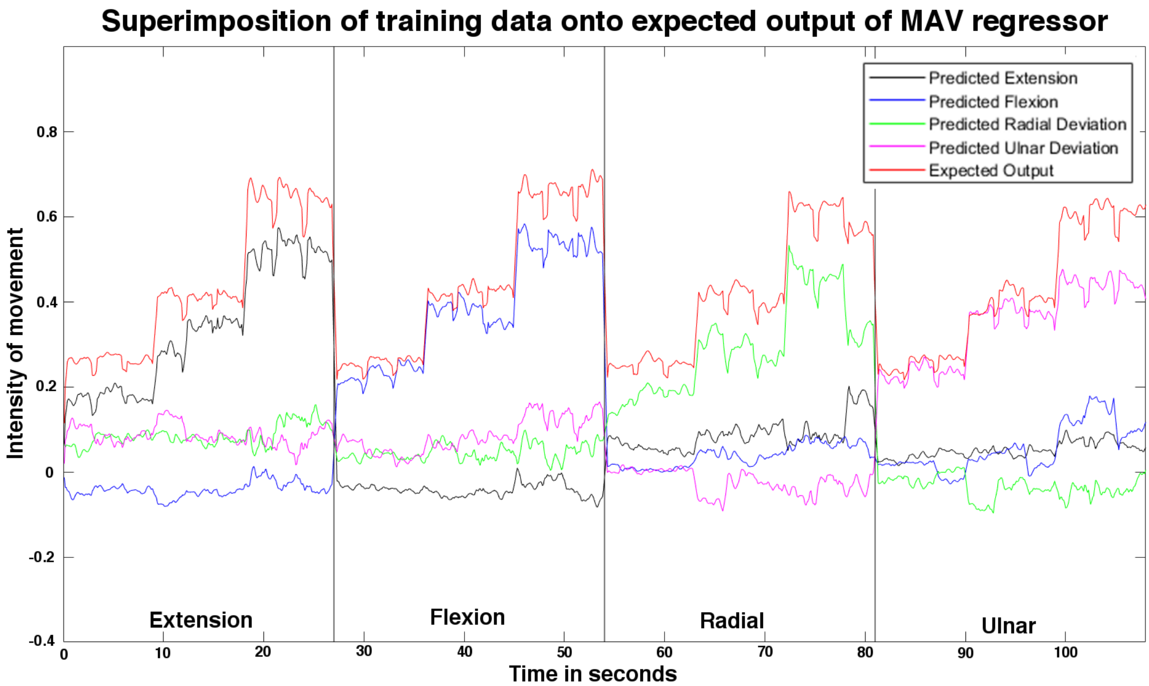
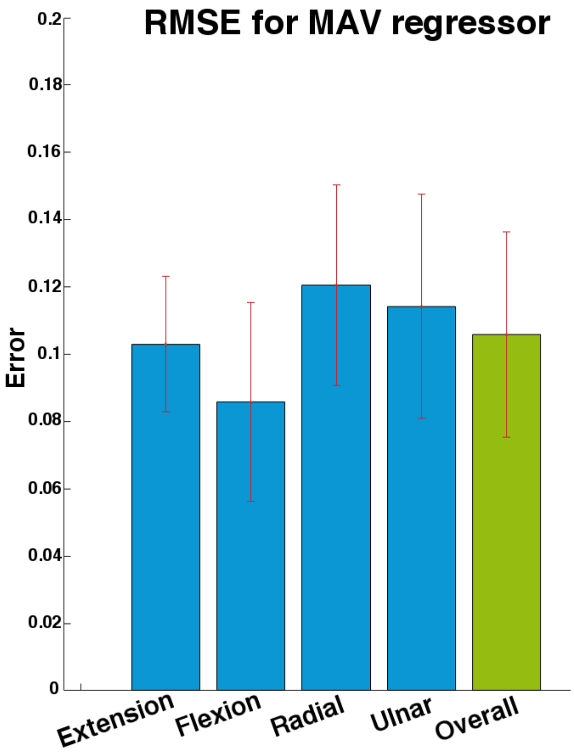



**Figure 4.4:** Plot of the actual data, red plot, superimposed on the output of the regressors trained with the MAV features. The plot is divided into four segments, where each segment shows a different movement performed. Each segment has the same sample size.

A qualitative examination of the plots shows that each regressor reacts on the movement it is fitted for, and remains inactive when another movement is performed. This accounts for both features. Both regressors has a lower accuracy in the high intensities, especially for the regressors trained with logarithmic variance features.

Calculating the RMSE of the regressors for the MAV and LogVar features of the training data across all subjects, yields the results depicted in figure 4.5.



