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

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

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***Abstract* — Electromyography (EMG) is widely used for controlling upper limb prosthetics. However, EMG signals for the same movements change with variations in limb position and this lowers the accuracy in control schemes [1]. Most previous studies testing the effect of limb position using classification have found a negative effect in performance. Linear regression is a newer method in control of myoelectric prosthetics, which has proven to yield robust simultaneous and proportional control. A novel approach would be to investigate the limb position effect with regression models. This study investigated the effect of limb position in a linear regression-based control scheme, when using Mean Absolute Value (MAV) and Logarithmic Variance (LogVar) as features. Inertial Measurement Unit (IMU) data was additionally included to improve the performance of the regression models. Twelve able-bodied subjects were recruited for data acquisition, performing four wrist movements in three limb positions. One regression model was build to recognize the different wrist movements under study, taking into account both features. The regressors were tested online in a virtual environment. The results showed that changes in limb position do not affect the control when using a linear regression model. This is opposed to previous studies using classification as control scheme. Inclusion of IMU data shows no significant improvement in performance. Linear regression has the potential to be used in future control schemes for myoelectric prosthetics in daily life tasks.**

***Keywords*—surface electromyography, inertial measurement units, simultaneous and proportional myoelectric control, linear regression, lower arm prosthetics.**

INTRODUCTION

In recent years the development of EMG controlled upper limb prosthetics has advanced considerably, due to an increased interest in the area along with higher demands for better prosthetics and more precise control [1]. In the early years most EMG prosthetics functioned by controlling one degree of freedom (DOF) with on-off control, mainly by linking antagonistic muscles to more than 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 is employed to generate the switching signals. [2] This type of control provided users a way to control more than one DOF, but never simultaneously. The switch-control requires the users to go through the movements of the prosthesis to find the one they wanted to perform. As the switching method was slow and non-intuitive, more complex methods were introduced to the EMG prosthetics scene. Classification methods effectively enabled users to use DOFs more freely because the switching was now replaced by direct recognition of different muscle contractions linked to specific prosthetic movements. However, classification methods proved to be sensitive to real life conditions, e.g. change in limb position, muscle fatigue and sweating [3]. Introducing regression as a new mapping method in myoelectric prosthetics provided a way to enable both simultaneous and proportional control of multiple DOFs. 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. [4, 5]

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 proportional control. Applying the regression as a mapping method in proportional and simultaneous control of multiple DOFs has been shown to perform well in recognition of movements and doing so with a low computation time. [4] A study by Fougner et al. [6] 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 changes position during daily life tasks.

When recording EMG signals it has been shown that some muscles can be activated despite not being directly linked to the performed movement [6]. This provides a problem, but can be explained by muscle-synergies [7]. 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 [8]. 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 those tested in a clinical environment. In order to overcome the problem of muscles-synergies, Fougner et al. [6] has suggested to combine recordings of EMG signals with inertial information to provide limb position data. This could be beneficial in increasing the accuracy of EMG controlled prosthetics for use in daily life tasks. Even though the combination of EMG and Inertial Measurement Unit (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. [9, 10, 11]

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 DOFs, where the inclusion of IMU data should provide more information on limb position to counter the effect of limb position.

METHODS

Subjects

For the experiment 12 able-bodied subjects were recruited (10 male, 2 female - 11 right-handed, 1 left-handed. Mean age = 25 $\pm$ 2.05) by contacting fellow undergraduate biomedical engineering students at Aalborg University. All subjects participated in the entire experiment, and were initially informed of the research aim, and instructed about the procedures during the experiment. Entire data sets from three subjects were excluded. The cause for exclusion for these subjects was due to data that did not correspond with the instructed movements. All subjects participated voluntarily, and did not receive any monetary reimbursement.

To implement online control a number of steps were executed: data acquisition, segmentation, feature extraction and training regression models. The extracted features from the acquired data was used to train the regression models used in online testing.

Data acquisition

EMG signals and inertial information were recorded with the Myo armband from Thalmic Labs - an 8 channel dry electrode armband with 200 Hz EMG sampling rate and 50 Hz IMU sampling rate. The recorded EMG data was filtered using a 2^{nd} order Butterworth high-pass filter with a 10 Hz cut-off to remove movement artefacts. Only accelerometer data from the IMU was acquired for data processing. The Myo armband has been suggested as a suitable data acquisition system for pattern classification [12], but not yet for a regression-based control scheme. The armband was placed around the thickest part of the dominant forearm, approximately 1/4 of the length of the forearm distal of the elbow. For a close contact between the forearm and armband, clips were used to tighten the fit if necessary. All data acquisition, processing, data analysis and testing was performed in MATLAB (2017b). In the training data acquisition the subjects were instructed to perform four different wrist movements along 2 DOFs depicted in figure 1 in three limb positions depicted in figure 2. Each movement was performed with four different contraction intensities namely, relaxed, 30%, 50% and 80% of the Maximum Voluntary Contraction (MVC). To ensure that correct fractions of the contraction intensity were recorded, a Graphical User Interface (GUI) was build to provide real-time feedback for the subject. Initially the MVC was recorded and set as reference point for the following trials.

The task for the subject was to activate their muscles to track a trapezoidal reference trajectory, where the plateau depicted the desired fraction of the MVC. The level of muscle activation was represented with a cursor, which moved horizontally and continuously with time over 10 s. The vertical position of the cursor was calculated as the mean of the absolute value of the EMG signal across all channels in a 200 ms window, scaled between 0 and 1 according to the MVC. The subject adjusted the height of the cursor by varying the contraction intensity, and was instructed to follow the trapezoidal trajectory as precise as possible. Only the plateau of the trapezoid was used in data processing. The duration of each data acquisition trial was 10 s, where the plateau phase was 3 s. To avoid fatigue the subjects had a 10 s break between trials of different intensities. Between limb position trials subjects were given a 5 min rest. Accelerometer data was additionally recorded in each trial. All trials were performed while standing. Additional 50% of MVC EMG data was acquired for each wrist movement in all limb positions to test the accuracy of the regressors on new data.

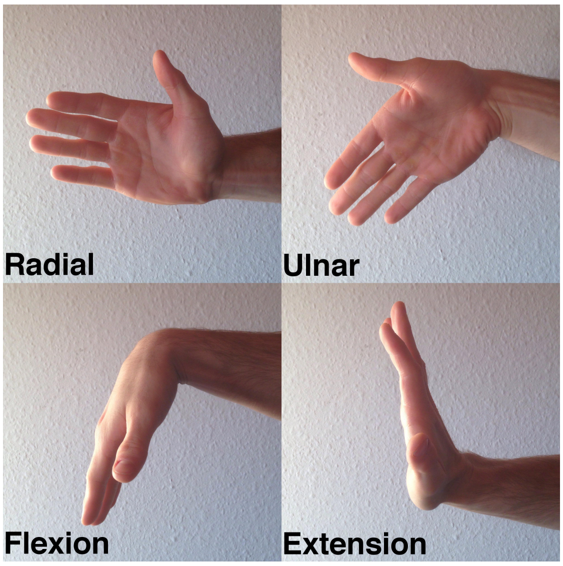


Fig. 1: Illustration of the two DOFs used in the study.

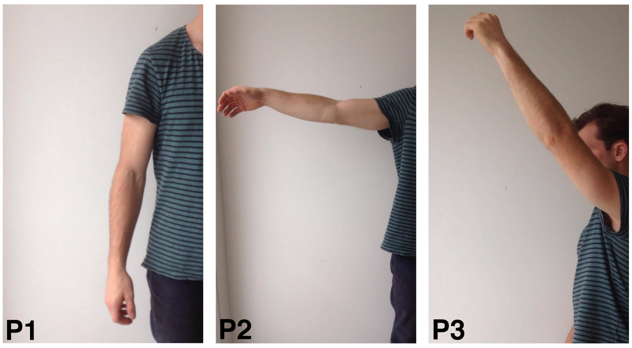


Fig. 2: Illustration of the limb positions performed. P1: relaxed along the torso, P2: 90° horizontally of the side of torso and P3: 135° vertically in front of the torso.

Feature extraction

The signals were segmented into 200 ms window with a 50% overlap, which is an acceptable segmentation for preserving information of the signal in static contractions [13]. The commonly used Mean Absolute Value (MAV) feature was additionally extracted, and calculated as given by equation 1 [14]:

$$MAV = \frac{1}{N}\sum_{i=1}^{N}|x_i| \quad (1)$$

where N is the length of the window, and x_i is the EMG signal of i^{th} sample of the recorded EMG signal.

MAV is directly correlated with change in EMG amplitude. No study has examined whether MAV contains linear properties, but EMG signals has heteroscedastic properties [15] and the MAV feature might therefore not contain direct linear properties.

In a previous study [4] it was shown that logarithmizing the variance of EMG the feature acquires linear properties, and has yielded robust control of wrist movements in a relaxed limb position when used in linear regression. The Logarithmic Variance (LogVar) was therefore extracted as a feature, and was calculated as given by equation 2:

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

where N expresses the length of the window, x_i is the i^{th} sample of the EMG signal and μ is the mean. The extracted EMG features for the individual wrist movements were examined through a Principal Component Analysis, to evaluate, whether the different movements were distinguishable or new training data should be acquired. The Mean Value (MV) was extracted from the accelerometer data, similarly to a previous study [16] testing the effect of limb position using classification as control scheme.

Regression model

As applied in a study by Hwang et al. [17] to achieve robust performance across variations in limb positions linear regression was used as control scheme. One regressor was trained for each wrist movement for both features; four regressors trained for each feature, and four for each feature where accelerometer data was included by expanding the dimension of the input matrix. Each regressor was trained based on multivariate linear regression and calculated as given by equation 3:

$$\hat{Y} = \alpha + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_i X_i \quad (3)$$

where $\hat{Y}$ is the control signal value, X_i are the computed features, β_i are the regression coefficients in the sampled population, and α is the predicted value of Y at $X_i = 0$. For training without inclusion of IMU data $i = 8$ and when including IMU $i = 11$. The control signal was the actual signal the subject generated by tracking the trapezoidal trajectory. The mean of the absolute values of the actual EMG across all channels scaled in relation to the MVC is set as estimator values. The features for all wrist movements in all limb positions were included as predictors in the training of each regressor. However, only the desired wrist movement the regressor was fitted for, was trained with the actual control signal. The remaining predictors were given 0 as control signal. This ensures that the trained regressor will estimate zero when recognising movements other than the one movement it is trained to estimate. This procedure was applied for the regressors to more precisely recognize the performed movement.

Offline testing

The accuracy of the regressors was examined both qualitatively and quantitatively when using both training and test data. A qualitative test was performed by superimposing the estimated signal on the desired signal. The superimposition illustrated whether the right regressor reacted on the performed movement, and how accurate it responded compared to the actual data. For the quantitative analysis the Root Mean Square Error (RMSE) was calculated to compare through statistical analysis, which feature had the lowest error, and whether the regressors were overfitted when tested with new input data. Furthermore, the accuracy of the regressors trained with inclusion of accelerometer data were compared to the regressors trained only using EMG feature data. The RMSE was calculated as given by equation 4:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y_i - \hat{y_i})^2}{N}} \tag{4}$$

where N is the length of the window, y_i is the i^{th} variable of the desired signal and $\hat{y_i}$ is the i^{th} estimated signal.

Online testing

To investigate the effect of limb position in the regression control scheme an online virtual environment was developed, depicted in figure 3. This approach have also been used on other studies [4, 17].

