RESEARCH ARTICLE

EMG-based Estimation of Wrist Motion Using Polynomial Models

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Abstract

Background: Myoelectric control is a method of decoding the motor intent from the electromyogram (EMG) data and using the estimated intent to control prostheses and robots. This work investigates estimation of the wrist kinematics from EMG signals using polynomial models. Due to their low complexity, polynomial models are potentially the perfect choice for EMG-kinematics modeling.

Methods: Ten ablebodied individuals participated in this study, where the EMG signals from the forearm and the wrist kinematics from the contralateral wrist were measured during mirrored contractions. Two sets of EMG features were employed including the time domain (TD) set, and TD features along with autoregressive coefficients (TDAR). Polynomial models of order 1 to 4 were applied to map the EMG signals to the wrist motions. The performance was directly compared to that of a multilayer perceptron (MLP) neural network.

Results: The estimation accuracy of the wrist kinematics improved with increasing the order of the model, but saturated at the 4th order. When using the TD set, the MLP significantly outperformed all polynomial models. However, when using the TDAR set, the polynomial models' performance improved so that the 4th order model performance was not significantly different than that of the MLP in two DoFs, although it was lower than MLP in one DoF.

Conclusion: These results indicate that polynomial models are not as effective as more complex models such as neural networks, in learning the highly nonlinear mapping between the EMG data and motion intent. However, using a sufficiently high number of various EMG features, would reduce the mapping nonlinearities, and thereby may increase the polynomial models' performance to levels similar to those of complex black box models.

Level of evidence: I

Keywords: EMG, Machine learning, Myoelectric control, Polynomial

Introduction

Decoding the motor information from electromyogram (EMG) signals and using the estimated intent to control prostheses, robots, and humanmachine interfaces are referred to as myoelectric control (1). In myoelectric prostheses, the motion intention of the missing limb, is estimated from the EMG signals of the residual muscles (2). Because the control mechanism of myoelectric prostheses is by thinking of an intended movement, similar to that of an intact limb, it is often said that myoelectric prostheses are controlled by thought. In order to control more than one movement, pattern recognition methods are necessary where a classification or regression model is deployed to estimate the motion intent from the EMG signals. One of the regression-based strategies is to map the EMG signals to the limb kinematics (3-12). However, this approach is not applicable to amputees, as it is not possible to measure an absent limb motions. To account for this issue, the

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movements can be measured form the opposite sound limb during mirrored contractions (9). This method is justified by studies that have shown high correlation between the left and right limbs during mirrored contractions (13, 14). With this approach, the EMG data from the residual muscles are mapped to the opposite sound limb motions during mirrored contractions. This method, however, is limited to unilateral amputees.

In regression-based methods, each independent movement direction around a joint is called a degree of freedom (DoF). The goal is to estimate the motion intent in several DoFs simultaneously, to provide a more natural intuitive control. For example, wrist movements involve simultaneous motions in three DoFs of flexion-extension, abduction-adduction, and pronationsupination. A natural prosthetic control would require simultaneous control of these DoFs. Several regression models have been proposed to map the EMG signals to the limb kinematics (9, 15-17). This study aims to evaluate the efficacy of polynomial models, as the simplest nonlinear models, in learning the nonlinearity of EMG-wrist kinematics relationship. Due to the low complexity of polynomial models, they allow fast training and computation, potentially making them a perfect choice for EMG-based motion intent estimation. The performance is directly compared to that of a complex black box model, i.e. a multilayer perceptron (MLP) neural network.

Materials and Methods

Data Collection

Ten ablebodied subjects (ages: 24-39, all righthanded) took part in this experiment. The protocol was approved by the ethics board of the University. The subjects sat in a chair with forearms secured to armrests and palms facing inward in a resting position. Six reflective ball shaped markers were attached to the skin on bony landmarks of the left hand and forearm as shown in Figure 1. The markers positions were captured by a Vicon 512 system with 8 infrared video cameras at 60 Hz. Eight bipolar EMG sensors (Delsys Inc.) were attached equally spaced around the right forearm, proximal to the elbow. The EMG data were recorded at 1 KHz via a 16 bit A/D converter. The Vicon system was synchronized with the EMG system through a digital trigger.