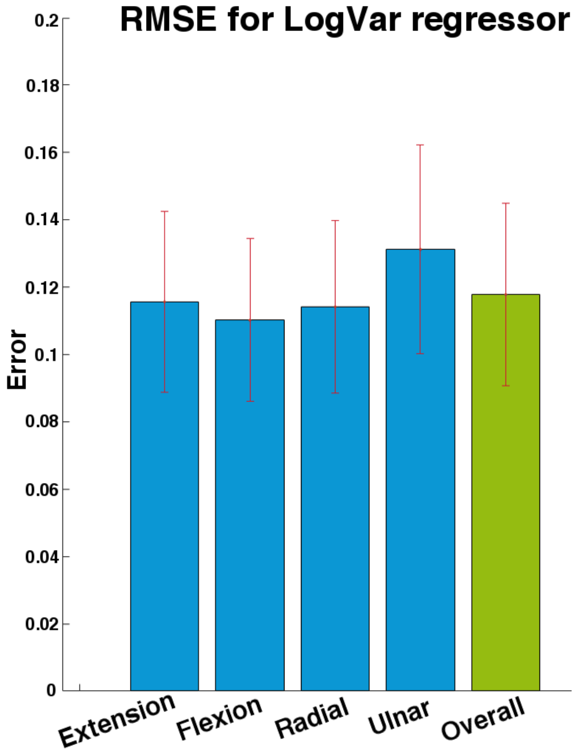




**Figure 4.5:** Bar plot of the error of MAV and the LogVar features for the four hand gestures. The bar chart illustrates the mean error and the error bar illustrates the standard deviation

| **Feature** | **Overall mean error** | **Standard deviation** |
|---|---|---|
| Extension | 0.1030 | ±0.0210 |
| Flexion | 0.1102 | ±0.0296 |
| Radial Deviation | 0.1206 | ±0.0298 |
| Ulnar Deviation | 0.1143 | ±0.0334 |
| Overall | 0.1059 | ±0.0306 |

**Table 4.1:** RMSE for the implemented MAV regressor

| **Feature** | **Overall mean error** | **Standard deviation** |
|---|---|---|
| Extension | 0.1157 | ±0.0469 |
| Flexion | 0.1102 | ±0.0241 |
| Radial Deviation | 0.1142 | ±0.0256 |
| Ulnar Deviation | 0.1312 | ±0.0310 |
| Overall | 0.1178 | ±0.0272 |

**Table 4.2:** RMSE for the implemented LogVar regressor

The overall mean of the RMSE of MAV is 0.0943 with a standard deviation of ±0.0290, where the highest mean of a regressor is 0.1088 and the highest standard deviation is ±0.0366. The overall mean of the RMSE of LogVar is 0.1107 with a standard deviation of ±0.0298, where the highest mean of a regressor is 0.1216 and the highest standard deviation is ±0.0402. MAV then yields a lower mean RMSE and a lower standard deviation than LogVar - both with the overall RMSE and for the movement with the highest RMSE.

**Strahija says that we should consider including RMSE of the different intensities individually, to quantitatively express that both features(but especially LogVar) do poor control of higher intensities.**

### 4.2.1 Accuracy of regressors with test data

This section contains the superimposition of the expected output of the regressors on the output of the regressors fed with test data. The plot in figure 4.6 depicts the superimposition the logarithmic variace trained regressors fed with the test data.


**Figure 4.6**

It is seen that regressors trained for different movements reacts on the same movement, especially for the flexion and ulnar deviation movement. However, the

