Myoelectric Feature Extraction Using Temporal-Spatial Descriptors for Multifunction Prosthetic Hand Control

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***Abstract*— We tackle the challenging problem of myoelectric prosthesis control with an improved feature extraction algorithm. The proposed algorithm correlates a set of spectral moments and their nonlinearly mapped version across the temporal and spatial domains to form accurate descriptors of muscular activity. The main processing step involves the extraction of the Electromyogram (EMG) signal power spectrum characteristics directly from the time-domain for each analysis window, a step to preserves the computational power required for the construction of spectral features. The subsequent analyses involve computing 1) the correlation between the time-domain descriptors extracted from each analysis window and a nonlinearly mapped version of it across the same EMG channel; representing the temporal evolution of the EMG signals, and 2) the correlation between the descriptors extracted from differences of all possible combinations of channels' and a nonlinearly mapped version of them, focusing on how the EMG signals from different channels correlates with each other. The proposed Temporal-Spatial Descriptors (TSDs) are validated on EMG data collected from six transradial amputees performing 11 classes of finger movements. Classification results showed significant reductions (at least 8%) in classification error rates compared to other methods.**

I. Introduction

Myoelectric control employs Electromyogram (EMG) signals that are collected from the muscles in the residual limb to control the degrees of freedom of powered prosthetic devices worn by amputees [1]. In such a control scheme, pattern classification algorithms are usually employed to extract a representative and repeatable set of features of muscular activation, from each analysis window of the EMG data, upon which the various tasks are discriminated [1, 2]. Previous research has shown that the success of the EMG pattern recognition system mainly depends on the quality of the extracted features, as they are of direct impact on clinical acceptance [3].

A number of feature extraction methods were utilized in the literature, these include the mean absolute value (MAV), waveform length (WL), sloop sign changes (SSC), and number of zero crossings (ZC) [4]; fast Fourier transform (FFT) [5], wavelets and wavelet packet transform (WPT) [6, 7]; cepstral coefficients (CC), Willison amplitude (WAMP) [3]; sample entropy (ENT) [8]; and the autoregressive (AR) model parameters [9]. Phinyomark et al. compared 50 feature extraction methods for EMG pattern recognition [10]. It was found that a combination of AR coefficients and time domain features with sample entropy presented the most stable feature set. Nonetheless, despite these advancements, there are still considerable challenges in applying research outcomes to a clinically viable implementation [11]. This is partially due to a big gap between academia and industry, which limits the clinical implementation for amputees' use. Such a gap is attributed to several factors including: lack of intuitive control, poor system reliability and the lack of robustness against practical problems like limb position change, electrodes shift, varying force levels, and signal non-stationarity. Recently, the extraction of features from the first and second derivative of EMG signal was shown to produce powerful features in EMG classification [12], with results suggesting that these feature can significantly outperform several well-known features in problems with changing limb position [13], varying contraction force levels and varying forearm orientations [14].

In this paper, we extend upon our recent work in this direction [12] by adopting an approach in which we, not only extract the features from the current analysis windows of each of the individual channels, but also utilize the differences between all channel pair combinations and their nonlinear mappings. In such a case, the extracted features not only look at the temporal evolution of the EMG patterns from each EMG channel but also at the spatial relation between the power spectrum activity of the different EMG channels.

II. Methodology

A. Signal Time-Domain Descriptors (TDD)

The block diagram of the TDD features is shown in Fig.1, with a full description provided in [12]. Assume a sampled version of the EMG signal denoted as $x[j]$, with $j=1,2,\ldots N$, of length N and a sampling frequency f_s. The EMG trace within a certain epoch can be expressed as a function of frequency $X[k]$ by means of Discrete Fourier transform (DFT). The derivations of the proposed method are based on Parseval's theorem, which states that the sum of the square of the function is equal to the sum of the square of its transform.