This experiment involved wrist motions in three DoFs. Fourteen trials corresponding to fourteen wrist motions (6 individual and 8 combined motions) listed in Table 1 were performed. Each trial was 24 s in duration and involved 4 repetitions of the following cycle: 1 s of initial *no-motion* (rest position), 1 s of moving to a maximum comfortable angle in the corresponding DoF(s), 2 s of maintaining the maximum angle, 1 s of returning to no-motion, and 1 s of keeping *no-motion*.

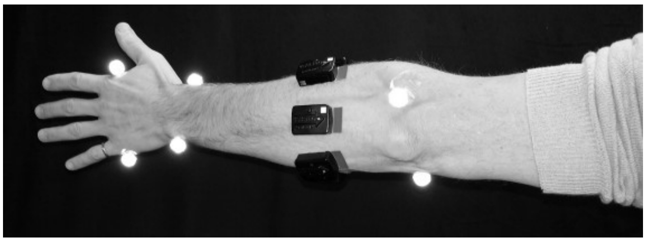

Figure 1. Six ball shaped markers were placed on bony landmarks of the left upper limb.

Table 1. The experiment involved 14 trials corresponding to 14 contractions

#	Contraction
1	Flexion
2	Extension
3	Abduction
4	Adduction
5	Pronation
6	Supination
7	Simultaneous Flexion and Pronation
8	Simultaneous Flexion and Supination
9	Simultaneous Extension and Pronation
10	Simultaneous Extension and Supination
11	Simultaneous Abduction and Pronation
12	Simultaneous Abduction and Supination
13	Simultaneous Adduction and Pronation
14	Simultaneous Adduction and Supination

Data Processing

The EMG signals were bandpass filtered between 10-450 Hz using a 3rd order Butterworth filter. The wrist joint angles in each DoF were computed from the marker location data and were lowpass filtered at 1 Hz using a 3rd order Butterworth. The EMG data were segmented into 200 ms windows with 50 ms increments. The average computed wrist angle across each EMG window was set as the corresponding angle for each EMG window. From each EMG window, the TD feature set including the mean absolute value (MAV), zero crossings (ZC), waveform length (WL), and slope sign changes (SSC) were extracted (18). Moreover, to investigate the effect of inclusion of additional features, a second feature set was tested which comprised the TD set as well as the root mean square (RMS), and the 6th order autoregressive (AR) model coefficients. This feature set is denoted as TDAR. The total number of features for all eight channels were 32 TD and 88 TDAR features. For each subject and each DoF, polynomial models of order 1 to 4 and also an MLP were trained to model the relationship between the EMG features and the corresponding wrist angles. The MLP parameters were determined empirically; one hidden layer with five neurons was used, where the hidden and output layers had tan-sigmoid and linear activation functions, respectively. Levenberg-Marquardt backpropagation was used as the training algorithm.

The estimated wrist angles were lowpass filtered at 1 Hz to match the frequency content of the measured angle data. Four-fold cross validation was conducted where in each trial three repetitions were included in the training set and one repetition was used in the test set. The coefficient of determination (R^2) (9) was computed to quantify the wrist angle estimation accuracy in each DoF. For a polynomial model of order *N*, the wrist angle in each DoF was estimated as in Eq 1.

$$f = \sum_{i=1}^{N} A_i \times X^i + a_0 \quad (1)$$

where *f* is the estimated angle, and for each *i*, A_i is a constant row vector with length *M* (*M* is the number of total features, for TD: 8×4=32, and for TDAR: 8×11=88), *X* is the EMG features column vector with length *M* and *a0* is a constant. The coefficient constants *Ai* and *a0* were determined using an iterative least squares approach in the training phase.