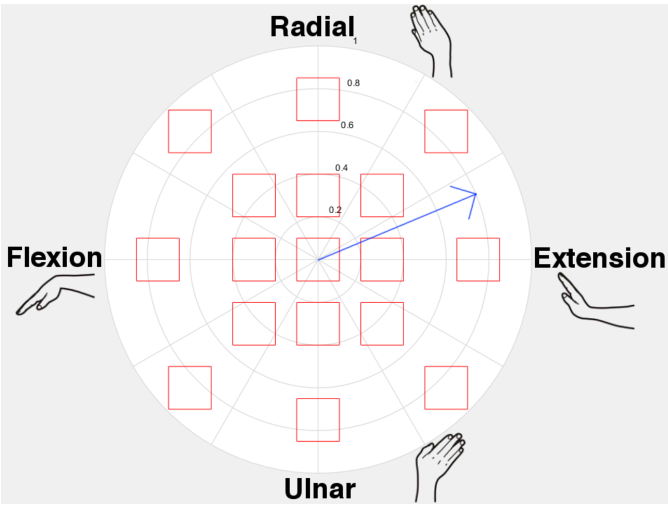


Fig. 3: A vector originating from origin depicted vector coordinates calculated from the regressor output, based on the recorded EMG signals. The length of the vector represented the feature intensity, and direction was based on the movement performed.

In figure 3 the wrist flexion-extension DOF was mapped to the x-axis, and the radial-ulnar deviation DOF was mapped to y-axis. The vector returned to the target located around origin when no contraction was made. For the subject to reach the targets in the diagonals, a simultaneous movement had to be performed. One target was shown at a time. When a target was reached, the vector had to return to the centred target for a new to appear. This gave the subject the same starting point when reaching each outer target. The procedure was performed until all targets had appeared. If a target was not reached within 30 s, it would disappear, and the vector had to return to the centred target.

The time to complete a target-reaching task of sixteen targets was measured. Twelve tests were performed by each subject; one in each limb position for each feature for the regressors trained with and without included accelerometer data. The performance score was calculated as the mean of time per reached target. Time to reach the centred target was not included in the performance score. Performance scores of the online test was compared between the limb positions of the same feature, between all limb positions of the two features and between performance score obtained when using regressors trained with and without inclusion of accelerometer data. The same comparison was additionally applied for the number of targets reached.

Statistical analysis

The statistical analysis was applied for both offline and online results. It was decided, which statistical analysis to apply, through a Kolmogorov-Smirnov test that assesses whether the data populations were normal distributed (α = 0.05). An ANOVA test was applied if the data population belonged to a normal distribution, if not a Friedman's test was applied, which is the non-parametric correspondent to an ANOVA test.

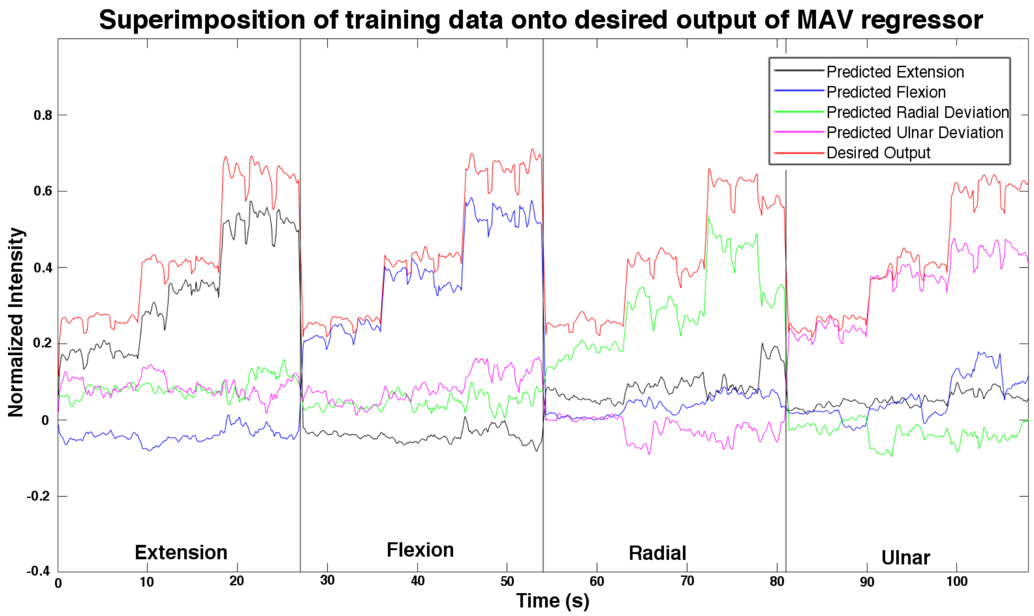
RESULTS

The following section contains the offline and online results. The offline results consist of a qualitative and quantitative analysis. The qualitative analysis is based on superimposiion of the estimated signal on the desired signal, while the quantitative analysis is based on the RMSE for different movements for both training and 50% contraction test data. This comparison is performed to examine the accuracy of the regressors.

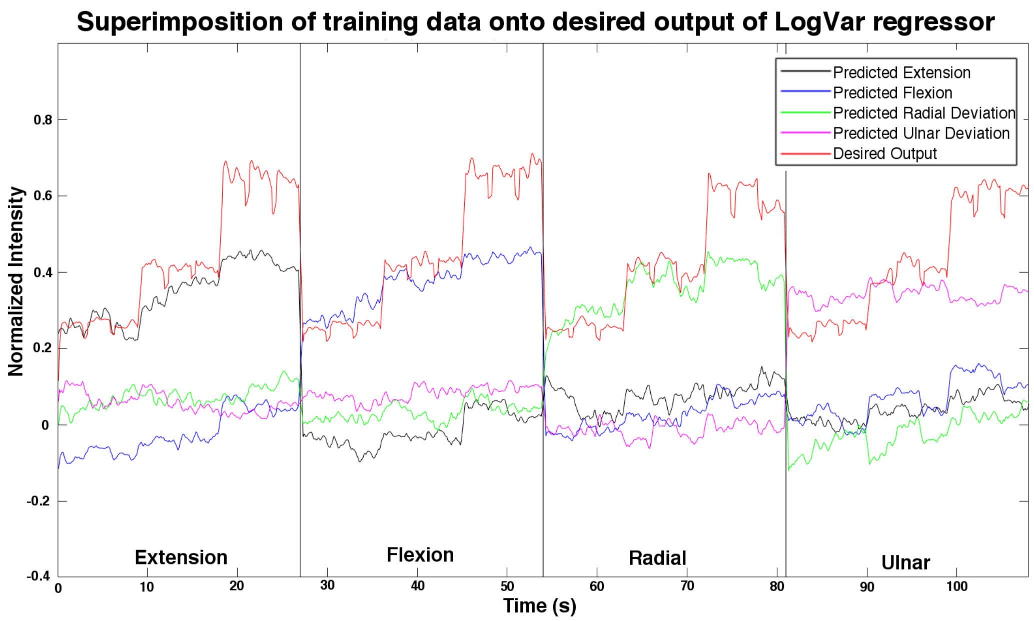
The online results will focus on the usability of the regressors in the target reaching test, where the results are based on the performance scores and number of targets reached. The performance across limb positions will be compared as well as the performance between the two features. Similar comparison is performed for the regressor with IMU data included. Additionally the usability when including IMU is examined by comparing regressors trained with and without inclusion of IMU data.

The Kolmogorov-Smirnov test indicated no dataset to be normal distributed ($p < 0.001$) in either offline or online data sets. Thus, a Friedman's test was applied for all statistical analysis.

Offline Results



(a)



(b)

Fig. 4: Plot of the desired output (red plot) superimposed on the estimate of the regressors trained with the MAV features (a) and LogVar features (b). The plot is divided into four segments, where each segment shows a different movement performed for all limb positions. Each segment has the same sample size and consist of the three contraction intensities.

A qualitative examination of the superimposition plots in figure 4 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. However, both regressors has lower accuracy in the high intensities, especially for the regressors trained with LogVar, which outputs similar values for the 80 % of MVC contractions as the 50 % of MVC contractions.

It is also seen that regressor fitted for the antagonistic movement is more inactive than the other regressors, when the other movement representing that DOF is performed. Furthermore, the regressor output is lower in intensity in all movements above 30% of the MVC.

Feature	Mean error	Std
MAV training	0.11	±0.03
MAV test	0.17	±0.08
LogVar training	0.12	±0.03
LogVar test	0.17	±0.06

Tab. 1: RMSE for the implemented regression models for both training and test input data.

Analysing the RMSE of the regression models' response to the training data, it was found that there was a significant difference ($p < 0.01$) between MAV and LogVar, where it was shown that LogVar has a higher mean than MAV, as seen in table 1.

A significant difference was found ($p < 0.001$) between the RMSE for test data and training data for LogVar. A significant difference ($p < 0.001$) was also found for the test data and training data for the MAV based regression models, where the test data had the highest RMSE. No significant difference ($p = 0.11$) was found between MAV and LogVar regression models with test data.

Online Results

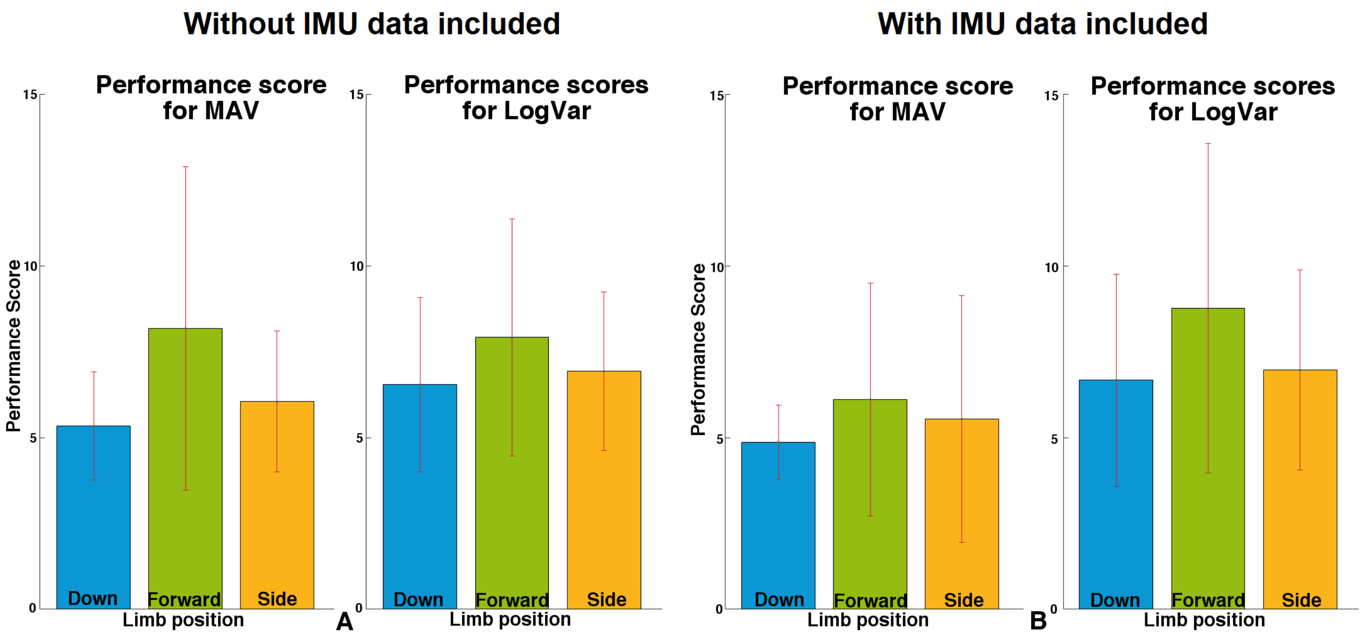


Fig. 5: Bar chart representing the mean and standard deviation of the performance scores for MAV and LogVar features without (figure A) and with inclusion of IMU data (figure B).