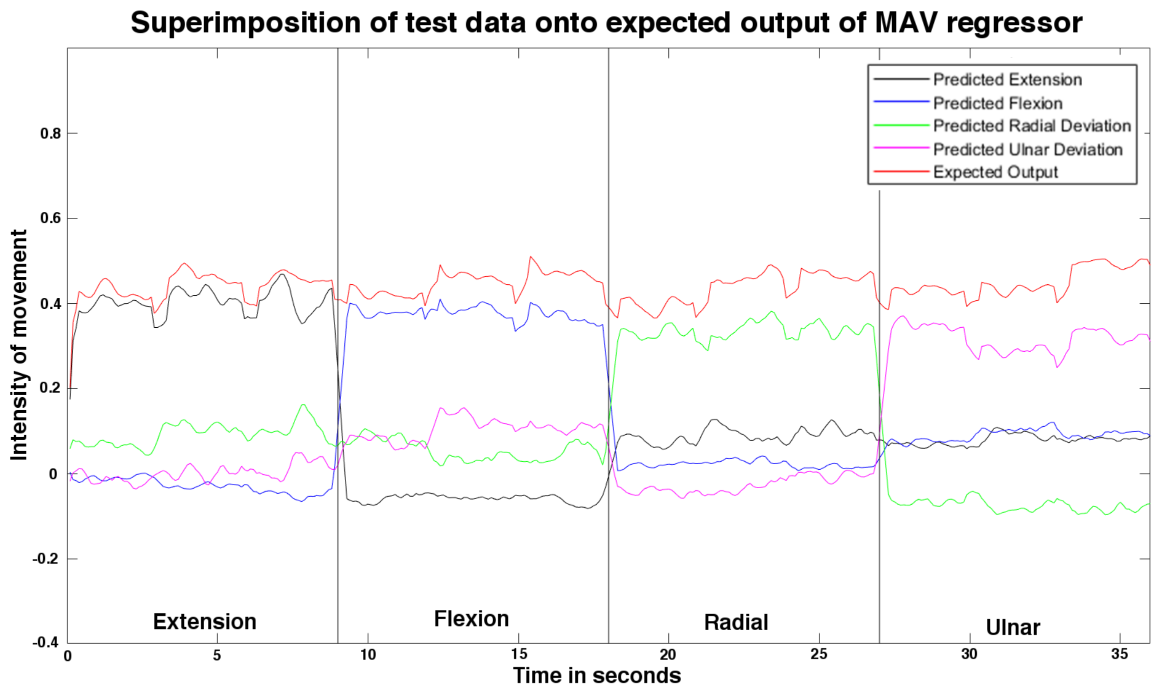
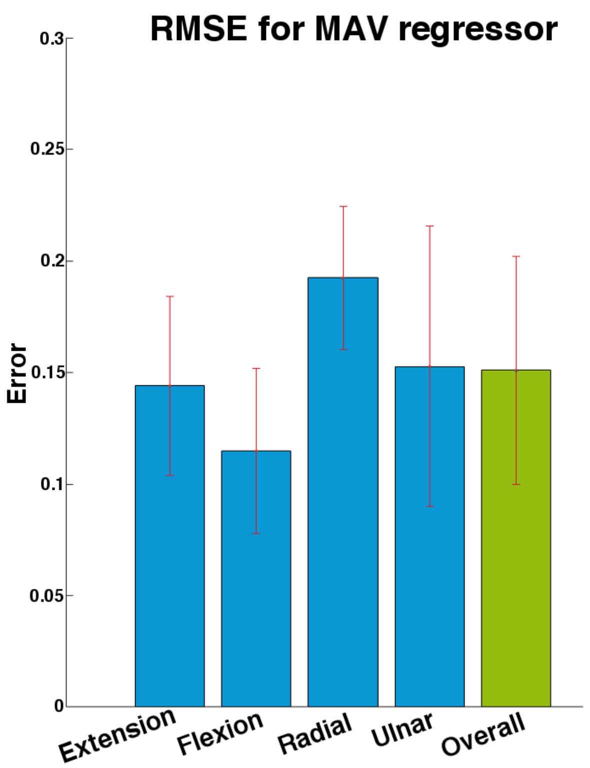



**Figure 4.7**



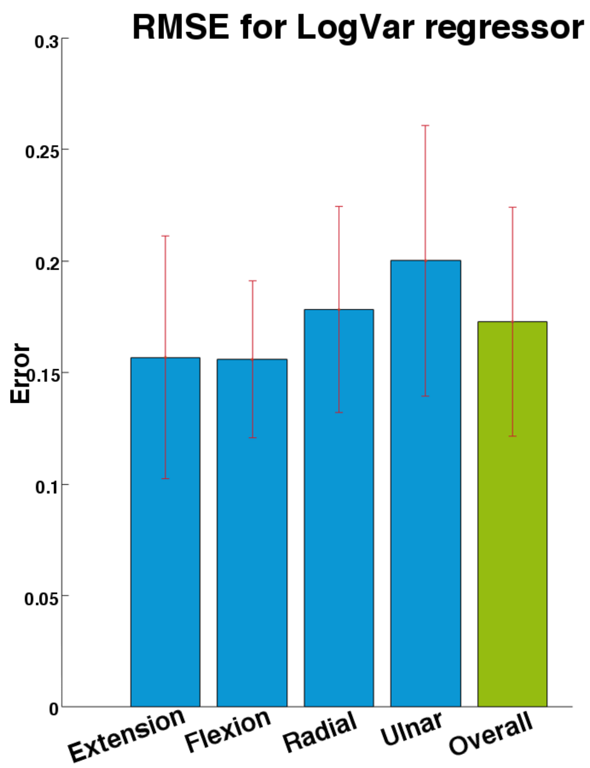




**Figure 4.8**

| Feature | Overall mean error | Standard deviation |
|---|---|---|
| Extension | 0.1646 | ±0.0753 |
| Flexion | 0.1391 | ±0.0841 |
| Radial Deviation | 0.2018 | ±0.0424 |
| Ulnar Deviation | 0.1743 | ±0.0905 |
| Overall | 0.1700 | ±0.0759 |

**Table 4.3:** RMSE for the implemented MAV regressor

| Feature | Overall mean error | Standard deviation |
|---|---|---|
| Extension | 0.1552 | ±0.0514 |
| Flexion | 0.1680 | ±0.0508 |
| Radial Deviation | 0.1681 | ±0.0540 |
| Ulnar Deviation | 0.2078 | ±0.0621 |
| Overall | 0.1748 | ±0.0563 |

**Table 4.4:** RMSE for the implemented LogVar regressor

| Feature | P-Value |
|---|---|
| LogVar and MAV | 0.0044 |
| LogVar new data and MAV new data | 0.1138 |
| LogVar new data and LogVar | 0.0001 |
| MAV new data and MAV | 0.000002 |

**Table 4.5:** P-Values for comparison of the features

It was found that the P-value of a Friedman's statistical test showed a significant difference ($p = 0.0044$) between the RMSE for the MAV and LogVar regressors with the training data as input, where LogVar has the higher mean. When examining the RMSE for the regressors with unknown test data consisting of 50% contractions of all movements in all limb positions, it was shown that there is no significant difference ($p = 0.1138$) between the offline performance of the two regressors. When comparing the offline tests with training data and 50% test data, it was shown that there's a significant difference for both LogVar ($p = 0.000002$) and LogVar ($p = 0.0001$), where the mean is higher for the unknown 50% data in both cases.