Statistics

The estimation accuracies (R^2) were compared between the MLP and each polynomial model using paired samples ttest. The significance level was set to 0.05.

Results

In order to better understand the EMG-kinematics relationship, an illustration is provided in Figure 2, which shows the EMG signal recorded from a channel over the extensor digitorum muscle during the extension trial for a representative subject, along with the measured wrist angle in the flexionextension DoF. For this EMG signal during the same period, the TD features are plotted in Figure 3.

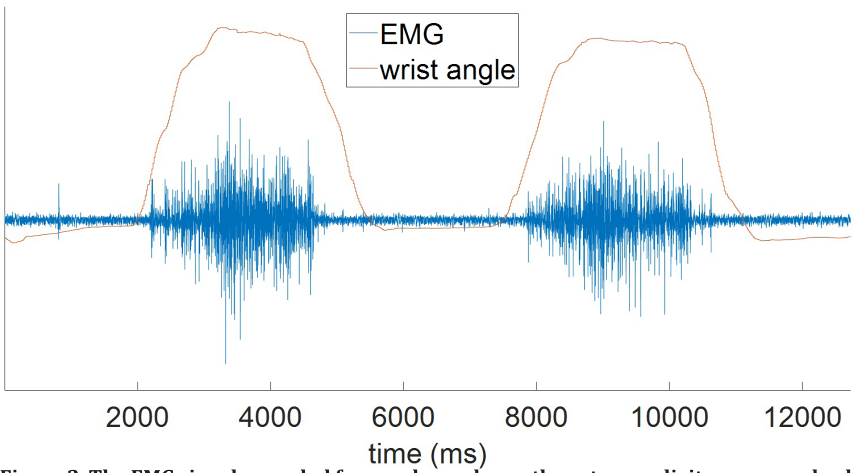

Figure 2. The EMG signal recorded from a channel over the extensor digitorum muscle along with the measured wrist angle in the flexion extension DoF, for a representative subject.

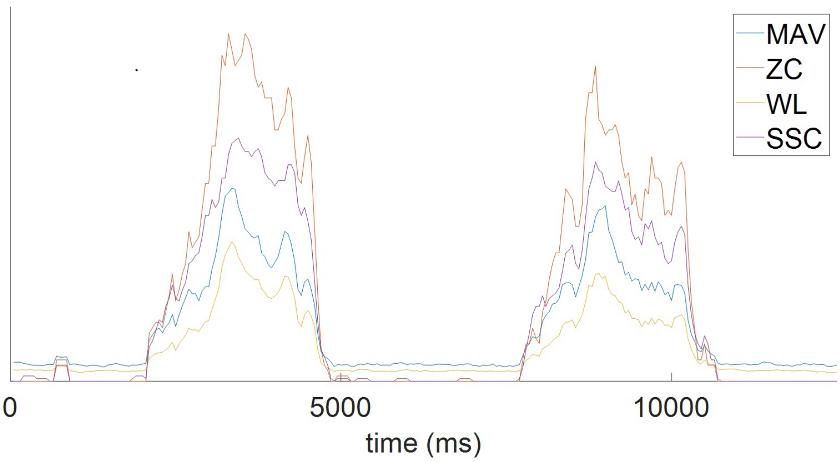

Figure 3. The TD features of the EMG signal of Figure 2 is plotted for the same period.

The wrist angle estimation accuracy (R^2) at each DoF, averaged across all subjects are plotted in Figure 4 for the polynomial models of order 1 to 4, and the MLP, when using the TD feature set. Paired samples ttests showed that at each DoF, the MLP significantly outperformed every polynomial model (*P<0.05*).