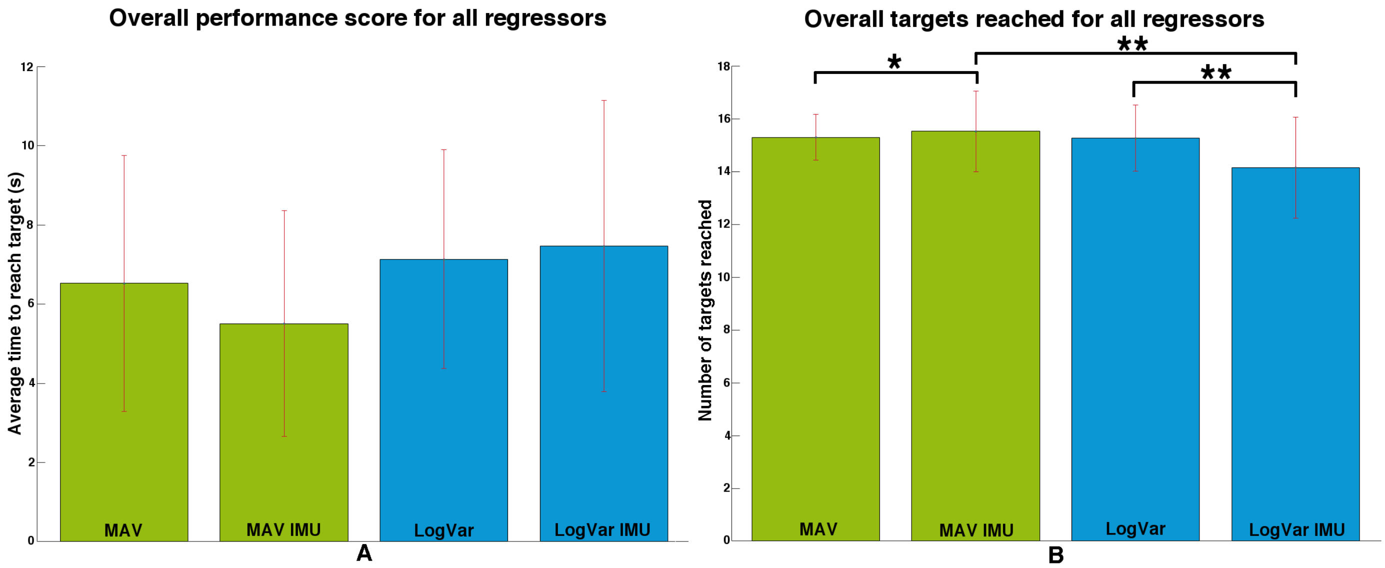


Fig. 6: Figure A shows the bar chart of the overall performance scores for MAV and LogVar features without and with inclusion of IMU data. Figure B shows the overall number of targets reached for MAV and LogVar features without and with inclusion of IMU data.

When comparing the score across limb positions, no significant difference was found for either MAV (p = 0.89) or LogVar (p = 0.24).

Position, feature	Mean TR	Std
Down, MAV	15.56	± 0.73
Forward, MAV	15.11	± 1.05
Side, MAV	15.22	± 0.83
Down, LogVar	15.44	± 0.73
Forward, LogVar	15	± 1.80
Side, LogVar	15.33	± 1.12

Tab. 2: Targets reached (TR) in the target reaching test with the MAV and LogVar regressors.

It was shown that there is no significant difference (p = 0.23) between the number of targets reached across limb positions for MAV. No significant difference (p = 0.78) was found between limb positions for LogVar. The mean number of targets reached for both feature regressors across limb positions are written in table 2.

The perforance scores were similar across limb positions for both MAV with IMU included (p = 0.89) and LogVar with IMU included (p = 0.24).

Position,feature	Mean TR	Std
Down, MAV	15.89	± 0.33
Forward, MAV	15.11	± 2.32
Side, MAV	15.56	± 1.33
Down, LogVar	14.78	± 1.72
Forward, LogVar	13.56	± 2.19
Side, LogVar	14.11	± 1.83

Tab. 3: Targets reached (TR) in the target reaching test with the MAV and LogVar regressors with inclusion of IMU data.

No difference were found for number of targets reached for either MAV with IMU included (p = 0.50) or LogVar with IMU data included (p = 0.10), where the mean and std are shown in figure 6. The mean number of targets reached for each limb position with IMU data included is shown in table 3.

A significant difference could not be proven between the scores of the target reaching test for LogVar with IMU data and MAV with IMU data (p = 0.56), or between the score of LogVar without IMU data and MAV without IMU data (p = 0.08). It was also found that there is no difference between regression models with and without IMU data for both MAV (p = 0.12) and LogVar (p = 0.56). The number of targets reached is illustrated in figure 6.

Feature	Mean TR	Std
MAV	15.30	± 0.87
MAV w/ IMU	15.52	± 1.53
LogVar	15.26	± 1.26
LogVar w/ IMU	14.15	± 1.92

Tab. 4: Average number of targets reached (TR) in the target reaching test for the four regressor designs.

A significant difference (p < 0.01) was found between targets reached when IMU was included, where LogVar was proven worse than MAV. There was a significant difference (p < 0.01) between LogVar with and without IMU data. The same significant difference (p < 0.05) between MAV with and without IMU data. There was no difference (p = 1) between targets reached with LogVar and MAV when IMU was not included. The mean number of targets reached are written in table 4.

DISCUSSION

The aim for this study was to investigate if it is possible to archive proportional and simultaneous control in myoelectric prosthetics across variations in limb positions using linear regression with inclusion of inertial information. This aim will be further discussed in the following section.

Stability across limb positions. Without IMU data there was no significant difference between the performance score for either MAV or logVar across limb positions. There was no significant difference between the number of reached targets for MAV or LogVar. This outcome shows that both MAV and LogVar yields stable performance in limb positions in a linear regression-based control scheme. This finding agrees with the recently published study by Hwang et al. [17], 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 no significant difference in scores across limb positions. Same results were yielded for LogVar. There was no significant difference in the amount of targets reached for the MAV trained regressors and the LogVar trained regressors.

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 performance scores, with no significant difference for either MAV or LogVar when comparing regression models trained with and without accelerometer inputs. Inclusion of the IMU data yielded significantly poorer results for the LogVar regression model, while it led to a significant improvement of the MAV regression model when examining the number of reached targets, despite the mean difference being less than one. 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 fitted for each limb position instead of the same regressors for all positions.

Comparison of features. The online results indicated no significant difference between LogVar and MAV in the performance scores both with and without IMU data included. Based on a study [4] 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. When IMU data was not included, there was no difference between the number of targets reached in the test. Further studies within this field should consider examining other features and studying the effect of combining several features in order to further improve performance independent of the limb position.

Offline vs. 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 was archived in the offline test, but no significant difference when using test data. Comparing RMSE of LogVar with training data and RMSE of LogVar with test data there was a significant difference, where RMSE of the test data had the higher mean. Same results were yielded for the MAV trained regressors. The online results yielded robust control across all limb positions, and therefore no apparent correlation between offline and online testing was found. This could be caused by the subjects ability to adjust to a poorer fitted model when given visual feedback while performing the target reaching test. This observation corresponds with findings in another study by Jiang et al. [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 s 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-reaching test as movements being performed at between 30% and 70% of the MVC. To improve the validity of the findings more test subjects should be included in future 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 100 Hz was affected by aliasing, since an anti-aliasing filter was not implemented. 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 sufficient sample rate, enabling the entire frequency band of EMG signals to be acquired correctly.

CONCLUSION

In conclusion linear regression can be implemented as control scheme in myoelectric prosthetic control to yield performance with no significant difference across variations of limb position. This is opposed to previous studies using classification as control scheme.

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Worksheets

Contents

1 | Background

1.1 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 DOFs, where the arm is defined as distal to the shoulder joint and proximal to the hand. This means DOFs of the hands and fingers and translation of the shoulder are not included. Thus the DOFs included in the arm 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. [1]
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 [2, 3]. 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 the hand can be opened and closed. This enables movement in seven 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 achieve proportional and simultaneous control in a virtual environment. These movements are depicted in figure 1.1. Therefore, only these muscles will be relevant to further investigate. The number of muscles involved in 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.

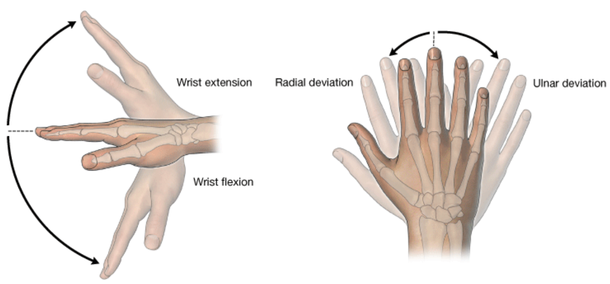

Figure 1.1: Flexion, extension and radial and ulnar deviation of the hand. Modified from [4]

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.
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 from these muscles when performing radial/ulnar deviation and flexion/extension at the wrist. [5] In figure 1.2 the muscles in the forearm both involved with extension/flexion and radial/ulnar deviation is marked with boxes around the name of the muscles.

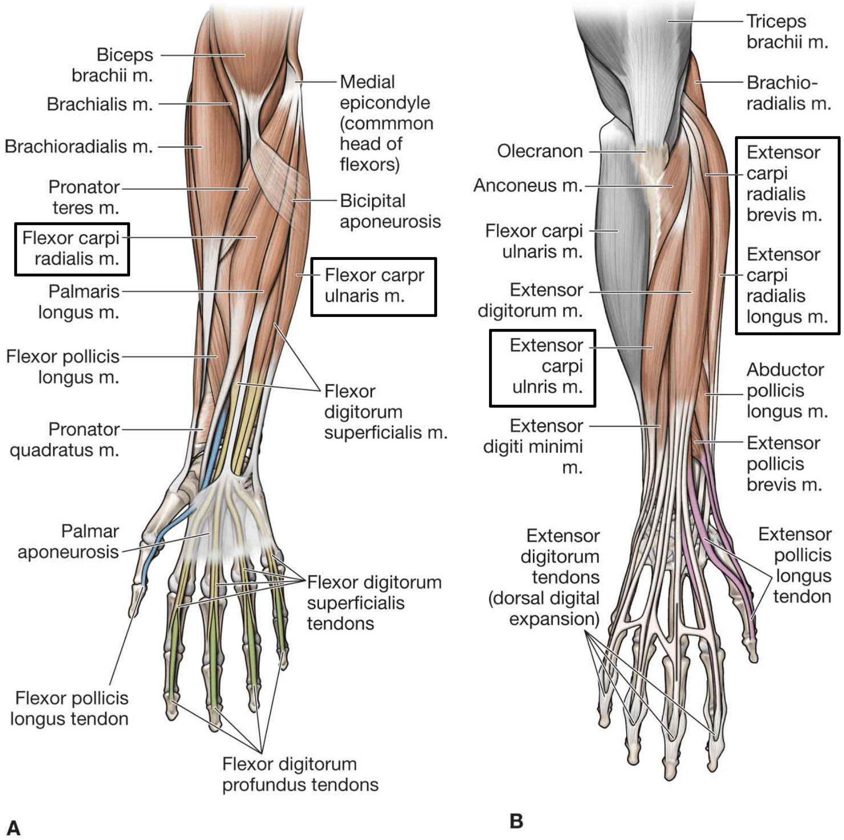

Figure 1.2: A) anterior view of lower muscles. **B)** posterior view of lower muscles. The muscle names in the boxes are muscles which are included in both extension/flexion and ulnar/radial deviation at the wrist. Modified from [4].

1.2 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. First off the motor unit needs to be activated. As depicted in figure 1.3 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 and lower neurons involved in this process are what makes up

one motor unit.