**LOOK AT ME: We should do statistics to see if the RMSE of training differs from the test RMSE**

## 4.3 Performance test

This section contains the results from the performance test done by the subjects. First of the results from the regressor trained only with EMG data are presented, and afterwards compared to the regressor trained with inclusion of IMU data. The boxplot in 4.9 shows the test scores of all limb positions for both features.

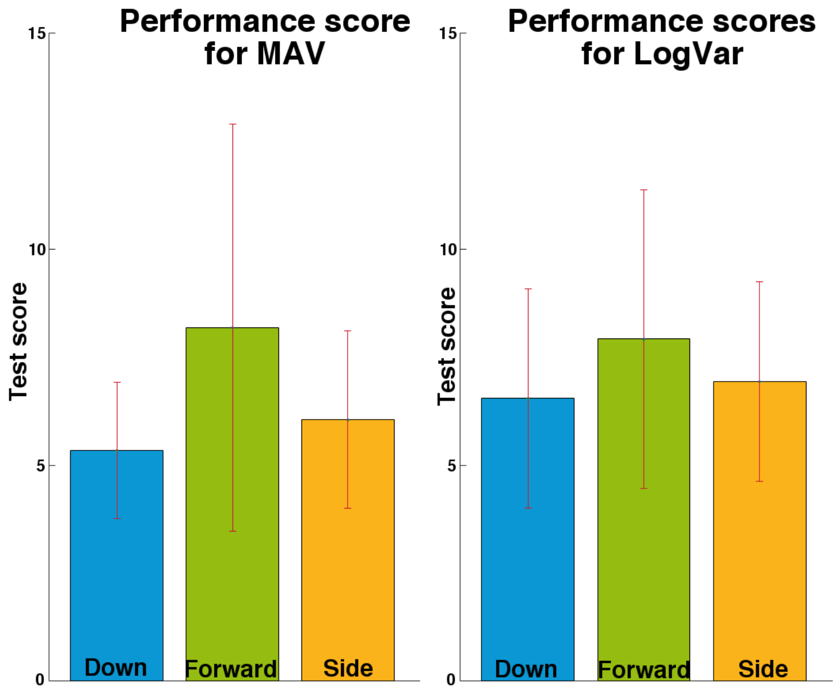



**Figure 4.9:** Calculated performance scores of the regressors. The bar chart illustrates the mean score across all subjects in the different limb positions, and the error bar illustrates the standard deviation

| Limb position and feature | Overall mean error | Standard deviation |
|---|---|---|
| Down, MAV | 5.3377 | ±1.5696 |
| Forward, MAV | 8.1791 | ±4.7145 |
| Side, MAV | 6.0490 | ±2.0490 |
| Down, LogVar | 6.5404 | ±2.5315 |
| Forward, LogVar | 7.9123 | ±3.4572 |
| Side, LogVar | 6.9325 | ±2.3036 |

**Table 4.6:** Test scores for the different limb for MAV and LogVar regressors

| Feature | P-Value |
|---|---|
| MAV | 0.0319 |
| LogVar | 0.4594 |

**Table 4.7:** P-Values for comparison of the score in different limb positions with MAV and LogVar

A one-sample Kolmogorov-Smirnov test was done on the scores from the MAV and LogVar respectively and showed no normality in both score sets($p = 7 * 10^{-20}, 8 * 10^{-20}$ ). A Friedman's test was therefore applied for statistical analysis. The performance scores between the three limb positions prove not to be significantly different ($p = 0.4594$), when applying the LogVar trained regressors in the online test. For the MAV trained regressors the performance score between all limb positions can be proven significantly different ($p = 0.0319$).