The wrist angle estimation accuracy (R^2) at each DoF, averaged across all subjects are plotted in Figure 5 for the 4th order polynomial model and the MLP, for the TD and TDAR feature sets (denoted as 4^{th}TD, 4^{th}TDAR, MLPTD, and MLPTDAR, respectively). Moreover, the results for the TD and TDAR feature sets are plotted in Figure 6 for individual subjects for the 4^{th} order polynomial model. As indicated in Figure 5, the TDAR feature set increased the estimation accuracy of the 4th order polynomial, but did not improve the MLP performance. The estimation accuracy of the 4^{th} order polynomial when using the TDAR feature set, were compared to that of the MLP model, using paired samples t-test, for each DoF. MLP-TD was used for comparison, because using the TDAR set did not enhance the MLP performance. The results indicated that no significant difference (*P>0.05*) was found between

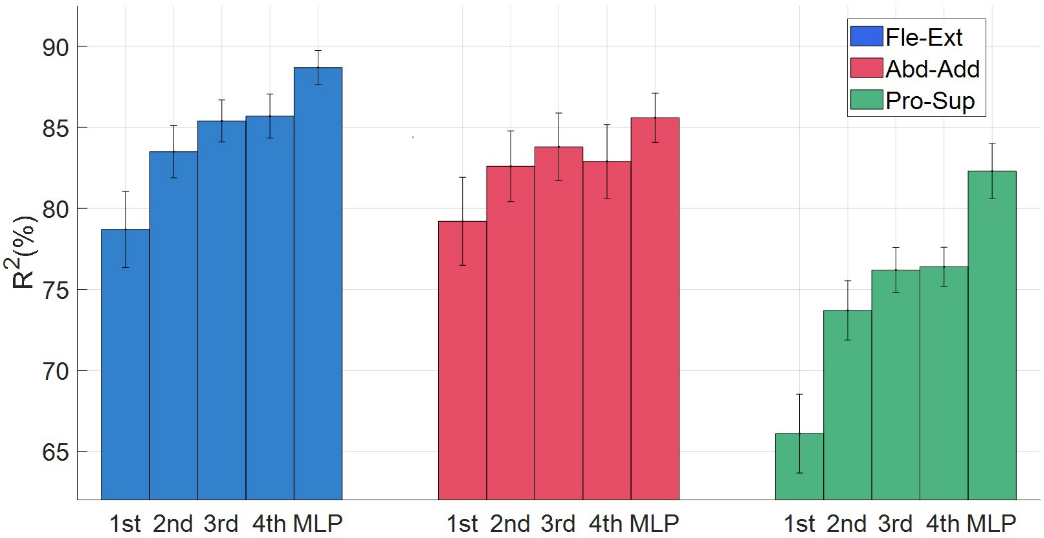

Figure 4. The wrist angle estimation accuracies (R^2) at each DoF, averaged across all subjects are shown with standard error (N=10) for the polynomial models of order 1 to 4 and MLP, with the TD feature set.