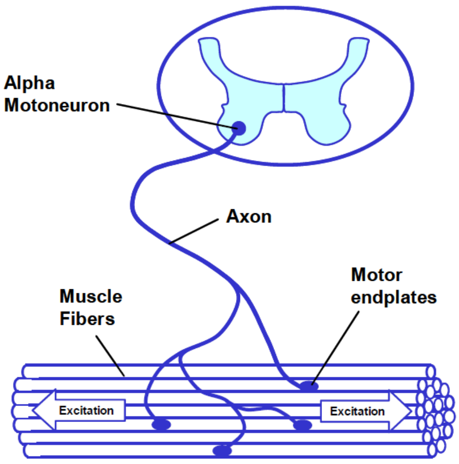

Figure 1.3: Illustration of the action potential exciting the muscle fibre, which causes the release of calcium ions and the muscle to contract. [6]

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, as visualised in figure 1.4. The sarcolemma, the membrane covering the muscle fibres, has sodium and potassium ion channels that maintains the resting potential and depolarizes the muscle fibre if the threshold is exceeded or repolarize the muscle fibre. [7]

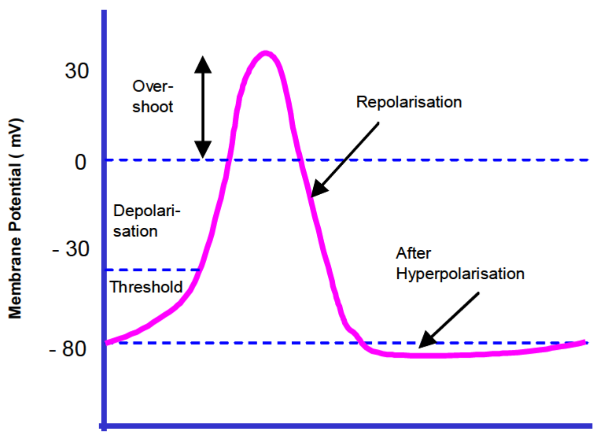

Figure 1.4: Illustration of the action potential exceeding the threshold for it to be generated and the following depolarization and repolarization. [6]

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. [7]
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 frequency of activation is also varying depending on the force needed to be applied. The higher the force, the more motor units are activated and with a higher frequency. 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. [7]

1.2.1 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. [7]
When acquiring sEMG signals the electrodes act as a transducer by converting the action potentials from the muscles into an electric potential. 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. [8, 7]
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. [7]

1.3 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.

1.3.1 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 1.5.

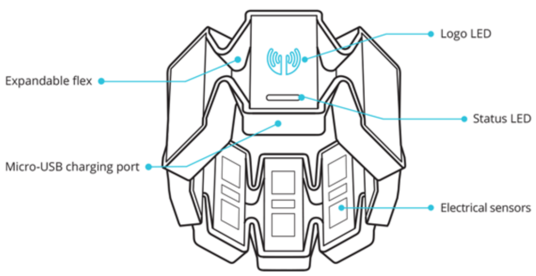

Figure 1.5: Main components of the Myo armband. [9]

The Myo armband has eight medical grade stainless steel surface EMG electrode channels. These elec-

trodes 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. [10] 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 has a 200 Hz sample rate. 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. [7]
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.

1.4 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, noise reduction and feature extraction.
As mentioned in section 1.3 on page 5 the frequency spectrum of EMG is 10-500 Hz. 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. [7]
In order to achieve a higher signal to noise ratio (SNR) it is common practice to perform preprocessing of the signal due to it being sensible to noise elements from the surroundings, as 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 [7].
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 amplitude of the signal.

1.4.1 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. [11]
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. [11] Different features are visualized in figure 1.6.

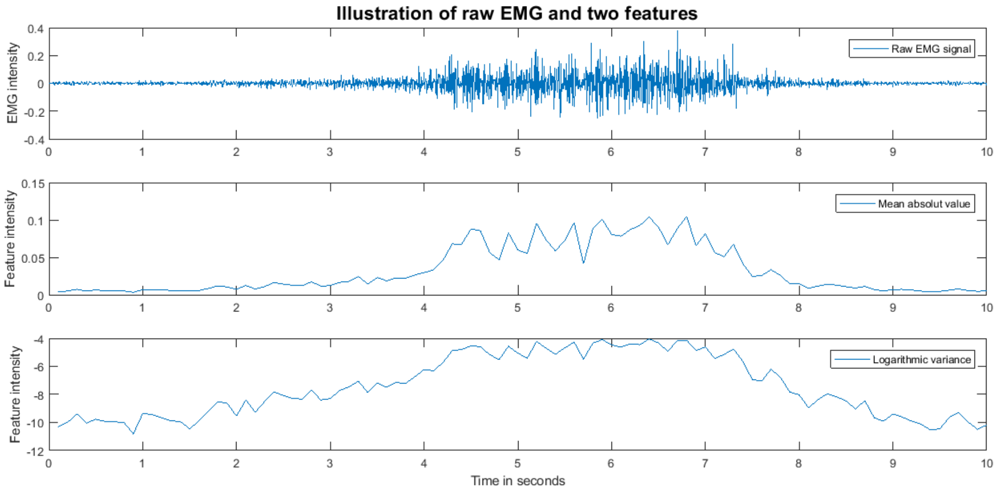

Figure 1.6: Above a raw EMG signal. Below are different features extracted from the EMG signal presented.

1.5 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 [12]:

$$\hat{Y} = \alpha + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_i X_i + \epsilon_i \tag{1.1}$$

Where Y is the dependent variable, X_i are the independent variables, β_i is the regression coefficient in the sampled population, α is the predicted value of Y at $X = 0$ and ϵ is the error. Since the goal of regression is to find an approximation of Y on some function of X, 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 ϵ.
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. [12]
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. [12]

The simple correlation coefficient is calculated as:

$$r = \frac{\sum xy}{\sqrt{\sum x^2 \sum y^2}} \tag{1.2}$$

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. [12]

1.6 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 [13, 3]. 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. [14]

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. [13] 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 robust performing support device.

In 2010, Scheme et al. [15] 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. [15]

Several studies have tried to address the problem of limb position and changes in classification accuracy in EMG controlled prosthetics, using pattern recognition. [13, 16, 17] 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. [13] 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. [16] 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 by Krasoulis et al. [17] no information on which limb positions being tested is reported, but the authors of this report assume thys test in an outer 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. [17]

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, a novel approach would be to investigate if it is possible to archive proportional and simultaneous control in myoelectric prosthetics across variations in limb positions using linear regression with inclusion of inertial information.

2 | Methods

2.1 Experiment 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 2.1. The order of the execution of the movements will be the same for each subject.

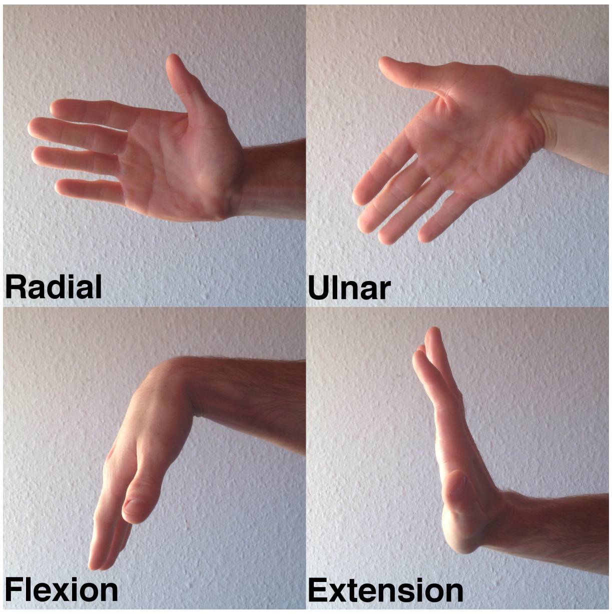

Figure 2.1: Flexion, extension, radial and ulnar deviation of the hand.

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 in each limb position depicted in figure 2.2. Additional 50% of MVC data will be recorded for offline test of the fitting of the regressors.

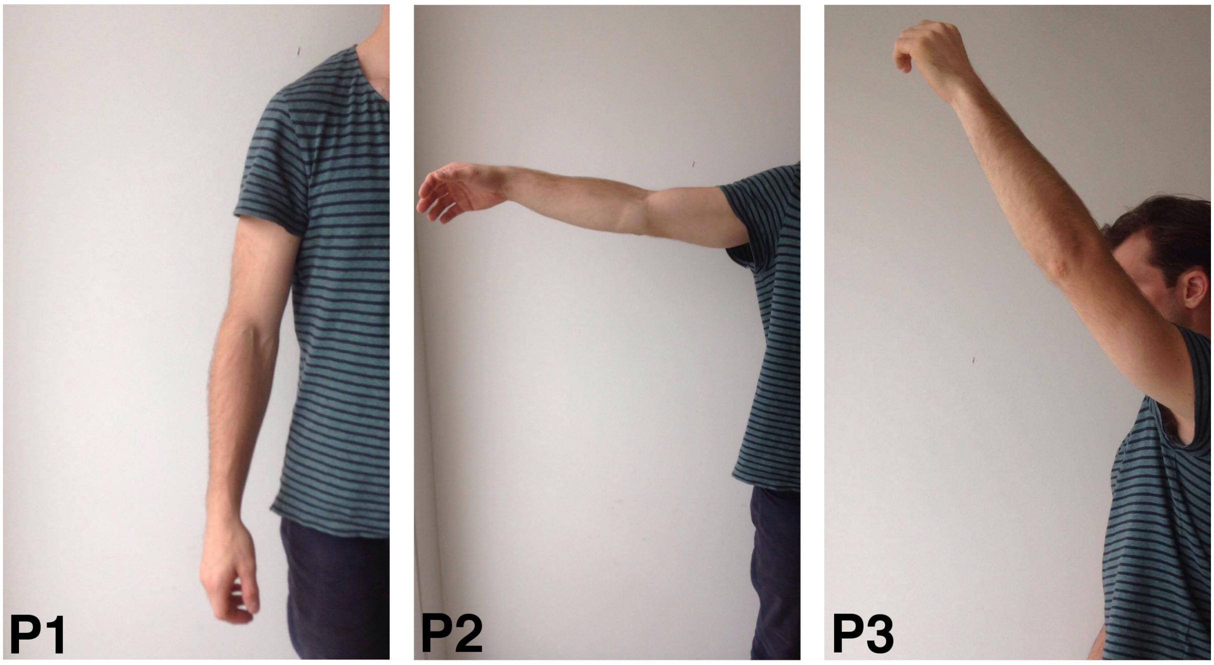

Figure 2.2: P1: relaxed along the torso, P2: 90° horizontally of the side of torso and P3: 135° vertically in front of torso.

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.

2.2 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 2.1 on page 10, 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.
Secondly, the MVC is recorded by the subject performing contraction of an intensity the subject 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 reference point for the following trials. Then the subject goes through three phases of performing the wrist movements at different contraction levels. 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 move continuously with time along the x-axis 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 2.3.

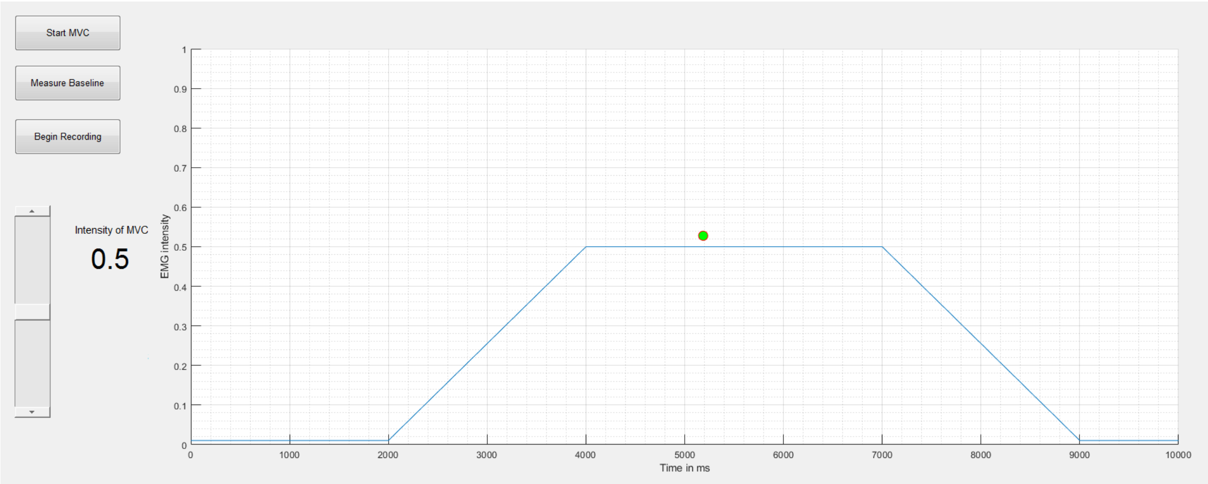

Figure 2.3: The training GUI implemented with Matlab GUI development environment. Control buttons to calculate MVC and perform MVC fraction recordings are placed on the left side. The trapezoid plot with the green dot controlled by the input EMG signal from the subject is shown on the right. The fraction 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 trapezoid, 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 [18], studies has shown that it is possible to achieve online continuous control using steady-state EMG signals. A study by Englehart et al. [19] 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 [20].
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. Meanwhile accelerometer data 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.