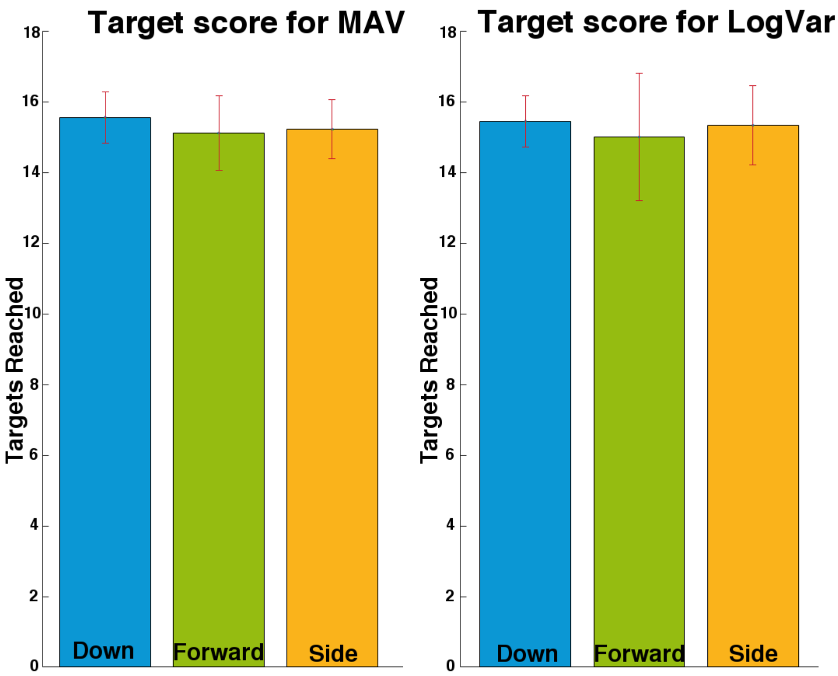



**Figure 4.10:** The boxplot illustrates the amount of targets reached for the respective limb positions for both features.

| Limb position and feature | Overall mean error | Standard deviation |
|---|---|---|
| Down, MAV | 15.5556 | ±0.7265 |
| Forward, MAV | 15.1111 | ±1.0541 |
| Side, MAV | 15.2222 | ±0.8333 |
| Down, LogVar | 15.4444 | ±0.7265 |
| Forward, LogVar | 15 | ±1.8020 |
| Side, LogVar | 15.3333 | ±1.1180 |

**Table 4.8:** Targets reached in the target test with the MAV and LogVar regressors.

| Feature | P-Value |
|---|---|
| MAV | 0.2285 |
| LogVar | 0.7788 |

**Table 4.9:** P-Values for comparison of the number of reached targets across different limb positions with MAV and LogVar

The Friedman's statistical test shows no significant difference ($p = 0.2285$) between the number of targets reached in the different limb positions for the MAV regressor. There was no significant difference ($p = 0.7788$) between the limb positions for the LogVar regressor either.

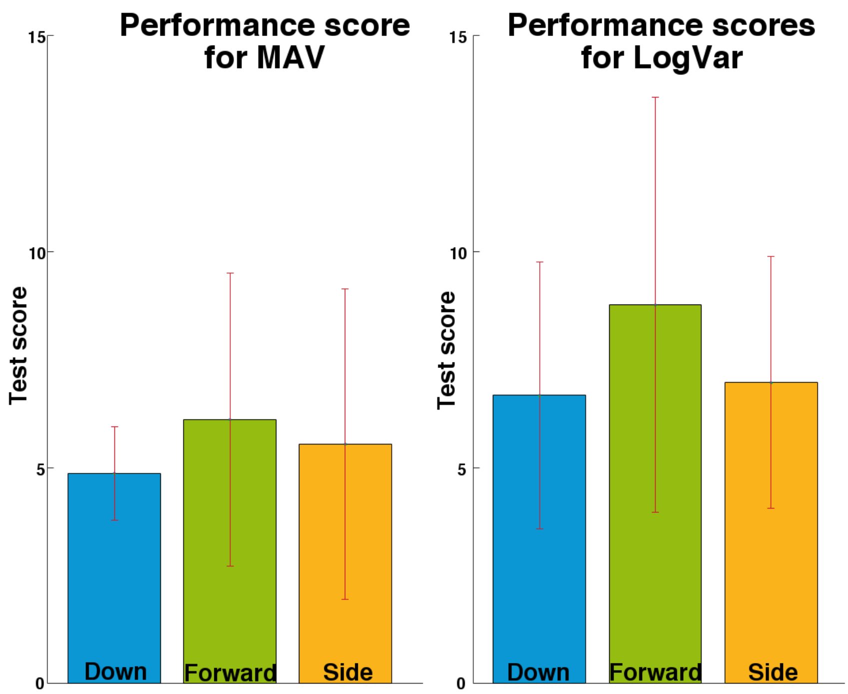



**Figure 4.11:** Calculated performance scores of the regressors with IMU data included. The bar chart illustrates the mean score across all subjects in the different limb positions, and the error bar illustrates the standard deviation

| Limb position and feature | Overall mean error | Standard deviation |
|---|---|---|
| Down, MAV | 4.8661 | ±1.0839 |
| Forward, MAV | 6.1094 | ±3.3852 |
| Side, MAV | 5.5442 | ±3.5847 |
| Down, LogVar | 6.6691 | ±3.0798 |
| Forward, LogVar | 8.7595 | ±4.7969 |
| Side, LogVar | 6.9652 | ±2.9144 |

**Table 4.10:** Test scores for the different limb for MAV and LogVar regressors with IMU included.

| Feature | P-Value |
|---|---|
| MAV | 0.8948 |
| LogVar | 0.2359 |

**Table 4.11:** P-Values for comparison of the score in different limb positions with MAV and LogVar with IMU data included

The test with IMU data included shows no significant difference (p = 0.8948) between the test score in different limb positions for the MAV regressor. No difference was proven in the LogVar test (p = 0.2359) either.