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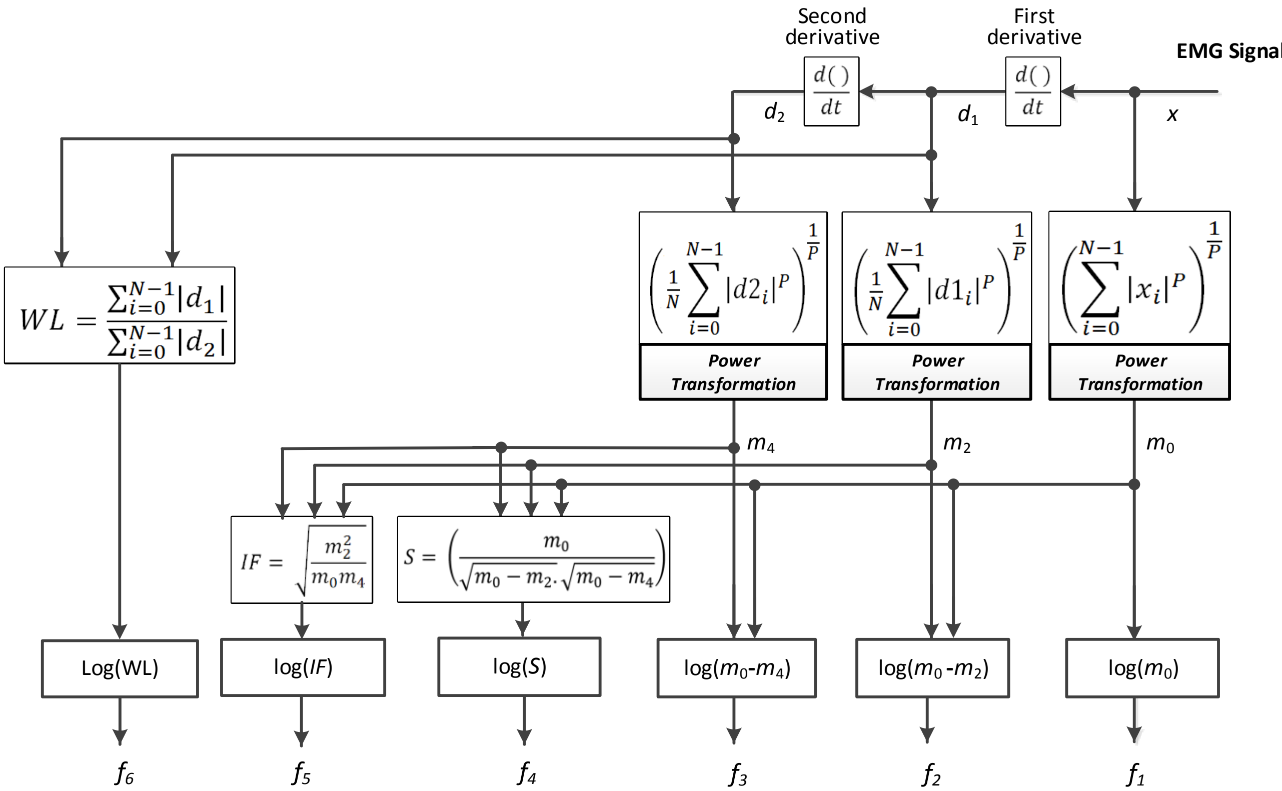

Figure 1. Block diagram for the derivation of the time-domain descriptors (TDD) feature extraction process.

$$\sum_{j=0}^{N-1}|x[j]|^2 = \frac{1}{N}\sum_{k=0}^{N-1}|X[k]X^*[k]| = \sum_{k=0}^{N-1}P[k] \qquad (1)$$

where $P[k]$ is the phase-excluded power spectrum, i.e., the result of a multiplication of $X[k]$ by its conjugate $X^*[k]$ divided by N, while k is the frequency index. Thus, the first feature is simply a representative of the signal energy.

$$\bar{m}_0 = \sqrt{\sum_{j=0}^{N-1} x[j]^2} \qquad (2)$$

The second and third features are based on the calculation of spectral moments. These were derived from the time-domain signal based on the time-differentiation property of the Fourier transform. This property simply states that the n^{th} derivative of a function in the time-domain, denoted as Δ^n for discrete time signals, is equivalent to multiplying the spectrum by k raised to the n^{th} power

$$F\left[\Delta^n x[j]\right] = k^n X[k] \qquad (3)$$

Therefore, the second and fourth moments are defined as

$$\bar{m}_2 = \sqrt{\sum_{k=0}^{N-1} k^2 P[k]} = \sqrt{\frac{1}{N}\sum_{k=0}^{N-1}(kX[k])^2} = \sqrt{\frac{1}{N}\sum_{j=0}^{N-1}(\Delta x[j])^2} \qquad (4)$$

$$\bar{m}_4 = \sqrt{\sum_{k=0}^{N-1} k^4 P[k]} = \sqrt{\frac{1}{N}\sum_{j=0}^{N-1}(\Delta^2 x[j])^2} \qquad (5)$$