2.3 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 MAV. The equation of MAV is as follows:

$$MAV = \frac{1}{N}\sum_{i=1}^{N}|x_i| \tag{2.1}$$

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.
According to a study by Hahne et al. [5], the variance of a signal has exponential properties, but taking the logarithm of it ($log(\sigma^2)$), gives it linear properties. This linearity 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 LogVar feature is calculated as in equation (2.2):

$$log(\sigma^2) = log(\frac{\sum_{i=1}^{N}(x_i - \mu)^2}{N}) \tag{2.2}$$

where N is the length of the sample window, 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.

2.3.1 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, by identifying 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. [21]
PCA 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, if only the first three principal components are used. 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. [21]

2.4 Regression model

Once the preprocessing and the feature extraction of the EMG data has been done, regression will be used as described in section 1.5 on page 7. The implementation follows multivariate linear regression as shown in equation (1.1). As mentioned in section 2.2 on page 11 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 one output for the eight input variables. The output is 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 2.3, 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%).

$$\begin{bmatrix} Flex30Down_{1,1}, Flex30Down_{1,2} \cdots Flex30Down_{1,8} \\ \vdots \qquad \ddots \qquad \vdots \\ Flex30Down_{n,1}, Flex30Down_{n,2} \cdots Flex30Down_{n,8} \\ Flex30Side_{o,1}, Flex30Side_{o,2} \cdots Flex30Side_{o,8} \\ \vdots \qquad \ddots \qquad \vdots \\ Flex30Side_{p,1}, Flex30Side_{p,2} \cdots Flex30Side_{p,8} \\ Flex30Up_{q,1}, Flex30Up_{q,2} \cdots Flex30Up_{q,8} \\ \vdots \qquad \ddots \qquad \vdots \\ Flex30Up_{r,1}, Flex30Up_{r,2} \cdots Flex30Up_{r,8} \\ Flex50Down_{s,1}, Flex50Down_{s,2} \cdots Flex50Down_{s,8} \\ \vdots \qquad \ddots \qquad \vdots \\ \vdots \qquad \ddots \qquad \vdots \\ Flex80Up_{t,1}, Flex80Up_{t,2} \cdots Flex80Up_{t,8} \end{bmatrix} \tag{2.3}$$

The input matrix will then consist of four segments, one for each movement in all three limb positions, as shown in 2.4:

$$\begin{bmatrix} Flex_{1,1}, Flex_{1,2} \cdots Flex_{1,8} \\ \vdots \qquad \ddots \qquad \vdots \\ Flex_{n,1}, Flex_{n,2} \cdots Flex_{n,8} \\ Exte_{o,1}, Exte_{o,2} \cdots Exte_{o,8} \\ \vdots \qquad \ddots \qquad \vdots \\ Exte_{p,1}, Exte_{p,2} \cdots Exte_{p,8} \\ Radi_{q,1}, Radi_{q,2} \cdots Radi_{q,8} \\ \vdots \qquad \ddots \qquad \vdots \\ Radi_{r,1}, Radi_{r,2} \cdots Radi_{r,8} \\ Ulna_{s,1}, Ulna_{s,2} \cdots Ulna_{s,8} \\ \vdots \qquad \ddots \qquad \vdots \\ Ulna_{t,1}, Ulna_{t,2} \cdots Ulna_{t,8} \end{bmatrix} \tag{2.4}$$

This matrix 2.4 including the baseline recordings, will be set as input to the training of the regressor. The output for training one regressor related to one movement are set to the desired values for the performed movement. The desired values are the mean of the absolute values of the data from all eight channels when the subject traced the trapezoid during data acquisition, as shown on figure 2.3 in section 2.2 on page 11.

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 2.4 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 regressors are 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 (1.1) in section 1.5 on page 7. 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 with the IMU data included are trained for each subject similar to the described procedure.

2.5 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.

To qualitatively 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.

When measuring the accuracy of the regressors quantitatively, 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:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y_i - \hat{y_i})^2}{N}} \tag{2.5}$$

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.

2.6 Performance test

A modified version of Fitts' Law will be used to quantify the performance of the trained 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. [22] Fitts' Law calculates an Index of Difficulty (ID) as given by equation (2.6)

$$ID = log_2 * (\frac{2D}{W}) \tag{2.6}$$

Where ID is Index of Difficulty, D is distance to targets and W is width of the target area. However, the system in this study does not provide a reasonable scale for distance and target width. Thus, Fitts' Law cannot be used as usual. Instead only the time is takes a subject to reach the targets and the number of targets reached will be noted to calculate a performance score. The score will be calculated as the average time per reached target. This performance score indicates that the lower the score the better the performance.

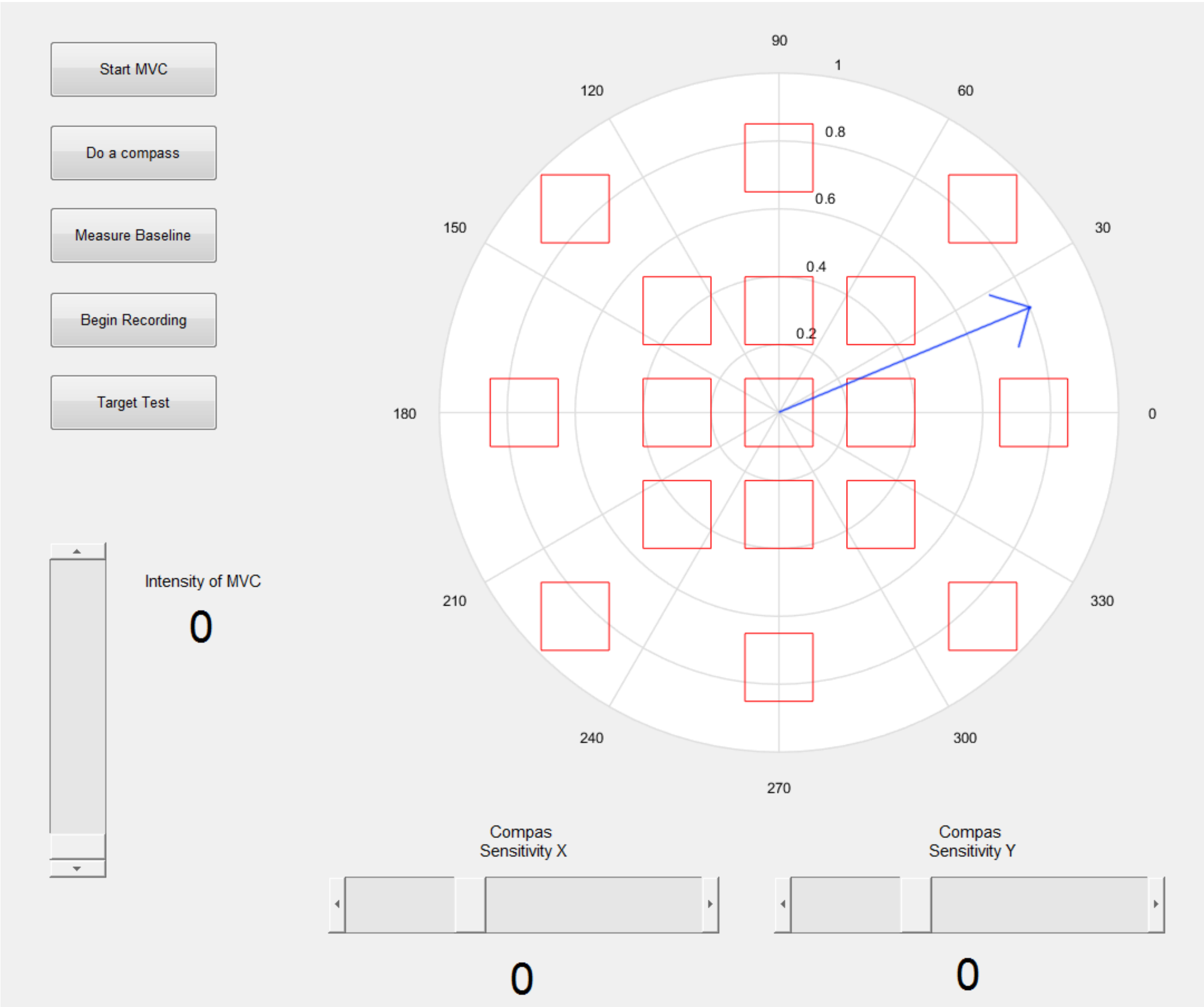

Figure 2.4: The compass plot shows the performed movements and the given intensity of the feature depicted as an arrow originated in origin. The movement performed decides the direction of the arrow and the length is decided by the contraction intensity. The red squares are targets the subject needs to reach. Only one target will be present at a time, but all the targets are depicted in this illustration to show which targets the subjects will be asked to reach.

The test will be done online and consist of reaching 16 targets on time, as shown in figure 2.4. Each target will be present for 30 seconds. If a target is not reached within that time the test will mark the target as missed and move on to the next target. The targets are oriented around origin in two different radii: eight targets close to origin and eight further away. This is done in order to test the proportional

control of the regressors. The targets will be fixed on the axes of the compass-plot and in the diagonals in order to test for simultaneous control.
The performance of the online test will be compared between the limb positions of the same feature and between the overall performance score of the two features through statistical analysis. After the inclusion of inertial information the performance of the control without IMU data will be compared to the control that includes IMU data. This comparison is additionally performed for the number of targets reached.
In the evaluation of the performance scores it will be measured whether the scores obtained from using regressors trained with MAV and LogVar respectively belongs to a normal distribution. This will provide information of which statistical analysis to use. If the data is normal distributed an ANOVA test will be performed, if not, a Friedman's test will be performed.

3 | Results

3.1 Separability of data

PCA is performed on all feature data from each test subject for both MAV and LogVar features. As described in section 2.3.1 on page 13 the PCA is only used as a tool to qualitatively evaluate the data. In figure 3.1 a PCA is shown from one test subject, performed with the MAV feature.

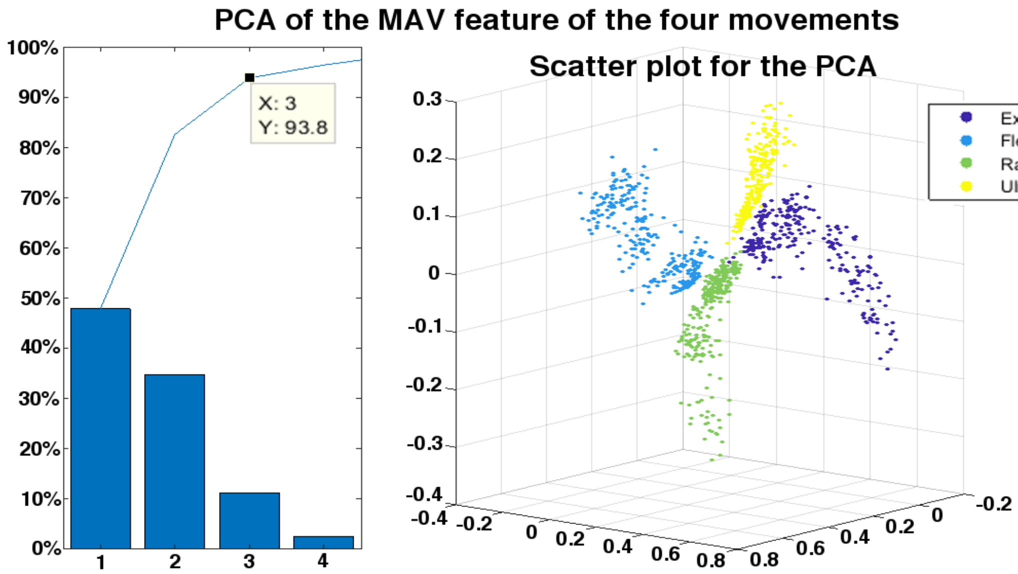

Figure 3.1: Plot of PCA of MAV feature. To the left is the amount of data that the first four principal components describe expressed in percentage. The first three principal components account for describing 93.8% of the data set. On the right is the data described by the first three principal components 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.

