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Single Channel-Based Myoelectric Control of Hand Movements with Empirical Mode Decomposition

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***Abstract*—Myoelectric control has been an important area of research for the past 40 years for prosthetic control, since it targets amputees who lost their body limbs. Advances were achieved concerning the number of movements to be classified with high accuracy. Hence, not much research was done to extract information from single channel Electromyogram (EMG). This paper presents Empirical Mode Decomposition (EMD) for Feature Extraction (FE) from single-channel EMG for ten class wrist movements and handgrips. Two classification schemes were applied based on Time Domain-Auto Regression (TDAR) features (a commonly used approach in the Literature) and EMD, with Principle Component Analysis (PCA) for dimensionality reduction, and Support Vector Machine (SVM) for classification. With the use of only one single-channel EMG, the EMD achieved an improvement in the classification rate for a single flexor and extensor EMG channel of 11.2% (from 83.7% to 94.4%) and 13% (from 80.16% to 93.16%), respectively. The results suggested that EMD remarkably improves the classification performance for a single-channel EMG over the traditional time domain FE technique. This will reduce the computational cost of applying only one channel EMG and facilitates the acquisition of the EMG. The main drawback of using EMD technique is that it is not suitable for real time processing of prosthetic control.**

I. INTRODUCTION

It has been reported that the EMG recorded from the forearm muscles after hand amputation is similar to that of healthy subjects [1, 2]. Therefore, there is still an EMG signal when the amputee intends to perform a movement. This fact has inspired researchers to develop myoelectric signal processing algorithms for the control of prosthetic hands. Myoelectric signal is the measurement of the electrical activity of the closely spaced muscles from the surface of the forearm [3]. It has played an important role in rehabilitation because of the non-invasive nature as well as ease of recording from the surface. As shown in the literature [4, 5], the general stages for a pattern-recognition-based myoelectric control system are signal conditioning, feature extraction, dimensionality reduction, and classification. To reduce classification errors, past research mostly has focused on how to improve specific information extraction from the EMG signals for the control of a myoelectric prosthesis. It has been shown that the classification performance is independent of the classifier choice [2]. Yet, there is little research done for extracting information from single channel EMG to classify multi-class hand movements. Traditional Feature Extraction (FE) techniques such as time domain features suffer from many problems. The main drawback of time domain analysis is that most of them are difficult to compute. Fourier Transform (FT) analysis is based on trigonometric functions which depend on a priori information [6]. Hence, the FT is not adaptive [6]. FT also assumes that the data is stationary and linear [7], which is not the case for the biomedical signals such as EMG [6]. Thus, Fourier domain analysis is also limited due to the highly non-linear and non-stationary nature of the EMG signal.

To accommodate different types of complex biomedical signals and to extract more information about particular movements from a single-channel EMG, an adaptive analysis method is needed to overcome these problems. One alternative is the Empirical Mode Decomposition (EMD) recently introduced by Huang et al. [8]. The EMD decomposes complex signals into a finite, and often small, number of Intrinsic Mode Functions (IMFs) that can be readily analyzed by means of the Hilbert spectrum [8]. Furthermore, this decomposition method is adaptive and highly efficient [8]. EMD shares similarities with techniques such as the Wavelet Transform (WT) [8]. The main difference is that the EMD only uses the information available in the data and is completely adaptive. Whereas, the WT employs a set of pre-fixed filters based on the selection of the mother wavelet. Since the EMD is based on the local characteristic time-scale of the data, it is applicable to complex signals, such as biomedical recordings [9-12]. Moreover, the IMFs provide accurate information about the frequency content of the signal [8]. Lei et al. [13] applied the EMD technique combined with Largest Lyapunov Exponent (LLE) for FE from four EMG channels. Back propagation neural networks were used to classify six hand and wrist motions. Accuracies of 70%, 73%, 69%, and 86% were achieved for each single EMG channel, respectively, with the EMD compared to values of 53%, 86%, 58%, and 83% obtained with the use of WT for FE. Their results suggested the potential of using EMD for information extraction from EMG signals. However, this study was based on limited quantities of

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data and a large analysis window of 1 s was used, which exceeds the optimal controller delay for myoelectric control of 300 ms. EMD suffers from the requirement for high computational power to calculate the IMFs. Thus, EMD analysis is normally performed offline.

This work presents an EMD technique to extract features from single-channel EMG recordings for pattern recognition based myoelectric control. The EMD is proposed to decompose EMG into IMFs that will be used for the classification of multi-class hand and wrist movements.

