

SIMULTANEOUS AND PROPORTIONAL CONTROL OF 2D WRIST MOVEMENTS WITH MYOELECTRIC SIGNALS

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ABSTRACT

Previous approaches for extracting real-time proportional control information simultaneously for multiple degree of Freedom(DoF) from the electromyogram (EMG) often used non-linear methods such as the multilayer perceptron (MLP). In this pilot study we show that robust control is also possible with conventional linear regression if EMG power measures are available for a large number of electrodes. In particular, we show that it is possible to linearize the problem with simple nonlinear transformations of band-pass power. Because of its simplicity the method scales well to high dimensions, is easily regularized when insufficient training data is available, and is particularly well suited for real-time control as well as on-line optimization.

Index Terms— Electromyography (EMG), myoelectric control, simultaneous control, linear regression, upper limb prosthesis.

1. INTRODUCTION

The signal processing and analysis of surface electromyogram (EMG) for the control of multifunction upper limb prostheses has been extensively investigated for over 30 years. Particularly, in the past decades, a number of studies have shown that classification algorithms for surface EMG can achieve close-to-excellent results (refer to [1] for a recent review). However, there is no commercially available prosthesis that utilizes this control approach. This constitutes a sharp contrast between the academic state-of-the-art (SOA) and the industrial SOA in this field. There are many reasons for such a dichotomy [2]. On the aspect of EMG signal processing, the sequential and on/off control approach

provided by classification algorithms is very different from the natural control approach of the neuromuscular system, i.e. simultaneous and proportional control of multiple degree-of-freedom (DoF). Therefore, natural control is still allusive. Consequently, the user acceptance of such control is very low, except for the few cases of targeted muscle reinnervation (TMR) patients, where nerves are surgically transferred to achieve additional control signals [3].

However, for many amputees, TMR is not possible. For example, trans-radial amputation, which corresponds to the largest portion of upper extremity deficiency, would not benefit from the TMR procedure. Therefore, extracting simultaneous and proportional control information from surface EMG remains a pressing and challenging problem. In recent years a number studies explored signal processing approaches that would allow for simultaneous and proportional control of multiple DoFs [4],[5],[6],[7],[8]. In these studies, it was shown that such an intuitive control approach is possible, by using methodologies such as non-negative matrix factorization (NMF) [4] or multilayer perceptrons (MLP) [7]. However, estimates obtained with NMF-based algorithm often have overshoots, particularly when muscle contractions are high. On the other hand, MLP-based approach need fine tuning of the model parameters, such as the number of hidden neurons, to avoid over-fitting. Also, the MLP is essentially a black-box approach, which makes it difficult, if not impossible, to interpret the physiological relevance of the internal parameters.

In this paper we show in an offline analysis that, for simultaneous and proportional control, it is possible to use a simpler model than MLP and increase performance, if suitable features are used.

Our approach is based on linear regression so it does not need any internal parameters to be chosen. This makes the results intrinsically more stable and allows a very fast and responsive implementation of the control system with more easily interpretable results.

*This work was funded by the Marie Currie IAPP grant "AMYO", project number 251555 and by the World Class University Program through the National Research Foundation of Korea funded by the Ministry of Education, Science, and Technology, under Grant R31-10008. ¹Machine Learning Laboratory, Berlin Institute of Technology, D-10587 Berlin Germany; ²Dep. of Neurorehabilitation Engineering, University Medical Center Göttingen, Georg-August University Göttingen, D-37075, Germany ³Strategic Technology Management, Otto Bock HealthCare GmbH, D-37115 Duderstadt, Germany; ⁴Bernstein Center for Neurotechnology Berlin, D-10587 Berlin, Germany; ⁵Department of Brain and Cognitive Engineering, Korea University, Anam-dong, Seongbuk-gu, Seoul 136-713, Korea; ⁶Department of Biomedical Engineering, City College of New York, New York, NY 10031 USA