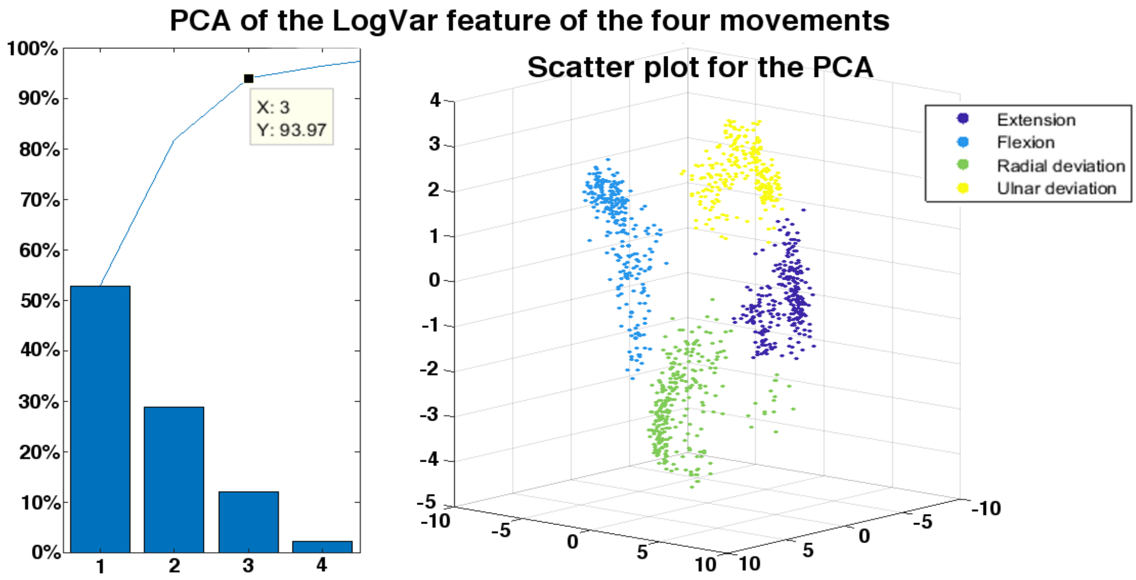

Figure 3.2: Plot of PCA of LogVar feature. The first three principal components account for describing 93.97% of the data set. Here the clusters for each movement are also distinguishable from each other and have no noteworthy outliers, so the data is considered of high quality.

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 3.1, 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 LogVar shown in figure 3.2, 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.

3.2 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 performed they were given a test data set as input to examine the accuracy of the trained regressors. Ths test data set consisted of the 50% contraction recording and were performed for all movements in all limb positions.

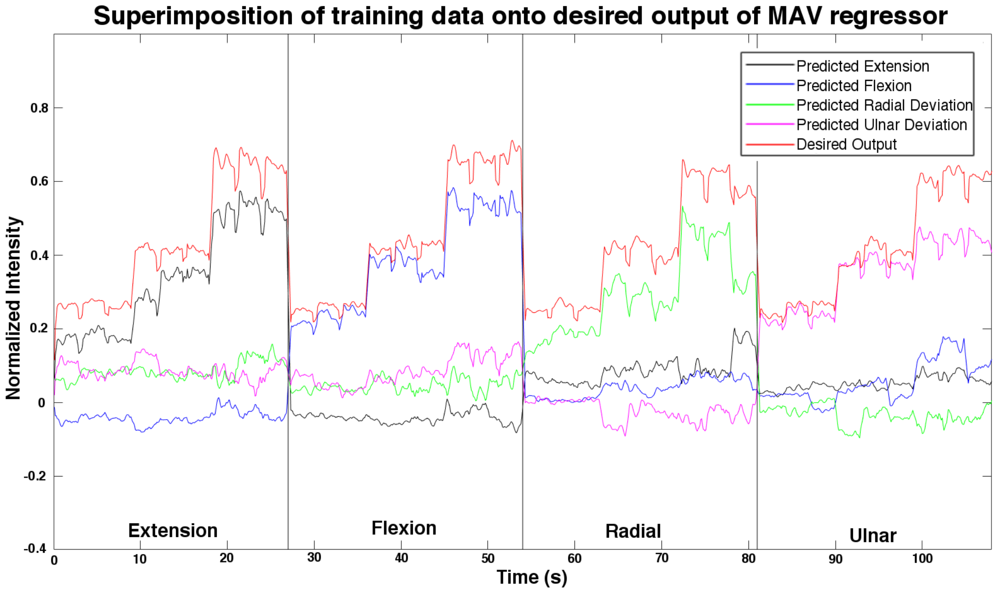

Figure 3.3: Plot of the expected data, red plot, superimposed on the output of the regressors trained with the MAV feature. The plot is divided into four segments, where each segment shows a different movement performed. Each segment has the same sample size.

The plot in figure 3.3 depicts the actual data superimposed on the estimated data from the regressors trained with the MAV features.

Figure 3.4: Plot of the expected data, red plot, superimposed on the output of the regressors trained with the LogVar feature. 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 3.4 depicts the actual data superimposed on the estimated data from the regressors trained with the LogVar features.

A qualitative examination of the plots depicted in figure 3.4 and figure 3.3 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 though, especially for the regressors trained with logarithmic variance features. It is also seen that regressor fitted for the antagonistic movement is more inactive than the other regressors, when the other movement representing that DOF is performed. Furthermore, the regressor output is lower in intensity in all movements above 30% of the MVC. 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 3.5.

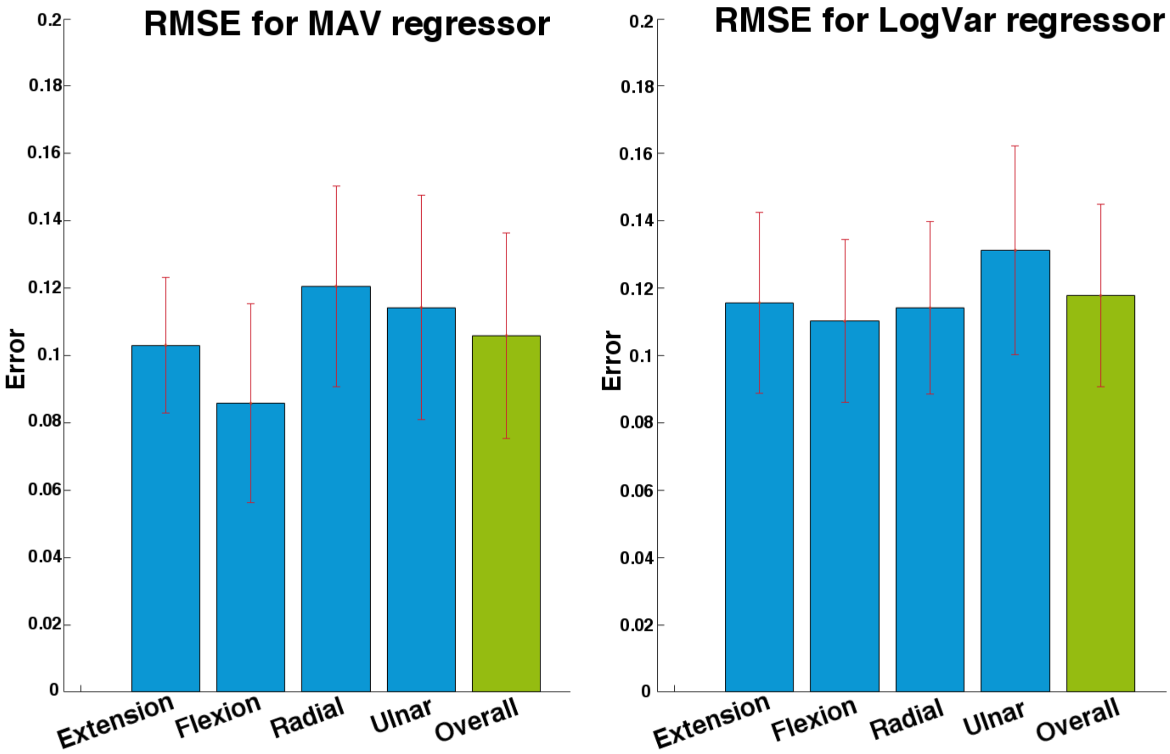

Figure 3.5: Bar plot of the mean error of MAV and the LogVar features for the four hand gestures. The bar chart illustrates the mean error and the error bar illustrates the standard deviation.

Feature	Overall mean error	Standard deviation
Extension	0.10	±0.02
Flexion	0.11	±0.03
Radial Deviation	0.12	±0.03
Ulnar Deviation	0.11	±0.03
Overall	0.11	±0.03

Table 3.1: RMSE for the implemented MAV regressor.

Feature	Overall mean error	Standard deviation
Extension	0.12	±0.05
Flexion	0.11	±0.02
Radial Deviation	0.11	±0.03
Ulnar Deviation	0.13	±0.03
Overall	0.12	±0.03

Table 3.2: RMSE for the implemented LogVar regressor.

The overall mean of the RMSE of MAV is 0.09 with a standard deviation of ±0.03, where the highest mean of a regressor is 0.12 and the highest standard deviation is ±0.04. The overall mean of the RMSE of LogVar is 0.11 with a standard deviation of ±0.03, where the highest mean of a regressor is 0.12 and the highest standard deviation is ±0.04. 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.

3.2.1 Accuracy of regressors with test data

This section contains the superimposition of the expected output of the regressors on the output of the regressors with test data. The plot in figure 3.7 depicts the superimposition the logarithmic variace trained regressors fed with the test data.

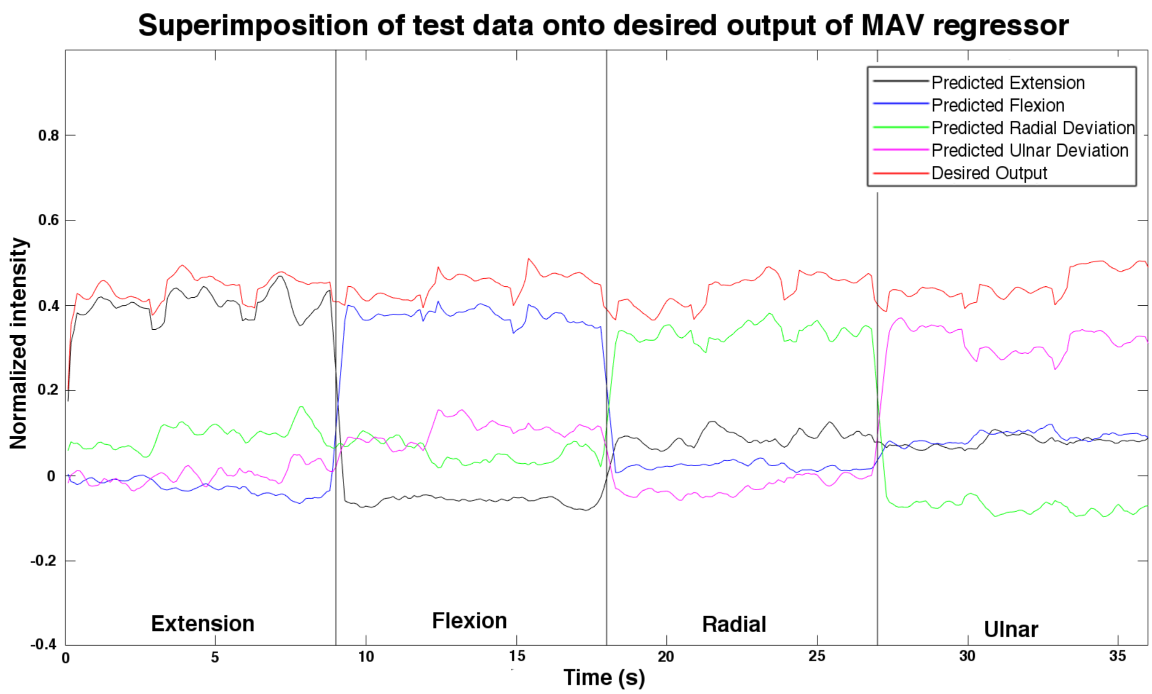

Figure 3.6: Plot of the expected output (red plot) for the regressors trained with the MAV feature , superimposed on the output of the regressors where 50% contraction test data is given as input. The plot is divided into four segments, where each segment shows a different movement performed. Each segment has the same sample size.