The use of single-channel recordings has significant advantages both in terms of computational complexity and practical application of electrodes since only one channel has to be set up instead of several channels.

II. Empirical Mode Decomposition

In this paper, EMD was applied to obtain the frequency components that compose the EMG signal. EMD [8] is a non-linear technique to adaptively represent non-stationary signals as sum of their IMFs. EMD considers the oscillations in signals at a very local level. Each resulting IMF satisfies two basic conditions [8]:

1. In the complete data set, the number of extrema and the number of zero crossings must be the same or differ at most by one.
2. At any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero.

The EMD of the signal $x(t)$ can be computed as follows [14]:

1. Set $g_1(t) = x(t)$.
2. Detect the extrema (both maxima and minima) of $g_1(t)$.
3. Generate the upper and lower envelopes $e_m(t)$ and $e_l(t)$, respectively, by connecting the maxima and minima separately with cubic spline interpolation.
4. Determine the local mean as:

$$m(t) = \frac{e_m(t)+e_{l(t)}}{2} \quad (1)$$

5. The IMF should have zero local mean. Thus, subtract $m(t)$ from the original signal as: $g_1(t) = g_1(t) - m(t)$.
6. Decide whether $g_1(t)$ is an IMF or not by checking the two basic conditions described above.
7. Repeat steps 2 to 6 and end when $g_1(t)$ is an IMF.

The IMF is subtracted from the signal and the process is repeated on the remainder to compute the other IMFs.

III. Methodology

The block diagram of our proposed system is shown in Fig. 1 with the EMD for FE from single channel EMG. The EMG data sets used in the current work were acquired originally by Hargrove et al. [5].

Sixteen bipolar surface EMG electrodes were mounted around the upper part of the forearm as shown in Fig. 2. The subjects were asked to perform ten combinations of wrist movements and hand grips, namely, forearm pronation, forearm supination, wrist flexion, wrist extension, radial deviation, ulnar deviation, key grip, chuck grip, hand open, and rest state. The recordings consisted of five trials for each of the six participants. Each trial consisted of performing a medium force isometric contraction of the nine movements for duration of 5 s followed by a rest period. The signals were sampled at 1024 Hz sampling frequency and band pass filtered (10-500) Hz. For additional details, refer to [5].

To reduce computational complexity and to evaluate the potential value of single EMG channel analysis for myoelectric control of multi-class movement, the authors decided to test the proposed approach in two experiments, based on channel 1 in the flexor compartment for the first and channel 10 in the extensor side of the forearm for the second. These channels are shown in Fig. 2.

Two classification schemes were used in this study. The first classification scheme consisted of FE performed by Time Domain-Auto Regression (TD-AR) features. PCA was used for dimensionality reduction for both schemes [12]. Hargrove et al. [15] showed that TDAR features achieved the highest performance for their experiment. TDAR features consisted of 6th-order AR models, root mean square value, zero crossings, integral absolute value and slope sign changes. For the second scheme, EMD was used to extract the features from a single EMG channel. The analysis window was 256 ms for both schemes with 64ms window overlap.

The number of extracted IMFs was different for each subject (19-22 IMFs). Then, mean and variance which are simple and easy to compute were taken for each IMF to create the feature vector after the EMD analysis.