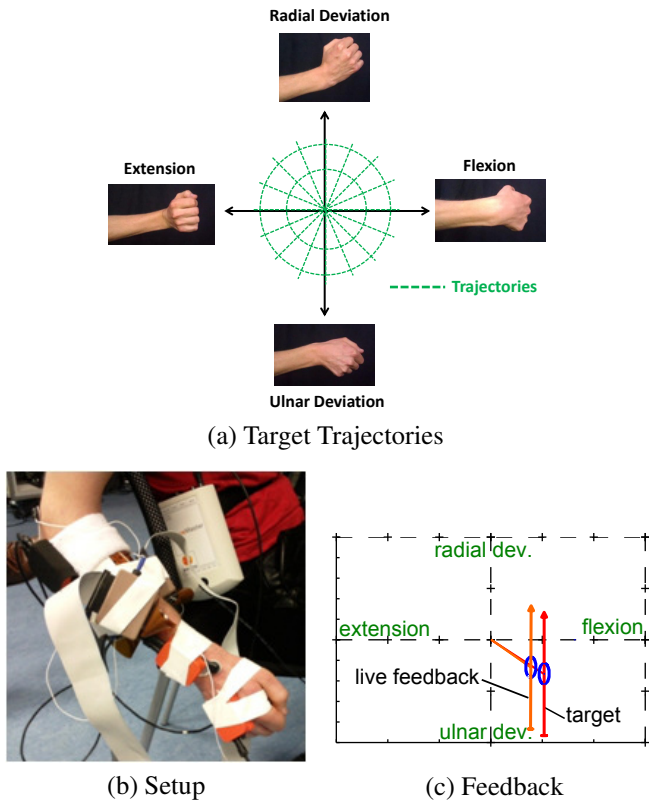


Fig. 1. Experimental Setup

2. METHODS

2.1. Experimental Setup

EMG was recorded from the forearm of one healthy subject performing a series of wrist movements. Accurate data labels were gained with a motion tracking system (figure 1b).

EMG was recorded with a high density 192-channel electrode array (ELSCH064NM 3-3, OT Bioelettronica, 18 x 24 channels, 10 mm inter-electrode-distance) in a monopolar derivation. The electrode was placed on the proximal portion of the upper forearm, covering a range of 8 cm.

The biosignal amplifier was a 12 bit "OT Bioelettronica EMGUSB-2", configured to a sampling rate of 2048Hz. Ground and reference electrodes formed by two electrode bands placed at the proximal end of the forearm. Motion signals were recorded with an Xsens motion tracking system with the MTx sensors, which is synchronized with the EMG amplifier by a customized Matlab interface [9]. The procedure of calculating the joint angles of the two DoFs of the wrist: flexion/extension and radial/ulnar deviation was presented in [10]. The experimental paradigm included extensive combinations of these two wrist DoFs. In previous studies, more DoF were investigated [4],[7],[6], but less data with gradually combined DoFs was used. The goal for the

present paradigm was to cover most of the possible range of simultaneous activations of these two DoFs.

The target trajectories that the subject was instructed to follow are shown in Figure 1a, and include moving the wrist in 16 different directions, and drawing contour lines of two different diameters, each in both directions (clock/counterclock). At the beginning of each session, the individual range of motion in both DoFs of the subject was measured, and the paradigm was automatically calibrated in such a way that the trajectories would move from the center (rest position) to the maximal range of motion for each direction, and that the two contour lines would be located at 90% and 60% of the maximal range of motion. The time from the center position to the maximal position was 3s, followed by 2s remaining in the maximal position and 3s for returning to center position. The time for a full contour movement was 10s. The experiment was divided into 18 runs, where each run contained each type of trajectory (16 lines and 4 ellipses) exactly once. During the recordings, the target wrist position was displayed on a computer screen together with the actual position obtained by the motion tracking system (fig. 1c). This online feedback helped the subject in better matching the target trajectories. An example of the recorded motion data is shown in figure 2. The experiment was in accordance with the declaration of Helsinki and was approved by the local ethics commission. (Ethikkommission d. Med. Fak. Göttingen, approval number 8/2/11)

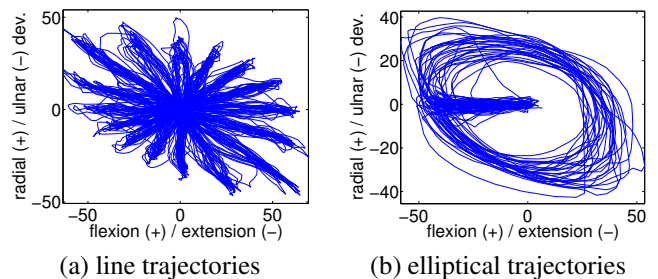


Fig. 2. Recorded motion traces

2.2. Preprocessing

The data were filtered using a 4th order Butterworth high-pass ($f_c = 20Hz$) to remove movement artefacts, a lowpass ($f_c = 500Hz$) to remove high frequency noise and a 50 Hz comb filter to remove line interference, including harmonics. Sample-wise common mean subtraction was performed to remove correlated noise and distortion that might be caused by activity at the reference electrode.