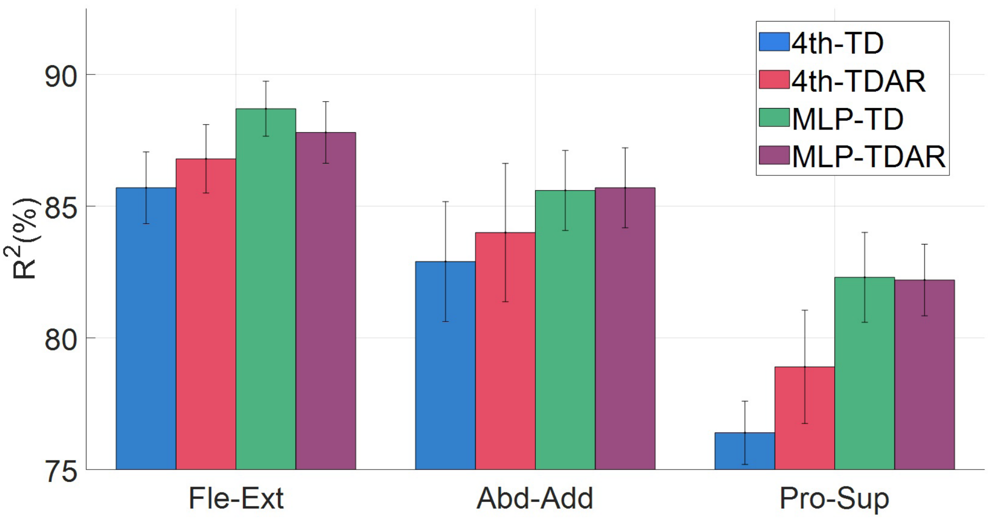

Figure 5. The wrist angle estimation accuracies (R2) at each DoF, averaged across all subjects are shown with standard error (N=10) for the 4th order polynomial model and MLP, with the TD and TDAR feature sets.

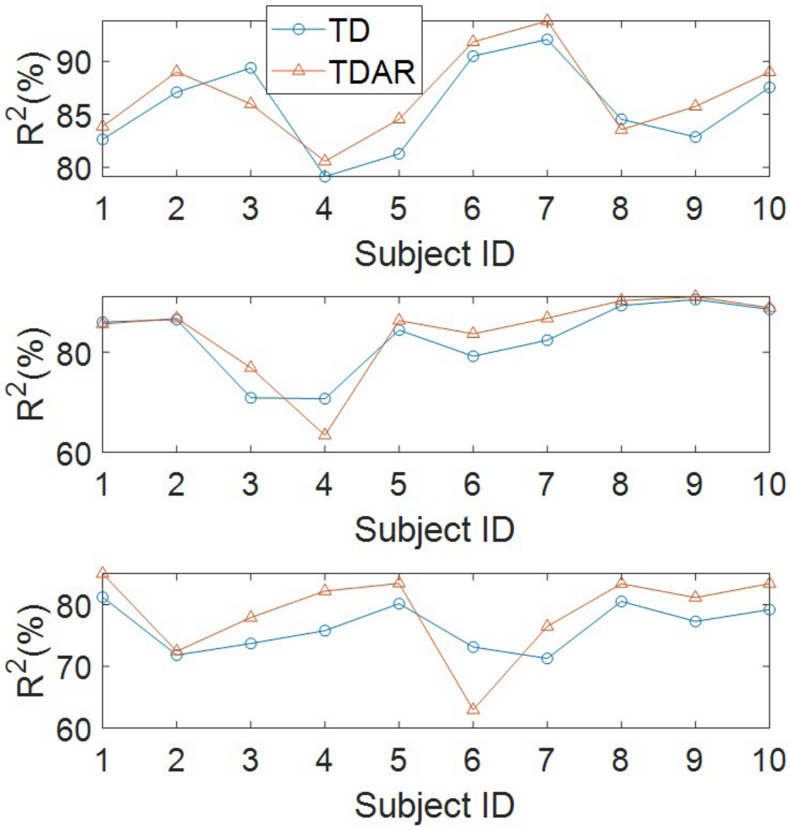

Figure 6. The wrist angle estimation accuracies (R2) at each DoF, for the 4th order polynomial model, with the TD and TDAR feature sets, for individual subjects. The top, middle, and bottom figures are for flexion-extension, abduction-adduction, and pronation-supination DoFs, respectively.

4th TDAR and MLPTD, in the abductionadduction and pronationsupination DoFs, whereas MLPTD outperformed 4th TDAR in the flexionextension DoF (*P≈0.009*).

Discussion

This work investigated the estimation of wrist motions from the EMG data of the contralateral forearm during dynamic individual and combined motions. The results were promising as a high performance was obtained for EMGkinematics mapping. Commercial prostheses use traditional direct control which only allows control of one DoF. However, the regressionbased systems in this study provide simultaneous control of multiple DoFs and therefore can significantly improve the control naturalness. The high estimation accuracy of the wrist angle achieved in this work support the high correlation between the left and right upper limbs during mirrored contractions.