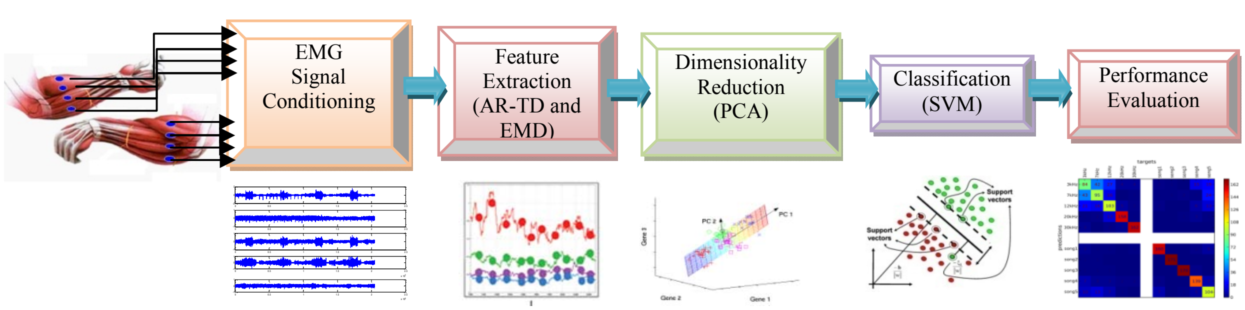

Figure 1. Block digram of the propsed myoelectric classifcation schemes

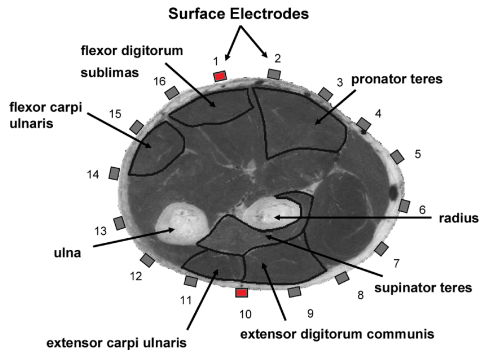

Fig. 2. Surface electrodes locations on a cross-section of the upper forearm.

SVM [16] classifier was used for both classification schemes since it works well in high dimensional spaces. A model is produced which predicts the target values of the unseen data given only the unseen data attributes by searching for a hyper-plane with the largest margin to classify different data sets. Half of the data was used to train the SVM classifier while the other half was used for testing.

IV. Results and Discussion

Fig. 3 displays the classification rate of channel 1 (flexor compartment of the forearm) for all subjects for classification schemes 1 and 2, while Fig. 4 shows the same results as in Fig. 3 of both classification schemes for channel 10 (extensor compartment of the forearm). From Fig. 3 and Fig. 4, it can be clearly seen that using the EMD for FE improves the classification accuracy for both flexor and extensor single-channel EMG over using AR-TD features with the same classifier. This represents relative improvements of 11.2% (from 83.7% to 94.4%) for channel 1 and 13.02% (from 80.16% to 93.16%) for channel 10. Fig. 5 displays classification errors for channel 1 and 10 across 6 subjects for classification scheme1 and 2. Standard deviation of the inter-subject variability is shown with error bars. Additionally, table 1 shows the confusion matrix for the 10 movements of subject 2 using 256 ms data analysis windows for classification scheme 1 and 2 with PCA used for dimensionality reduction. The values in white (left columns show the classification accuracies for classification scheme 1 with AR-TD features while the accuracies in grey (right column) display the classification accuracies with EMD features. The accuracies for radial deviation and ulnar deviation were (67.5% and 71.9%) respectively with the use of AR-TD features. After using of EMD for feature extraction, the accuracies increased to 94.49% and 96.9% respectively. It is remarkable that EMD consistently improves the performance for single channel EMG for all hand and wrist movements. In addition, better classification accuracy was achieved with use of EMD features than the traditionally known TD-AR features.

These results suggest that it is possible to achieve high accuracy in the classification of hand and wrist movements with the recording of only one myoelectric channel. The application of the EMD to only one recording reduces the computational power needed to run the classification in comparison with applying this decomposition to all EMG electrodes. Additionally, the setting up of the electrodes for the prosthetic hand would be facilitated if only one channel was to be recorded. However, EMD is not suitable for real time processing of the EMG at the current time.

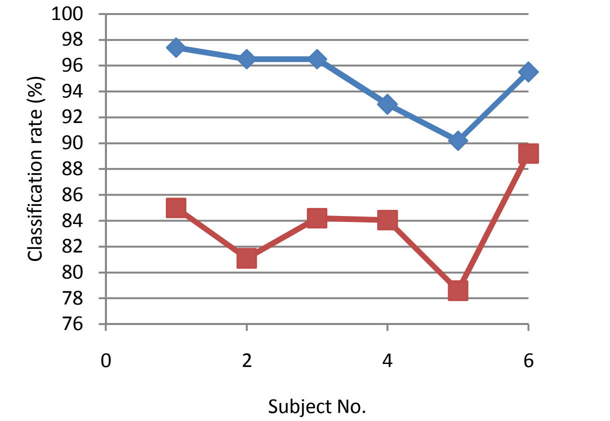

Fig. 3. Classification rate of all subjects for channel 1(flexor compartment) for classification scheme 1 (AR-TD features) and classification scheme 2 (EMD features)

