Group 7404

THE EFFECT OF LIMB POSITION ON MYOELECTRIC PROSTHETIC CONTROL USING LINEAR REGRESSION

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Introduction

Electromyography (EMG) is widely used for controlling functional prosthetics. However, EMG signals for the same movements change with variations in limb position and lowers the accuracy in control schemes [1]. Most previous studies have utilized classification for pattern recognition when changing limb position, with 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 [2]. Only the RMS feature was previously tested in variations of limb positions in regression-based control [3]. This study investigated the effect of limb position in a linear regression-based control scheme, when using the commonly used Mean Absolute Value (MAV) and Logarithmic Variance (LogVar) feature, where the latter has shown linear properties [2].

Methods and Material

Surface EMG (sEMG) data was collected from seven able-bodied subjects. The subjects were instructed to performed four different hand gestures (flexion, extension, radial deviation and ulnar deviation), in three limb positions (down the side, lifted to the side, lifted forward). sEMG signals were recorded with Myo armband, positioned on the right forearm of the subjects while standing.
The sEMG was recorded from eight channels with a 200Hz sample rate. Filtering was done with a second-order Butterworth highpass filter (f_c = 10Hz).
Features were extracted using a window of 40 samples with 50% overlap. MAV represent the amplitude of the signal. It is defined as the average of the absolute values of the sEMG signal:

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

where N is the length of the signal, and x_i is the signal of i samples. LogVar is a nonlinear transformation of the variance:

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

where N is the length of the signal, x_i is the i^{th} sample of the signal and μ is the mean. PCA is applied to qualitatively determine the separability of the feature data. The regression models (regressors) are calculated as following:

$$Y = \alpha + \beta X \qquad (3)$$

where Y is the estimated output, X is the extracted feature data, β is the regression coefficient, and α is the Y intercept.
One regressor was build for each wrist movement for each test subject: four for each feature. The offline regressor accuracy was tested qualitatively through superimposition of the output of the regressors build for each feature onto the actual data. The regressors were tested quantitatively by calculating the Root Mean Square Error (RMSE) between the expected movement and the regressor output. This was done for both training and test data to evaluate if the regressor had over- or under-fitted to the training data. The regressors were tested online in a virtual environment, where the time to complete a target-reaching task of sixteen targets was measured. The performance (time per reached target) of the online test was compared between the different limb positions of the same feature and between all limb positions of the two features through statistical analysis.

Aim

The aim for this project is expressed in the following hypothesis:

- It is possible to yield similar performance in different limb positions in myoelectric prosthetic control using a linear regression based control scheme.

Online Results

Results for the online test of regressor accuracy and control. The test is performed in a modified Fitts' Law test of reaching targets. The score is calculated as the relation between time and number of targets reached.

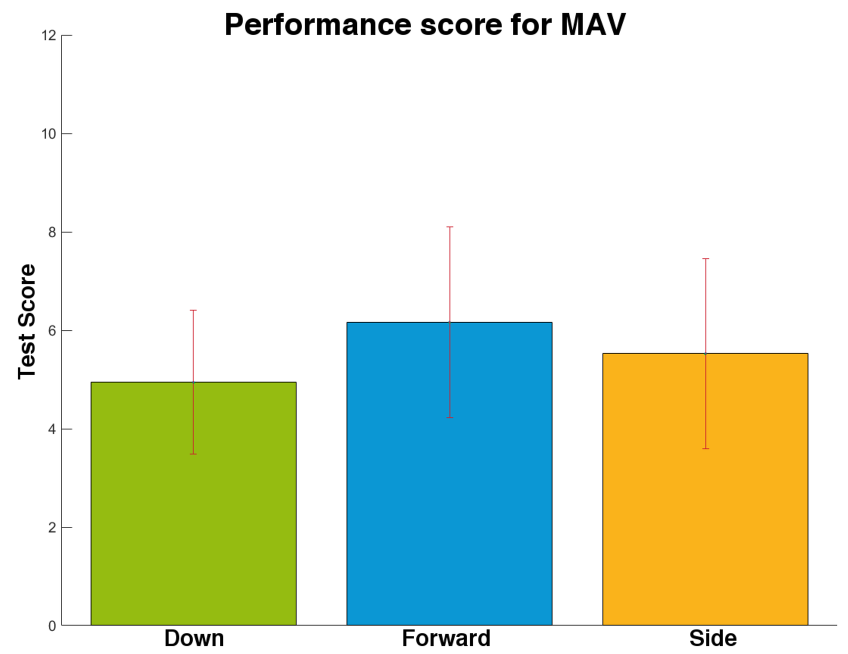


Figure 3: The mean test score among seven subjects when using regressors trained with MAV