In this case, taking the 1st and 2nd derivatives of the signal reduce the total energy of the signal; hence, we square the signals before applying the derivatives and apply a power transformation to normalize the range of m_0, m_2, and m_4 and to reduce the effect of noise on all moment based features as follows

$$m_0 = \frac{\bar{m}_0^{\lambda}}{\lambda}, \quad m_2 = \frac{\bar{m}_2^{\lambda}}{\lambda}, \quad m_4 = \frac{\bar{m}_4^{\lambda}}{\lambda} \qquad (6)$$

With λ empirically set to 0.1. Once m_0, m_2, and m_4 are calculated, the remaining features f_2 to f_6 can be easily calculated as shown in Fig.1. Simply speaking, f_1, f_2, and f_3 are normalized versions of the power spectrum moments, f_4 is a measure of sparsity, f_5 is a measure of irregularity of the signal and f_6 is a measure of the waveform length ratios. Further details about these features are in our original article [12]. In the remaining analyses, we denote the process of extracting the six features in Fig. 1 as TDD, as we use this as a basic building block upon which the rest of the analyses depend on.

B. Temporal-Spatial Correlation Features

According to the schematic of the proposed temporal-spatial descriptors (TSD) in Fig. 2, we first extract the TDD features to represent window i of channel C_x and form a vector denoted as $\mathbf{a}_{xi}$ = [a1, a2, a3, a4, a5, a6]. An additional feature vector, denoted as $\mathbf{b}_{xi}$ = [b1, b2, b3, b4, b5, b6] is then extracted from a logarithmically scaled version of the same window $\log(C_{xi}^2)$ to end up with two feature vectors: $\mathbf{a}_{xi}$ (from the EMG record) and $\mathbf{b}_{xi}$ (from a nonlinearly scaled version of the EMG record), each made up of 6 elements.

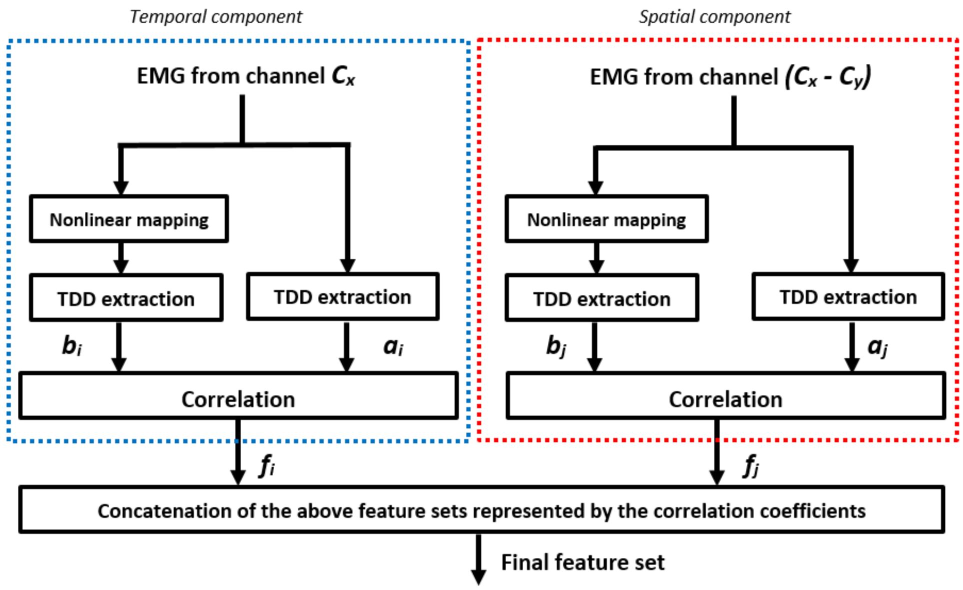

Figure 2. Block diagram of the proposed TSD feature set, which is made of a temporal component correlating TDD features extracted from each channel with those extracted from a nonlinear/smoothed version of it, and a spatial component correlating the TDD parameters from each possible channels' difference with those extracted from a nonlinear version of it.