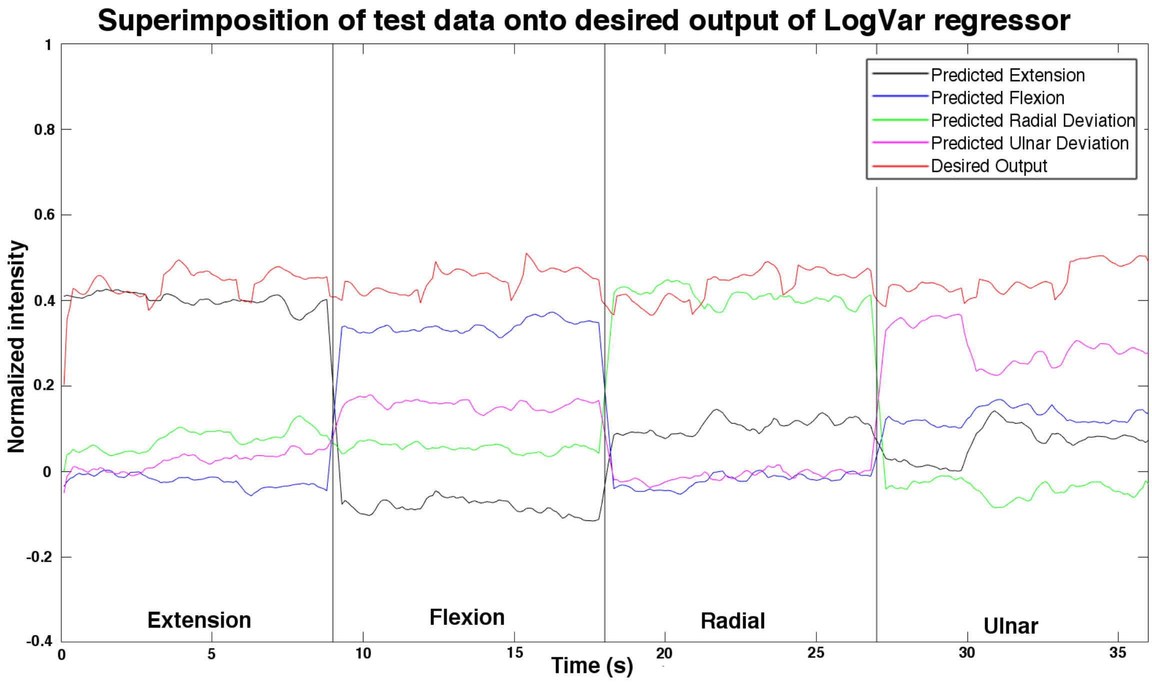

Figure 3.7: Plot of the expected output (red plot) for the regressors trained with the LogVar feature , superimposed on the output of the regressors where 50% contraction test data is given as input. The plot is divided into four segments, where each segment shows a different movement performed. Each segment has the same sample size.

The superimpositions in figure 3.6 and figure 3.7 show a similar pattern as the superimpositions for the output of the regressors given training data as input, but with a higher error.

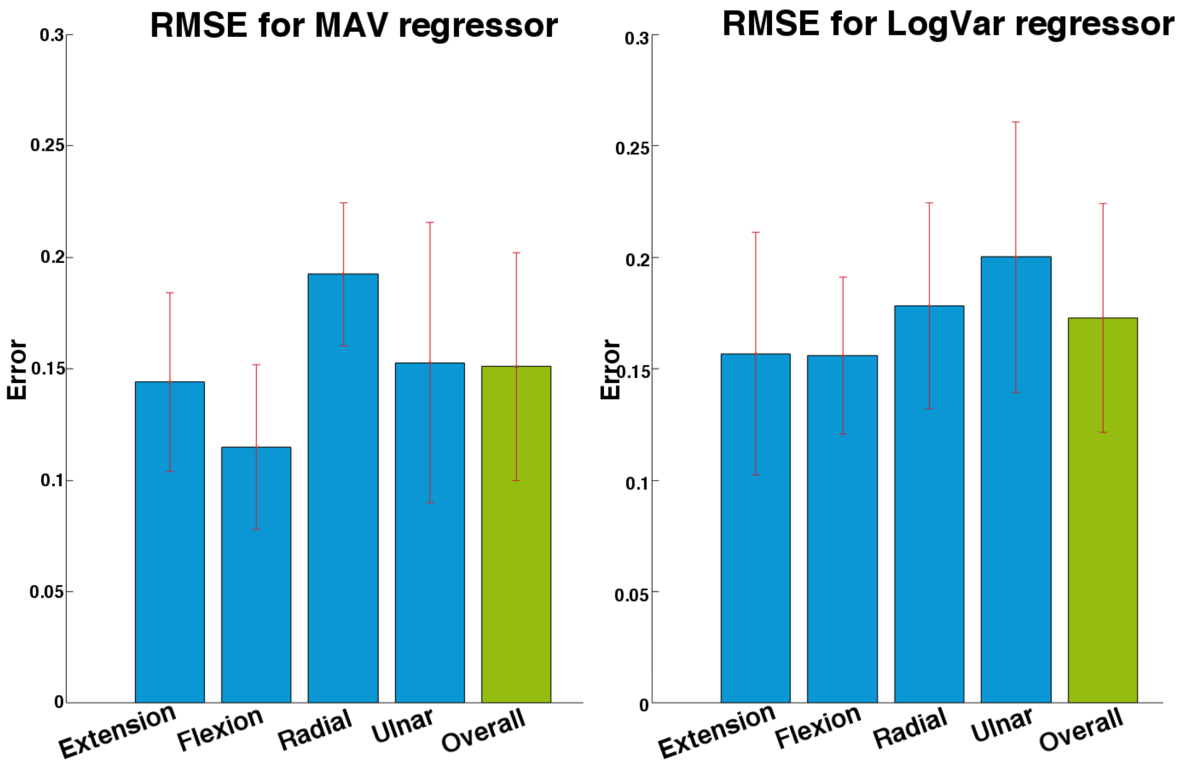

Figure 3.8: Bar plot of the mean error of the MAV and LogVar features for the four hand gestures when the regressors are given test data as input. The bar chart illustrates the mean error and the error bar illustrates the standard deviation.

Feature	Overall mean error	Standard deviation
Extension	0.14	± 0.04
Flexion	0.11	± 0.04
Radial Deviation	0.19	± 0.03
Ulnar Deviation	0.15	± 0.06
Overall	0.15	± 0.05

Table 3.3: RMSE for the implemented MAV regressor.

Feature	Overall mean error	Standard deviation
Extension	0.16	± 0.05
Flexion	0.16	± 0.04
Radial Deviation	0.18	± 0.05
Ulnar Deviation	0.20	± 0.06
Overall	0.17	± 0.05

Table 3.4: RMSE for the implemented LogVar regressor.

Feature	P-Value
LogVar and MAV	< 0.01
LogVar new data and MAV new data	0.1138
LogVar new data and LogVar	< 0.001
MAV new data and MAV	< 0.001

Table 3.5: P-Values for comparison of the features.

A Friedman's statistical test showed a significant difference ($p < 0.01$) 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 test data, showed 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 ($p < 0.001$) and LogVar ($p < 0.001$), where the mean is higher for when setting the test data as input.

3.3 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 bar chart in 3.9 shows the performance scores of all limb positions for both features.

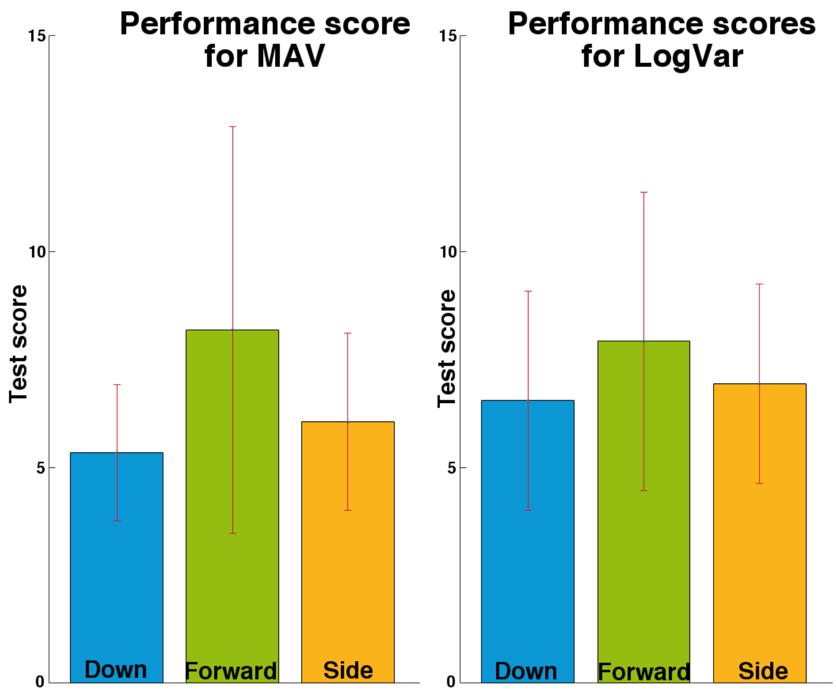

Figure 3.9: Calculated performance scores of the regressors. The bar chart illustrates the mean score across all subjects across limb positions, and the error bar illustrates the standard deviation

Limb position and feature	Performance score	Standard deviation
Down, MAV	5.34	±1.57
Forward, MAV	8.18	±4.71
Side, MAV	6.05	±2.05
Down, LogVar	6.54	±2.53
Forward, LogVar	7.91	±3.46
Side, LogVar	6.93	±2.30

Table 3.6: Performance scores across limb for MAV and LogVar regressors.

Feature	P-Value
MAV	0.03
LogVar	0.46

Table 3.7: P-Values for comparison of the performance score across 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 performance score sets ($p < 0.001$, $p < 0.001$). A Friedman's test was therefore applied for statistical analysis. The performance scores between the three limb positions prove not to be significantly different ($p = 0.46$), 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 ($p = 0.03$).