2.3. Feature Extraction

The features were extracted from non-overlapping intervals of 200 ms. This window duration is within the acceptable time

delay between user command and prosthesis action [11],[12]. The power of the EMG signal increases monotonically with increased contraction force of the underlying muscles. Thus, features that reflect the power of the EMG contain relevant information for myocontrol.

To obtain good estimation results when using linear methods the relationship between the features and the target labels (i.e., the motion data) should be as linear as possible. In the current study, we evaluated three different features. The first is the EMG band power signal that we denote as $x_{\text{power}}(t_i) \in \mathbb{R}^{192}$, where each t_i corresponds to the average over one 200 ms window. The other two features are root-mean-squares (rms) $x_{\text{rms}}(t_i) = \sqrt{x_{\text{power}}(t_i)}$ and log-var [13] $x_{\text{log-var}}(t_i) = \log x_{\text{power}}(t_i)$ that are just non-linear transformations of $x_{\text{power}}(t_i)$. These transformations aim to linearize the relationship between features and joint angle (the label y), as seen in figure 3 a-f.

2.4. Linear Regression

In linear regression [14, 15] a target variable $y \in \mathbb{R}^{D_y}$ is modeled as a linear mapping $W \in \mathbb{R}^{D_y \times D_x}$ from the D_x -dimensional space of input variables to the D_y -dimensional target space

$$Y = W^T X \quad (1)$$

where the matrix $X \in \mathbb{R}^{D_x \times T} = [x(t_1), x(t_2), \dots, x(t_T)]$ contains a set of feature vectors from T time instances and the matrix $Y \in \mathbb{R}^{D_y \times T} = [y(t_1), y(t_2), \dots, y(t_T)]$ contains the true target variable values. In our scenario the dimensionality of the input space is the number of sensors on the electrode grid, i.e. $D_x = 192$; the dimensionality of the labels is $D_y = 2$, corresponding to the joint angles of two DoFs (vertical and horizontal deflections). The maximum likelihood solution to (1) in the case of multivariate target variables is the same as for univariate targets, see e.g. [16]. We obtain the optimal W that minimizes the mean-squared error by the ordinary least squares solution

$$W = (XX^T)^{-1}XY^T. \quad (2)$$

Note that in (2) the mapping W from sensors to joint angles is optimized for all DoFs simultaneously. The only computations involved are the pseudo-inverse $(XX^T)^{-1}X$ and a matrix multiplication with the training labels Y , which are of negligible computational cost. If needed, the estimate of W can be made more robust by including a ridge on the covariance matrix XX^T , a standard regularization technique known as Tikhonov regularization [17]. This can be useful, e.g. if the amount of training data is limited.

2.5. Reference method MLP

The proposed method was compared with results obtained by the MLP approach presented in [7],[6]. Briefly, two MLP networks were used to estimate the joint angles of the two DoFs,

respectively. For each MLP, a 3-neuron hidden-layer with hyperbolic tangent sigmoid transfer function was implemented. The input layer and the output layer had linear transfer functions. The inputs were formed by the features, projected down to the strongest PCA components describing 98% of the variance. The MLP was trained with the Levenberg-Marquardt back-propagation algorithm. All MLP training was implemented with the Matlab neural network toolbox.

2.6. Cross-validation

To evaluate the performance five-fold-crossvalidation was applied. The folds were formed by entire runs and only the first 15 runs were included. This was done in order to keep training and test set not only disjoint but as independent as possible and to guarantee a balanced appearance of movements within both sets. As a performance metric we used the r-square value[18]:

$$r^2 = 1 - \frac{\sum_d \text{Var}(y^d - \hat{y}^d)}{\sum_d \text{Var}(y^d)} \quad (3)$$

where y^d are the observed wrist deflections angles and \hat{y}^d are the estimated angles predicted by the models. An r-square value of one corresponds to perfect estimation and zero to chance performance.

3. RESULTS

Figure 3 provides visualization of the linearization of the feature space and the effects to the estimation.

Since it is impossible to visualize the relationship between the labels and the feature space in full dimension, the features were averaged over all channels. Although this "feature intensity" does not contain enough information for the regression task, it could give insights to the complexity of the underlying relationship.