The results reveal that the polynomial models performance improve with increasing the model order until it saturates at the 4th order. The first order polynomial is a linear model, and demonstrated a significantly lower performance compared to higher order models. This clearly shows that the motion intent relationship with EMG features is nonlinear. Based on the results, this nonlinearity is more pronounced in pronationsupination [Figure 4]. This may be because the muscles responsible for pronationsupination are deeper and may slide under other superficial muscles during dynamic contractions. This makes it more difficult to measure the EMG signals from these muscles by surface sensors.

Increasing the order of a polynomial model increases its capacity to capture nonlinearity. Hence, the performance improves with increasing the model order, but it saturates at the 4th order. Nevertheless, the MLP significantly outperformed the 4th order model, when using the TD feature set, indicating that complex black box models can be more efficient in modeling the nonlinear relationship between the EMG features and wrist angle. This demonstrates the limited capacity of polynomial systems in modeling the highly nonlinear EMGkinematics relationship. However, when using the TDAR feature set, the estimation accuracy of the polynomial models improved [Figure 5]. This is because inclusion of the additional features, reduced the nonlinearity of the mapping between the EMG features and kinematics, and thereby enhanced the polynomial models' performance. However, the addition of the AR features did not increase the MLP performance, suggesting that the AR features did not provide additional information. Moreover, the simplified mapping due to the addition of AR features, did not benefit the MLP, as it has high efficacy in learning the nonlinearities. It should be noted however, that further inclusion of other features may enhance the performance of the MLP, if those features provide additional information from the EMG signals.

When using the TDAR feature set, the 4^{th} order polynomial model performance was not significantly different than that of the MLP, in abductionadduction and pronationsupination, although it was lower than the MLP in flexionextension. This suggests that when using a sufficiently high number of various EMG features, polynomial models' performance may increase to levels similar to those of complex black box models such as the MLP.

A constant wrist angle was considered as the regression target during each EMG window. Although this assumption may result in some motion information loss, but it is inevitable, because due to the stochastic nature of EMG signals, the motion intent at each instant cannot be estimated from the corresponding instantaneous EMG amplitudes. Instead, the EMG signals must be windowed and a set of features would have to be extracted from each EMG window, to be used for estimation of the motor intent. The length of EMG windows is recommended to be between 100-250ms for optimal performance (19). In this way, each window is considered as a time sample, and therefore would have to correspond to only one motion intent. It should be noted that the error resulting from this assumption is negligible because the motions of myoelectric prostheses are not fast. This paradigm of EMG-kinematics mapping has shown excellent control performance in a previous study with an MLP-based system for real-time control of a cursor to reach virtual targets (12).

As illustrated in Figure 3, the EMG features grow with increasing the muscle contraction. The MAV and WL carry temporal information of the EMG signal, whereas the WL, ZC, and SSC contain spectral characteristics of the EMG data. With increasing the contraction, the number of active motor units as well as the firing rate of active motor units grow. This would increase both the amplitude and frequency of the EMG signal. As a result, both the temporal and the spectral features i.e. the MAV, WL, ZC, SSC will grow with increasing the contraction. Moreover, the AR features are frequency features, and therefore they also increase as the contraction grows. This suggests that these features would be useful for estimation of the wrist motions.

This work studied the application of polynomial models for the EMG-based estimation of wrist motions in three DoFs during individual and combined DoF movements. It was found that the polynomial models performance improved with increasing the model order, but it was saturated at the 4^{th} order. Moreover, when using the TD feature set, an MLP neural network significantly outperformed the polynomial models. This shows that the EMGbased motion intent estimation is a highly nonlinear mapping task which is beyond the capacity of polynomial models. However, when using the TDAR feature set, the 4^{th} order polynomial model performance was close to that of the MLP. This indicates that by using a high number of various EMG features which capture the nonlinearities of the EMGmotion intent mapping, the polynomial models' performance may become similar to that of complex black box models.

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