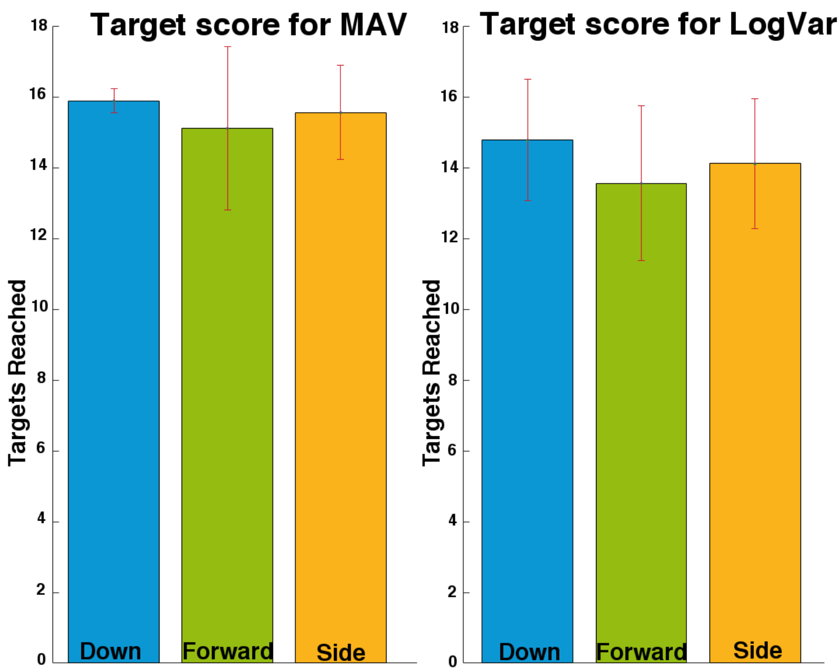



**Figure 4.12:** The boxplot illustrates the amount of targets reached for the respective limb positions for both features with IMU data included.

| Limb position and feature | Overall mean error | Standard deviation |
|---|---|---|
| Down, MAV | 15.8889 | ±0.3333 |
| Forward, MAV | 15.1111 | ±2.3154 |
| Side, MAV | 15.5556 | ±1.3333 |
| Down, LogVar | 14.7778 | ±1.7159 |
| Forward, LogVar | 13.5556 | ±2.1858 |
| Side, LogVar | 14.1111 | ±1.8333 |

**Table 4.12:** RMSE for the implemented LogVar regressor

| Compared Features | P-Value |
|---|---|
| MAV | 0.4966 |
| LogVar | 0.0957 |

**Table 4.13:** P-Values for comparison of the number of targets reached in different limb positions with MAV and LogVar with IMU data included

The number of targets reached in the different limb positions can be proven to be significantly different ($p = 0.0957$) for the LogVar feature with IMU data included, where the lowest number of targets reached (mean = 13.5556) was found when the subjects pointed their arm forward. There was no significant difference found for the MAV regressor with IMU data included ($p = 0.4966$).

### 4.3.1 Comparison of regressors with and without IMU data

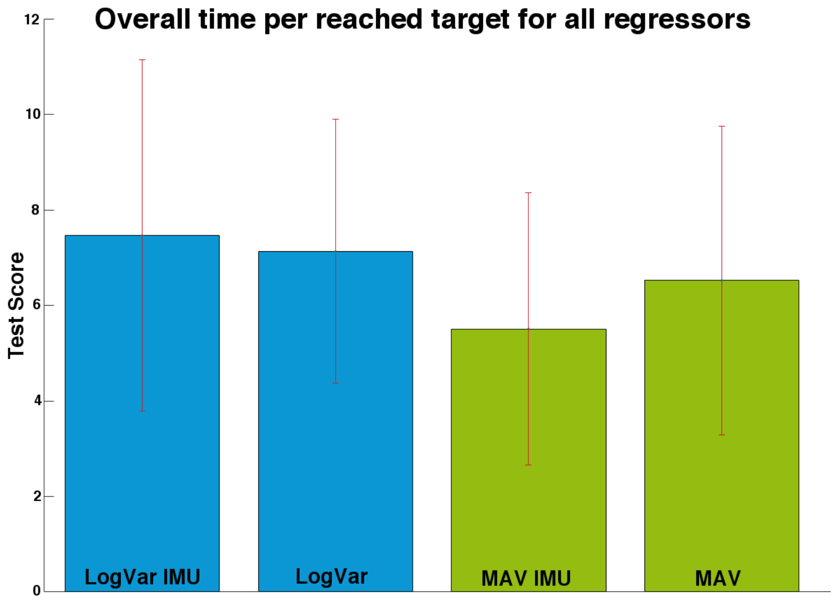



**Figure 4.13:** Calculated overall performance scores of the regressors with and without IMU data included. The bar chart illustrates the mean score across all subjects, and the error bar illustrates the standard deviation

| Feature | Mean score | Standard deviation |
|---|---|---|
| MAV | 6.5219 | $\pm 3.2253$ |
| MAV w. IMU | 5.5066 | $\pm 2.8477$ |
| LogVar | 7.1284 | $\pm 2.7619$ |
| LogVar w. IMU | 7.4646 | $\pm 3.6740$ |