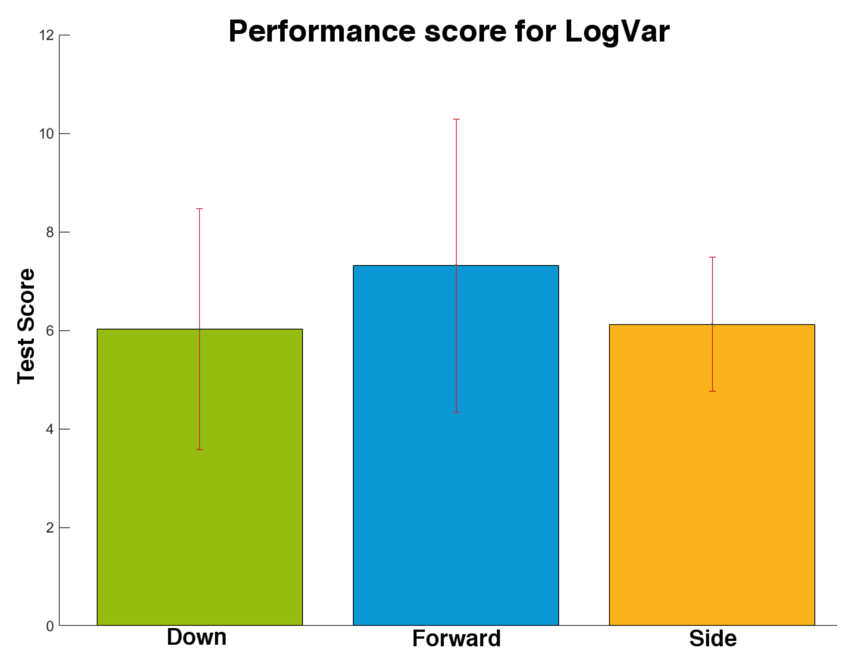


Figure 4: The mean test score among seven subjects when using regressors trained with LogVar

Using a Friedman's test the performance scores between the three limb positions prove not to be significantly different (p = 0.5647), when applying the LogVar trained regressors in the online test. For the MAV trained regressors the performance score between all limb positions cannot be proven significantly different either (p = 0.1561). There was no significant difference in the time to reach the targets across the two features (LogVar: 6.5 s, MAV: 5.5 s; p = 0.13).