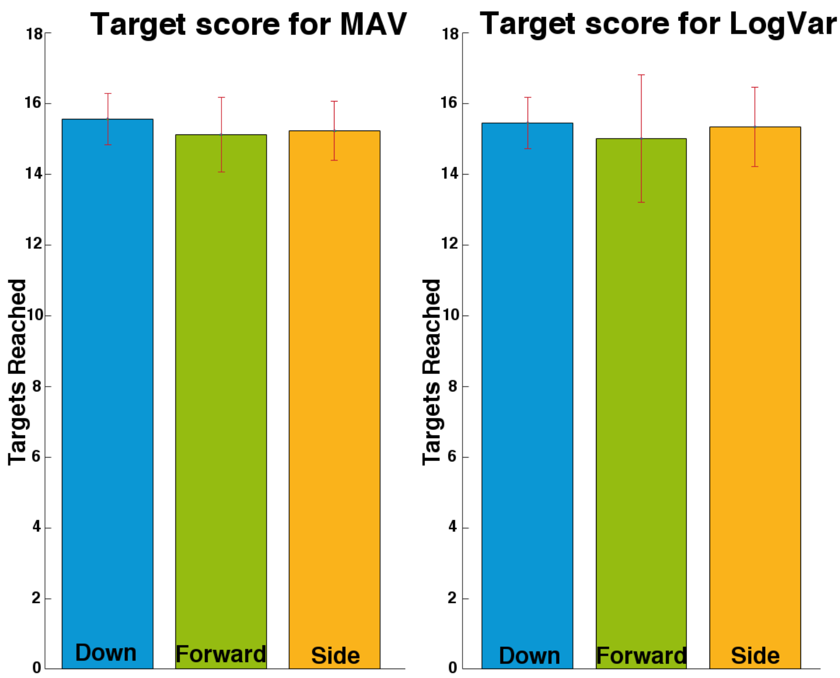

Figure 3.10: The bar chart illustrates the amount of targets reached for the respective limb positions for both features.

Limb position and feature	Overall TR	Standard deviation
Down, MAV	15.56	±0.73
Forward, MAV	15.11	±1.05
Side, MAV	15.22	±0.83
Down, LogVar	15.44	±0.73
Forward, LogVar	15	±1.80
Side, LogVar	15.33	±1.12

Table 3.8: Targets reached (TR) in the target reaching test with the MAV and LogVar regressors.

Feature	P-Value
MAV	0.23
LogVar	0.78

Table 3.9: P-Values for comparison of the number of reached targets across limb positions with MAV and LogVar.

The Friedman's statistical test shows no significant difference (p = 0.23) between the number of targets reached across limb positions for the MAV regressor. There was no significant difference (p = 0.78) between the limb positions for the LogVar regressor either.

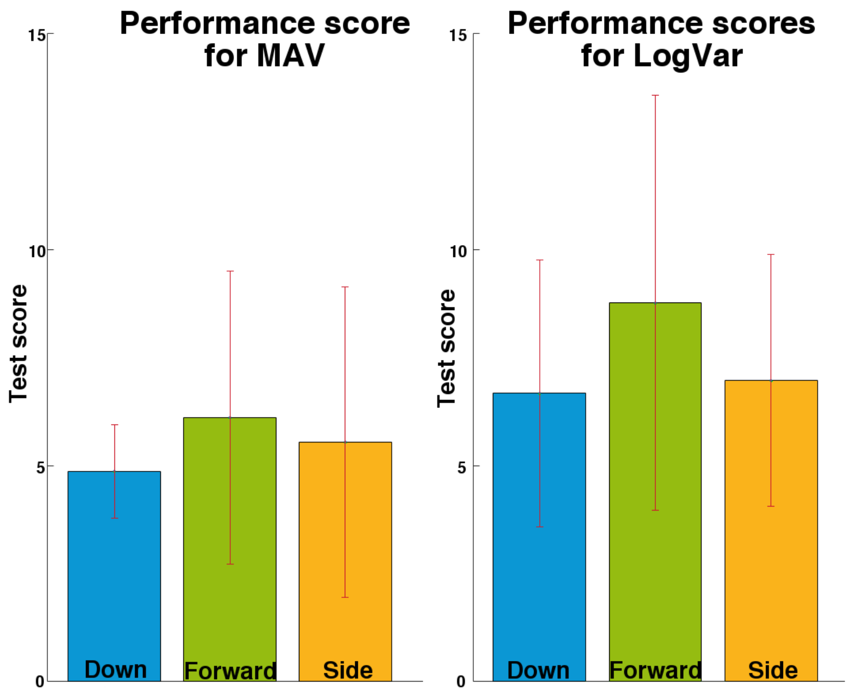

Figure 3.11: Calculated performance scores of the regressors with IMU data included. The bar chart illustrates the mean score across all subjects in the limb positions, and the error bar illustrates the standard deviation.

Limb position and feature	Performance score	Standard deviation
Down, MAV	4.87	±1.08
Forward, MAV	6.11	±3.39
Side, MAV	5.54	±3.58
Down, LogVar	6.67	±3.08
Forward, LogVar	8.76	±4.80
Side, LogVar	6.97	±2.91

Table 3.10: Performance scores across limb positions for MAV and LogVar regressors with IMU included.

Feature	P-Value
MAV	0.90
LogVar	0.24

Table 3.11: P-Values for comparison of the performance score across limb positions with MAV and LogVar with IMU data included.

The test with IMU data included shows no significant difference (p = 0.90) between the performance score across limb positions for the MAV regressor. No difference was proven in the LogVar test (p = 0.24) either.

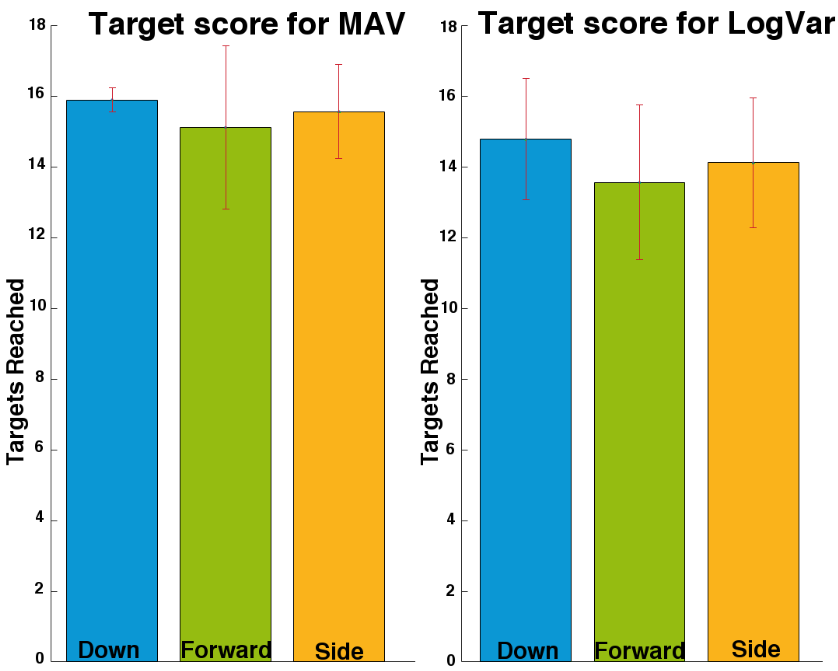

Figure 3.12: The bar chart illustrates the amount of targets reached for the respective limb positions for both features with IMU data included.

Limb position and feature	Overall TR	Standard deviation
Down, MAV	15.89	± 0.33
Forward, MAV	15.11	± 2.32
Side, MAV	15.56	± 1.33
Down, LogVar	14.78	± 1.72
Forward, LogVar	13.56	± 2.19
Side, LogVar	14.11	± 1.83

Table 3.12: Targets reached (TR) in the target reaching test with the MAV and LogVar regressors with IMU data included.

Compared Features	P-Value
MAV	0.50
LogVar	0.10

Table 3.13: P-Values for comparison of the number of targets reached across limb positions with MAV and LogVar with IMU data included.

The number of targets reached across limb positions can be proven to be significantly different ($p = 0.10$) for the LogVar feature with IMU data included, where the lowest number of targets reached (mean = 13.56) was found when the subjects pointed their arm forward. There was no significant difference found for the MAV regressor with IMU data included ($p = 0.50$).

3.3.1 Comparison of regressors with and without IMU data

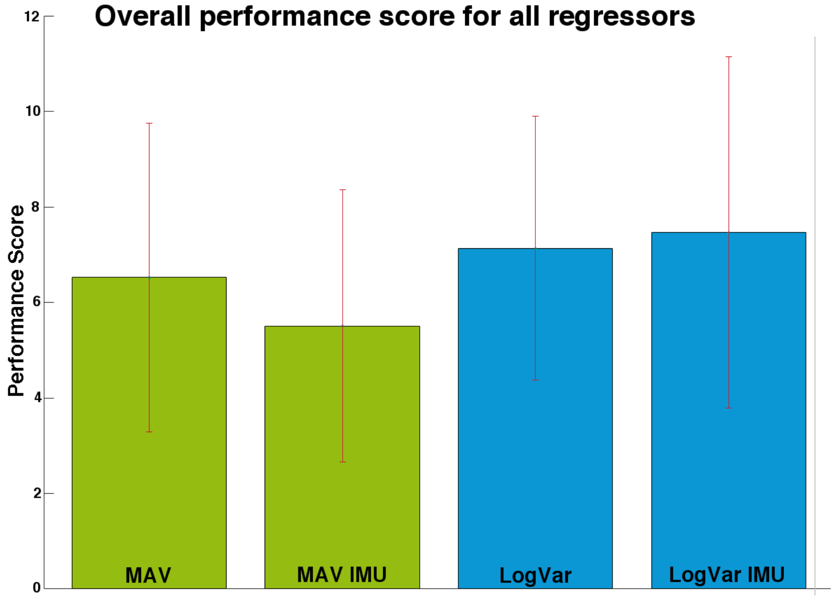

Figure 3.13: Calculated overall performance scores of the regressors with and without IMU data included. The bar chart illustrates the mean score across all subjects, and the error bar illustrates the standard deviation

Feature	Mean score	Standard deviation
MAV	6.52	±3.23
MAV w. IMU	5.51	±2.85
LogVar	7.13	±2.76
LogVar w. IMU	7.46	±3.67

Table 3.14: Average performance score of the target reaching test for the four regressor designs.

Compared features	P-Value
LogVar, MAV	0.08
LogVar w. IMU, MAV w. IMU	0.56
MAV w. IMU, MAV	0.18
LogVar w. IMU, LogVar	0.56

Table 3.15: P-Values for comparison of the overall performance scores of the target reaching 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: 7.13 s, MAV: 6.52 s; $p = 0.08$). There is no significant difference to be found between LogVar and MAV with IMU data included (LogVar w. IMU: 7.46, MAV w. IMU: 5.51, $p = 0.56$), 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).

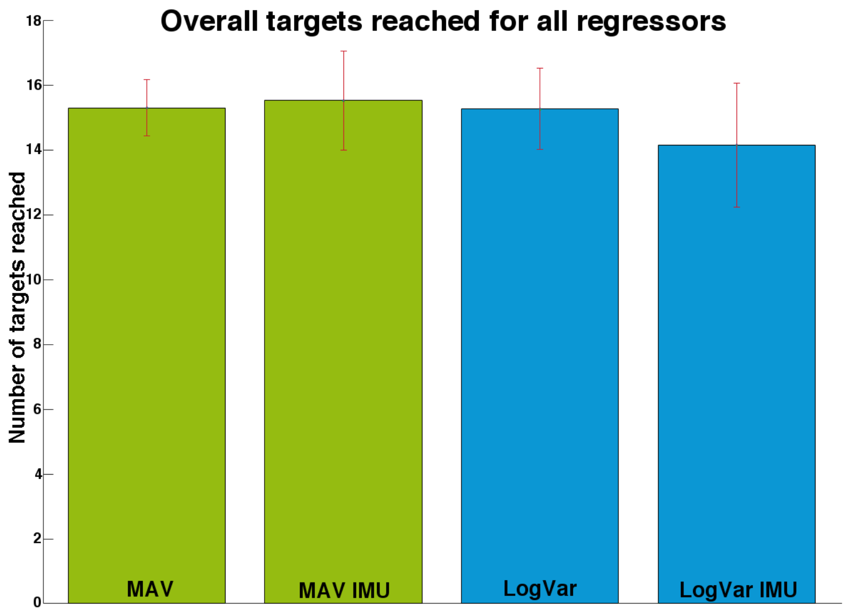

Figure 3.14: The bar chart illustrates the amount of targets reached for all limb positions for the two features with and without IMU data included.

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 3.16: Average number of targets reached in the target reaching test for the four regressor designs.

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

Table 3.17: P-Values for comparison targets reached in the target reaching 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 ($p = 1$).

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