The top row (a-c) illustrates the relationship between joint angle in polar coordinates and EMG feature intensity. Several trials of the wrist movements from the origin to eccentric positions are reported. The x-axis shows the distance from center position, y-axis feature intensity and different target directions are distinguished by the different colors. The lines are curves obtained by polynomial fitting. This fitting is biased by the chosen model complexity, but the order was the same for all three cases and chosen sufficiently high.

Prediction with band power features Plot (a) in figure 3 illustrates the nonlinear relationship between EMG band power and joint angle; for joint angles close to the origin, there is an almost linear relationship between $x_{\text{power}}(t)$ and $y(t)$, whereas for positions far from the origin the EMG band power is disproportionately increased. When estimating the mapping W on this data with linear regression (eq. 1), the

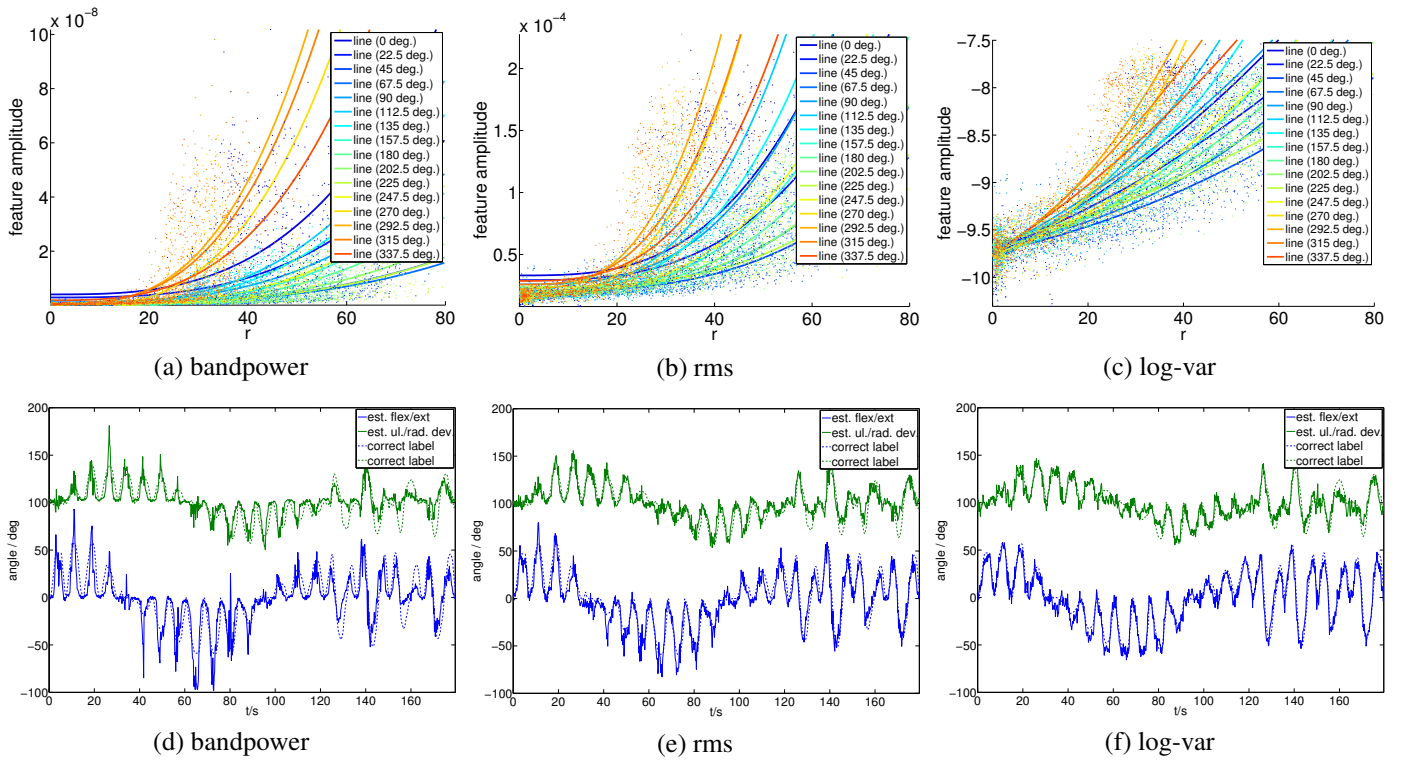


Fig. 3. Visualization of mean features vs. joint angle in polar coordinates (a-c), and corresponding label estimation from cross-validation (d-f)

predicted joint angles cannot be modeled well, as depicted in figure 3d: for joint angles close to the origin, the predicted joint angle is *underestimated* while at joint angles far from the origin, the predicted joint angles tend to be *overestimated*. This is due to the fact that linear combinations of band power signals cannot compensate for the nonlinearity mentioned above. The suboptimal performance is also reflected in a rather low r^2 value of 0.67 ± 0.04 (mean \pm std.), see figure 4.