**Table 4.14:** Average score of the target test for the four regressor designs

| Compared features | P-Value |
|---|---|
| LogVar w. IMU, MAV w. IMU | 0.5637 |
| LogVar, MAV | 0.0833 |
| LogVar w. IMU, LogVar | 0.5637 |
| MAV w. IMU, MAV | 0.1779 |

**Table 4.15:** P-Values for comparison of the overall scores of the target tests

When comparing all performance scores from the two feature trained regression control schemes without IMU, the Friedman's test proves no significant difference (LogVar: 7.1284 s, MAV: 6.5219 s; p = 0.0833). There is no significant difference to be found between LogVar and MAV with IMU data included (LogVar w. IMU: 7.4646, MAV w. IMU: 5.5066, p = 0.5637), and no difference was found between features with and without IMU for either MAV (wo. IMU: 6.5219, w. IMU: 5.5066, p = 0.1779) or LogVar (wo. IMU: 7.1284, w. IMU: 7.4646, p = 0.5637).

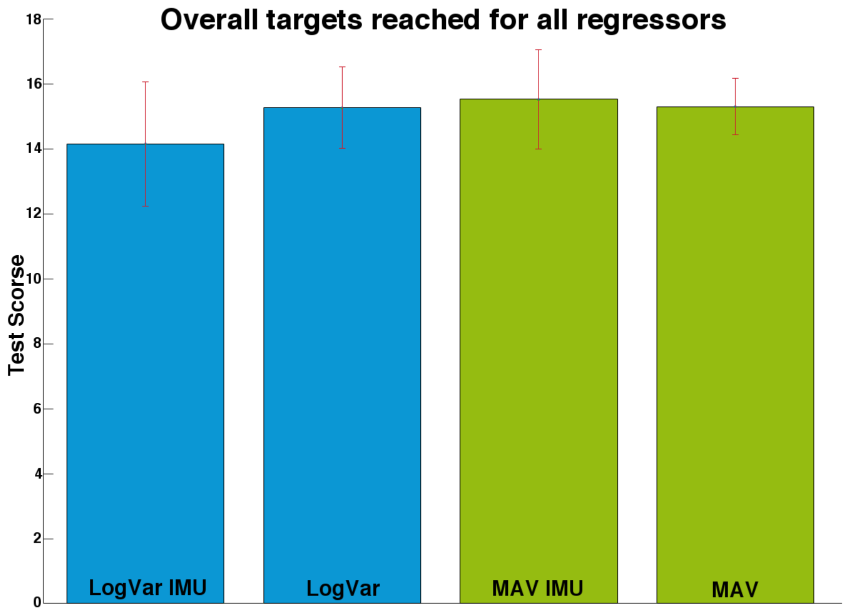



**Figure 4.14:** The boxplot illustrates the amount of targets reached for all limb positions for the two features with and without IMU data included.

| Feature | Overall mean error | Standard deviation |
|---|---|---|
| MAV | 15.2963 | ±0.8689 |
| MAV w. IMU | 15.5185 | ±1.5285 |
| LogVar | 15.2593 | ±1.2586 |
| LogVar w. IMU | 14.1481 | ±1.9156 |

**Table 4.16:** Average number of targets reached in the target test for the four regressor designs

| Compared Features | P-Value |
|---|---|
| LogVar w. IMU, MAV w. IMU | 0.0017 |
| LogVar, MAV | 1 |
| LogVar w. IMU, LogVar | 0.0016 |
| MAV w. IMU, MAV | 0.0124 |

**Table 4.17:** P-Values for comparison targets reached in the target tests

A significant difference was found between LogVar and MAV when IMU was included (LogVar w. IMU: 14.1481, MAV w. IMU: 15.5185, $p = 0.0017$), and the same was found when including IMU data for both MAV (wo. IMU: 15.2963, w. IMU: 15.5185, $p = 0.0124$) and LogVar (wo. IMU: 15.2593, w. IMU: 14.1481, $p = 0.0016$). The performance was similar when comparing the overall number of targets reached for LogVar and MAV ($p = 1$).

# 5 | Discussion

## 5.1 Discussion

### 5.1.1 Comparison of features

In the results it was found that there was no significant difference between the performance of LogVar and MAV for the performance scores both with (p = 0.5637) and without (p = 0.0833) IMU data included. Based on a study [5] showing LogVar as a feature with linear properties, it would be expected that this feature would perform better in a linear regression model, than a feature which to the authors knowledge has not been proven to be linear. On the contrary it was shown that a significantly higher number of targets was reached with a linear regression models based on the MAV feature with IMU included, compared to the LogVar regression model with IMU included (p = 0.0017). When IMU data was not included, there was no difference between the number of targets reached in the test (p = 1).