Offline Results

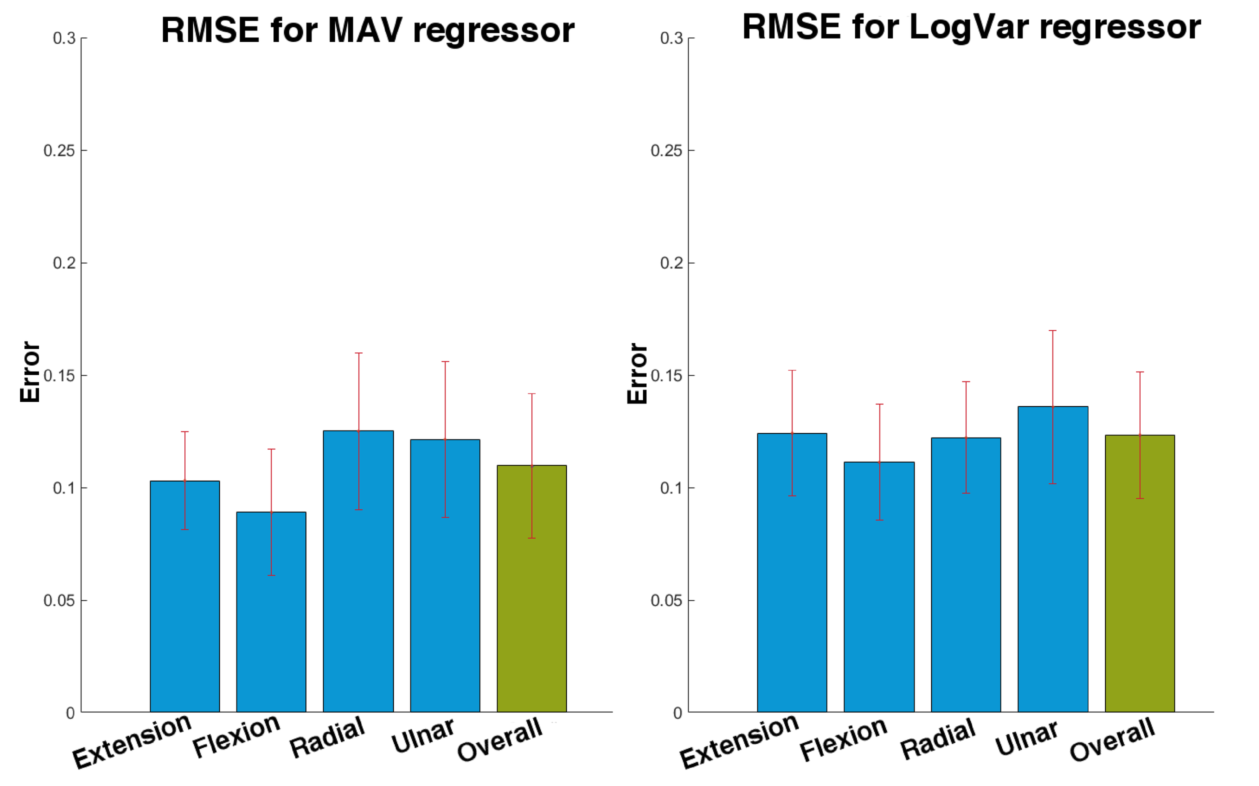


Figure 1: RMSE when using training data.

Comparing the RMSE of MAV and LogVar through a Friedman's test indicates a significant difference (p = 0.0007), where LogVar has the higher mean.

Feature	Overall mean error	Standard deviation
MAV	0.1096	±0.0321
LogVar	0.1234	±0.0281

Table 1: Overall mean RMSE when using training data as input in the regression model