Prediction with rms features The panels in the middle column of fig. 3 show data and results for the square root of the band power features. Panel b illustrate that the nonlinearity between joint angle and EMG features is not as pronounced as in the case of the band power features in panel a. This leads to a better prediction performance, as visualized in fig. 3e. A direct comparison of the cross-validation results in fig. 4 shows that joint angle is better predicted when using rms features, as indicated by a better r^2 value of 0.84 ± 0.03 .

Prediction with log band power features The results obtained when taking the log of the EMG band power are depicted in the panels in the right column of fig. 3. In contrast to the other two features, the relationship between joint angles and EMG log band power is approximately linear, as illustrated in panels c/f. This leads to a significantly better pre-

diction accuracy as shown qualitatively in fig. 3f. In contrast to the other two feature types, there is less under or overestimation at small or large targets.

Figure 4 shows that log band power features predict the joint angle best as indicated by a competitive r^2 value of over 0.88 ± 0.03 .

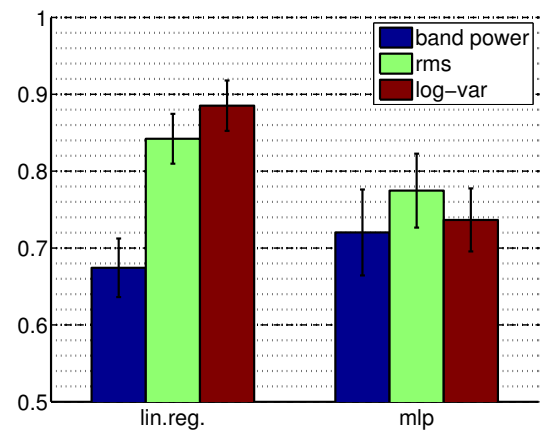


Fig. 4. xval results (r-square value), the error bars indicate inter fold standard deviation

Comparison with Baseline Method MLP For the band power features with no linear relationship the non-linear baseline method MLP performs better than linear regression, as indicated by a higher r-square value. For the transformed features rms and log-var linear regression performs better than MLP. Especially for the log-var features that have an almost linear relationship to the targets linear regression performs significantly better than MLP.

4. DISCUSSION

We showed that a simple linearization of the feature representation in combination with linear regression can lead to results that are better than those obtained with the nonlinear MLP method. The approach presented here has several advantages over more complex nonlinear models. First, we can interpret the estimated parameters. The mapping W , directly resides in the sensor space. The better accessibility of the model parameters in our approach allows for incorporation of prior knowledge into the model. Another advantage is that the simpler the model the less likely is the danger of overfitting. This is a very desirable feature for real world applications in prostheses. Often not all regimes of the EMG input space can be sampled equally well when acquiring training data. Generalization to new data from these under-sampled regimes is difficult when nonlinear methods are over-fitted to only those data regimes where training data was available. A standard method to prevent overfitting to the training data is to restrict the predictor to a simple model class. In our approach we restricted the predictor functions to the class of linear models, thereby ensuring that not too complex mappings from EMG signals to joint angles can be learned.

5. CONCLUSION

We presented a simple, robust and efficient method for linearizing the problem of simultaneous and proportional myoelectric control of multiple DoFs. Our approach is based on a log transform of the EMG band power signal. This linearization of the nonlinear relationship between EMG signal and joint angles allows for applying a simple linear model for myoelectric control of prostheses. Future work includes more empirical evaluations on a larger group of subjects and more DoFs. Also subjects with uni-lateral limb deficiencies will be included where the position labels might be gained from the intact-side when performing mirrored movements (see also [7]). A special focus will have to be placed on the evaluation in an online setting. In the online setting, future work will have to compare our approach with complex nonlinear prediction methods. We expect that the robustness and efficiency of linear regression will make training easier as compared to nonlinear methods. This will be of special importance in future applications in real prostheses.

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