Further studies within this field should consider examining other features, while studying the effect of combining several features in order to further improve performance independent of the limb position.

### 5.1.2 Inclusion of IMU data

The IMU data included in this study was based on a single accelerometer, where it was expected that the Myo armband would give a similar output as long as the subjects were performing both training and testing from the same starting position. Inclusion of the IMU data was shown to yield the same results in the online test scores, with no significant difference for either MAV (p = 0.1779) or LogVar (p = 0.5637) when comparing regression models trained with and without accelerometer inputs. It was found that the inclusion of the IMU data yielded significantly poorer results for the LogVar regression model (p = 0.0016), while it led to a significant improvement of the MAV regression model (p = 0.0124) when examining the number of reached targets. The inclusion of IMU data could be a subject of further investigation, as the results might be improved by implementing a system capable of measuring the angles of the joints, in order to create a more versatile and usable regression model outside the clinical environment. Including IMU data could additionally be used to select specific regression models, if a system was build with models for different limb positions instead of the same regressors for all positions.

### 5.1.3 Stability in limb positions

When excluding IMU data, there was no significant difference between the target score for either LogVar (p = 0.2359) or MAV (p = 0.8948) in the different limb positions, while there was a difference between the number of reached targets for MAV (0.0212) but no difference for LogVar (p = 0.4220). This outcome shows that both MAV and LogVar yields rather stable performance in different limb positions in a linear regression-based control scheme. This finding agrees with Hwang et al. [29], who equivalently found stable online performance across limb positions in a linear regression-based control scheme applying RMS as feature.

When including IMU data the MAV based regression model was shown to have a significant difference in scores between limb positions (p = 0.0319), while LogVar did not show any difference (p = 0.4594). While the target reaching time were shown to be different depending on limb positions when using MAV, the number of targets reached was improved, as there was no significantly difference (p = 0.2957) in the amount of targets reached. The LogVar feature based regression models were shown to have a difference between reached targets when using IMU data (p = 0.0037).

Overall the LogVar regression models were observed as being the most unstable in the different limb positions when looking at the test subjects performance in the target test. This might be a result of the LogVar feature being based on the change of the signal, as this could lead to problems with crosstalk, when the arm is not in a relaxed state. The MAV was observed as being more stable, with the subjects being able to create more smooth movements as well as being able to controllably return to the resting position. Based on the findings of this study, it would be recommended to examine features based on the amplitude rather than the variance in future studies within this area.

### 5.1.4 Offline and online training

Offline testing was only done for MAV and LogVar without IMU data included. A significant difference between the two features when testing with training data ($p = 0.0044$) was archived in the offline test, but no significant difference when testing with new data ($p = 0.1138$). Comparing RMSE of LogVar with training data and RMSE of LogVar with new data there is a significant difference ($P = 0.0001$) where RMSE of the test with new data has the higher mean. Same results are yielded for the MAV trained regressors ($P = 0.000005$). This indicates that the regression models are overfitted when exposed to new data. The online results yielded robost control across all limb positions, and therefore no apparent correlation between offline and online testing. This could be caused by the subjects ability to adjust to a poor fitted model when given visual feedback while performing the target-reaching test. This observation corresponds to findings in another study [6].

### 5.1.5 Limitations of the study

This study was based on data from 12 test subjects, where three had to be excluded. One subject was excluded due to misunderstanding the given instructions and thereby creating an unusable set of training and test data. This limited the control of the regression models giving the subject a mean score above 25 seconds per target reached and average number of reached targets below 10 for all tests.

Two other subjects were excluded as the recorded intensities were not high enough to differ between the baseline and the higher EMG intensity. This caused the regression models to interpret the baseline in the target test as movements being performed at between 30% and 70% of the MVC.

To improve the validity of the study more test subjects should be included in further studies within this field. Subjects with transradial amputations should also be taken into consideration if regression based control schemes were to be considered for future use in myoelectric prosthetic devices.

Using the Myo armband for data acquisition limited the sampling rate to 200 Hz. Only the 0-100 Hz spectrum of the EMG was represented correctly, where frequencies above 100Hz was affected by aliasing. Along with frequency representation limitations, the Myo armband restricted the number and placement of electrodes to eight channels placed at the same distance distal to the elbow joint, where it might be possible to yield better results with a different electrode placement and number of channels. Further studies should implement conventional EMG electrodes and an ADC with a sample rate, enabling the entire frequency band of EMG signals to be acquired correctly.

# 6 | Conclusion

## 6.1 Conclusion

This study found that linear regression yields simultaneous and proportional control of multiple degrees of freedom in a stable way independent of limb positions, as it was found that the precision of the regression models enabled the test subjects to perform a target test with similar results independent of the positioning of the arm. Linear regression should be investigated further, as a control scheme with precise, simultaneous and proportional control in more than one limb position. Regression based control schemes could have the potential to be implemented in myoelectric prosthetic devices to improve the functionality, and thereby improving life quality for amputees.

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