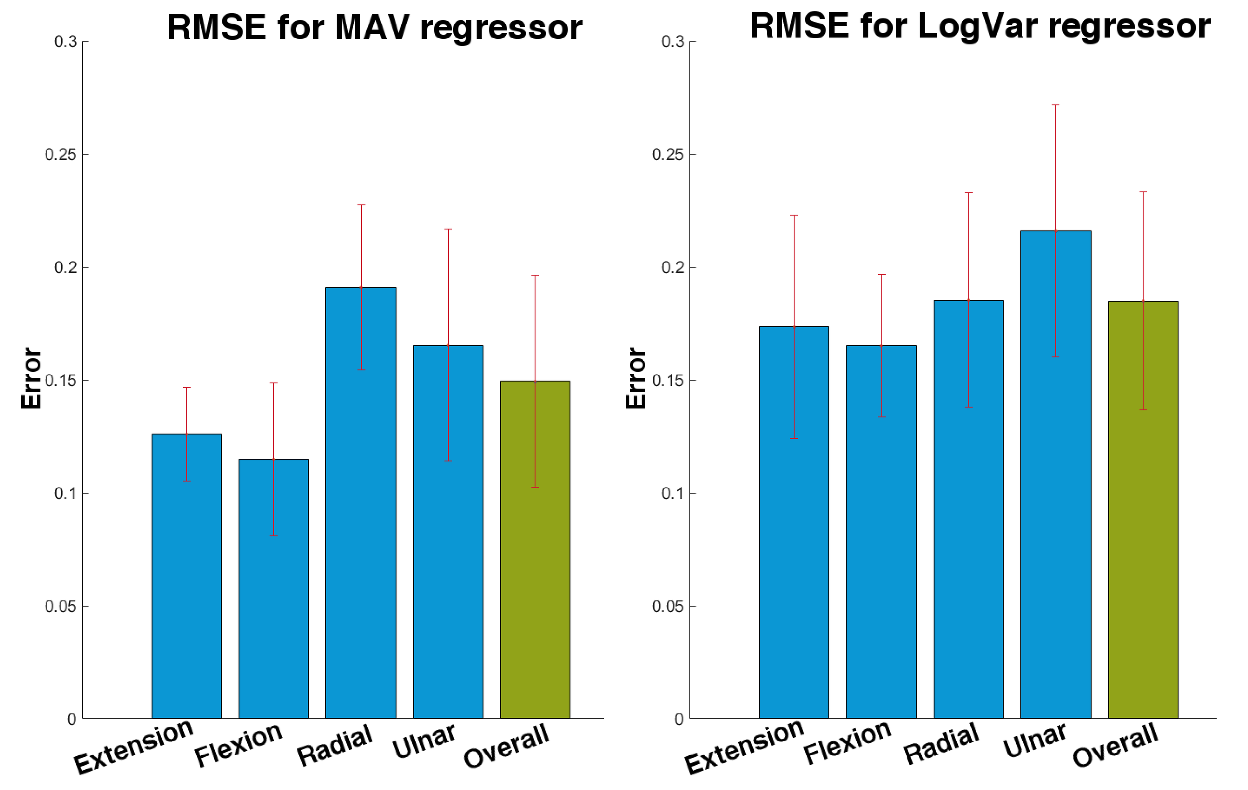


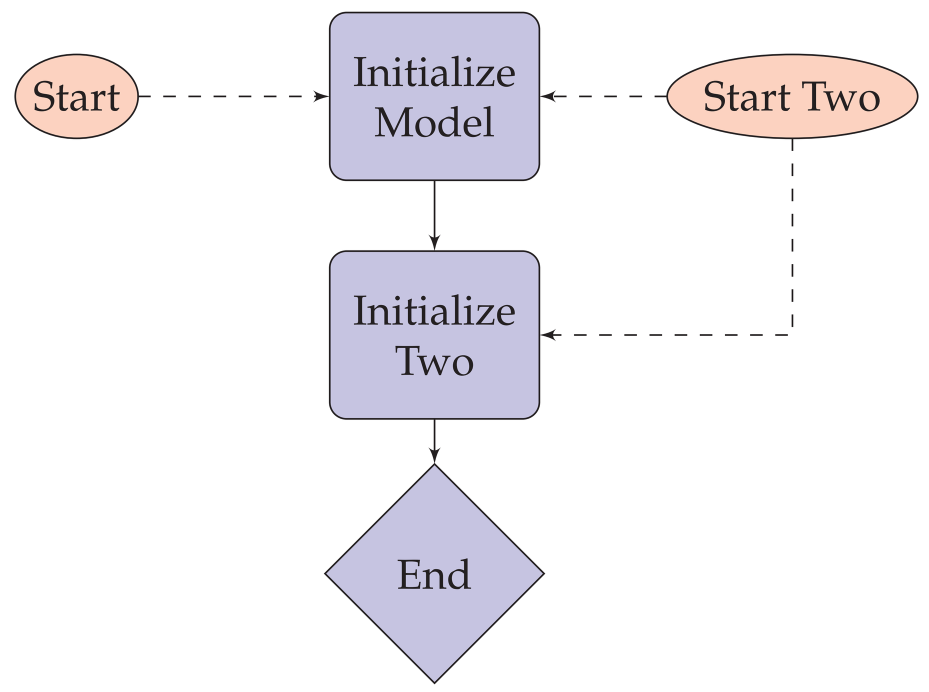
Figure 2: RMSE when using test data

Feature	Overall mean error	Standard deviation
MAV	0.1493	±0.0469
LogVar	0.1850	±0.0484

Table 2: Overall mean RMSE when using test data as input in the regression model

Comparing the RMSE of MAV and LogVar when using test data again indicated significant difference (p = 0.0082), where LogVar again has the higher mean. The RMSE of the MAV when using training data proves significantly smaller than the RMSE when using test data (p = 0.0002). Similar results are obtained for the LogVar regressor (p = 0.0002).

Conclusion



- Pellentesque eget orci eros. Fusce ultricies, tellus et pellentesque fringilla, ante massa luctus libero, quis tristique purus urna nec nibh. Phasellus fermentum rutrum elementum. Nam quis justo lectus.
- Vestibulum sem ante, hendrerit a gravida ac, blandit quis magna.
- Donec sem metus, facilisis at condimentum eget, vehicula ut massa. Morbi consequat, diam sed convallis tincidunt, arcu nunc.
- Nunc at convallis urna. isus ante. Pellentesque condimentum dui. Etiam sagittis purus non tellus tempor volutpat. Donec et dui non massa tristique adipiscing.

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