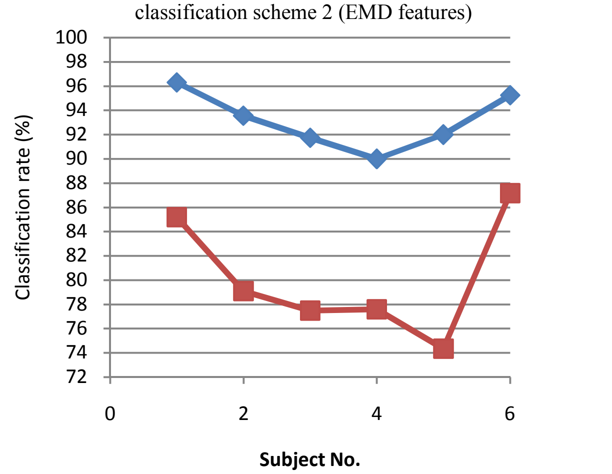

Fig. 4 Classification rate of all subjects for channel 10 (extensor compartment) for classification scheme 1 (AR-TD features) and classification scheme 2 (EMD features)

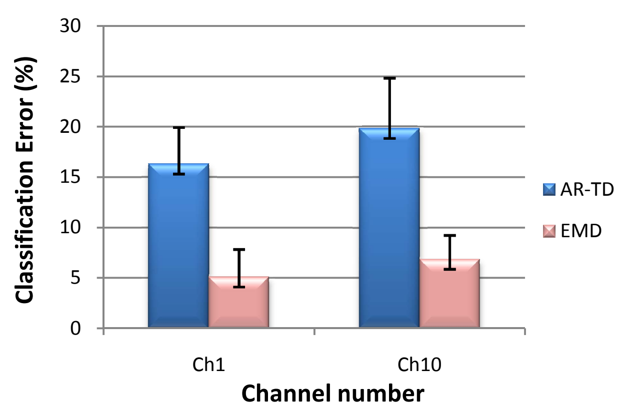

Fig. 5. Classification errors for channel 1 and 10 across 6 subjects for classification scheme 1 and 2. Standard deviation of the inter-subject variability is shown with error bars

V. CONCLUSION

The use of EMD for FE from single-channel EMG for myoelectric control was proposed. Two single channel EMG signals for ten hand movements were tested with two classification schemes with 256 ms window length. The classification schemes consisted of FE performed by Time Domain-Auto Regression (TD-AR) features (a commonly used approach in the Literature) for the first scheme and EMD for the second classification scheme with PCA for dimensionality reduction. SVM was used as a classifier for both schemes. The use of EMD for extraction of features from the single channel EMG increased the classification accuracy by 11.2 % for channel 1(from 83.7% to 94.4%) and 13.02% (from 80.16% to 93.16%) for channel 10. The results suggested that EMD consistently achieves higher performance across all subjects over the traditional TD-AR features. Additional data collection from more subjects to take into account the inter-subject variability on a large scale is being done to test them with EMD for pattern recognition based myoelectric control.

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Table 1. Confusion matrix in percentages for channel 1 of the second subject (AR-TD and EMD)

Output class

Predicted class	Pronation		Supination		Flexion		Extension		Radial dev		Ulnar dev.		Key		Chunk		Open		Rest	
Pronation	76.7	98.7	4.4	0	0	0	0	0	3.8	0	6.3	0	0.6	0	1.3	0	5.7	0	1.3	1.3
Supination	3.8	3.8	82.5	93.1	0.6	1.3	0.6	1.9	5	0	0	0	0.625	0	0	0	0	0	6.9	0
Flexion	0.6	0	1.9	1.3	90.6	97.5	0	0	0	0	0	0.6	2.5	0	4.4	0	0	0	0	0.6
Extension	0	0	0.6	0	0.6	0.6	98.8	99.4	0	0	0	0	0	0	0	0	0	0	0	0
Radial dev.	5	0	4.4	0	3.1	0	1.9	3.75	67.5	94.4	7.5	1.9	0	0	2.5	0	3.75	0	4.4	0
Ulnar dev.	3.8	0	0	0	0.7	0	0	0	13.1	3.1	71.9	96.9	0	0	2.5	0	8.1	0	0	0
Key	0	0	0	0	5	0	0	0	0	0	1.25	1.2	92.5	98.1	0.6	0.6	0.6	0	0	0
Chunk	1.25	0	0	0	8.1	0	0	0	3.8	0	5.6	0	0.6	1.3	79.4	98.8	1.25	0	0	0
Open	6.3	0	1.9	0	0	0	0	0	7.5	0	5.625	0	0	0	5.6	1.3	73.1	98.8	0	0
Rest	1.3	0	11.3	0	0	0	0.6	10.7	5.7	0	1.9	0	0	0	0	0	1.9	0.6	77.4	88.7