The first part of the final feature set is obtained by calculating the element wise similarity between $\boldsymbol{a}_{xi}$ and $\boldsymbol{b}_{xi}$, i.e., made of 6 features per each EMG channel. This is achieved by calculating the cosine similarity of the two vectors given by

$$f_i = \frac{-2\, a_i b_i}{{a_i}^2 + {b_i}^2}, \qquad i = 1,2,3, \dots 6 \tag{7}$$

In a similar way, we also extracted the similarity features between the 6 TDD features from each possible difference of channels C_{xi} - C_{yi} and those extracted from a nonlinear version of them, forming the second part of the final feature set. Therefore, we focus on the temporal evolution of the EMG characteristics from each channel by using a sliding window approach as well as on how the TDD from different channels relate to each other.

C. Data Collection

The EMG signals were originally used in [15], with 11 surface EMG sensors sampled at 2000 Hz with a custom-built data acquisition system (NI USB 6210, National Instruments, USA) with 16-bit resolution. A Virtual Instrument (VI) was developed in LABVIEW (National Instruments, USA) to display and store the EMG signals. The data from six transradial amputees (TR1 to TR6) persons were collected at the artificial limbs and rehabilitation center in Baghdad and Babylon. Eleven classes of finger movements were carried out by each amputee, including: little flexion (f1), ring flexion (f2), middle flexion (f3), index flexion (f4), rest position, little extension (e1), ring extension (e2), middle extension (e3), index extension (e4), thumb flexion (f5), and thumb extension (e5). During the recording of the EMG signals, each participant sat on a chair in front of a computer with the Labview interface screen to view all the EMG sensors in real-time, while imagining the movements. Six trails of each movement were conducted. Ethical approval was obtained from the Human Ethics Committee of the Faculty of Science and Technology at Plymouth University. All Subjects gave their written informed consent to participate in the study.

D. EMG Pattern Recognition Analysis

In the experiments, an overlapping windowing scheme was utilized to extract the proposed features, with an analysis window size of 150ms and an increment of 75ms. MATLAB® 2015b software (Mathworks, USA) was used to perform the analyses. To evaluate the performance of the proposed feature set, denoted as Temporal-Spatial Descriptors (TSD), we compare the achieved classification performance against the classification performance of some well-known EMG feature extraction methods from the literature. These include: a combination of Autoregressive model parameters (5th order) with signal root mean square denoted as AR-RMS [16]; the combination of MAV, ZC, SSC, WL denoted as TD feature set [4]; the same combination with the WAMP features denoted as TD1 feature set; and the wavelet features extraction method, utilizing the mean of the squared wavelet coefficients at each level as features, with Symmlet family of wavelets and 5 decomposition levels, denoted as Wavelet; and our original TDPSD feature extraction method [12]. The dimensionality of all of the extracted feature sets was reduced using the Spectral Regression (SR) dimensionality reduction method proposed by Cai et al. [17]. SR maps the original feature set into a new domain with c−1 features only, with c being the number of classes, i.e., 10 features in this problem. Finally, in terms of classification accuracy, we have utilized a Linear Discriminant Analysis (LDA) classifier with quadratic function as well as the *k*-Nearest Neighbour (*k*NN) classifier, with k=1, which was chosen empirically. In all analyses, features extracted from the first trial of each hand movement were assigned to the training set, while features extracted from the remaining trials were assigned to the testing set. This would in turn make the classification task more challenging for any feature extraction method due to the small size of the training feature set.

III. RESULTS AND DISCUSSION

The average classification error rates across all of the six amputees are shown in Fig. 3 for all of the utilized feature extraction methods across the two classifiers of LDA and *k*NN. These results clearly depict few important points, the first is that the error rates achieved by the proposed TSD feature extraction method were much lower than that achieved by all other methods across both classifiers. An analysis of variance tests with a significance level of 0.05 revealed significant differences between TSD and the remaining methods (p-value<0.01 for all tests). Secondly, there were no significant differences between the performances of the two different classifiers for the different feature extraction methods. This is an important property, which reflects the fact that the extracted features were robust against the change of the classifier.

Finally, it is important to mention here that TDPSD which we presented earlier in [12] is only focusing on the temporal part of the feature extraction and that it does not look at the relation between the EMG signals from the different channels. In comparison to TDPSD, and all other feature extraction methods, our new TSD method also looks at how the EMG power spectrum characteristics of the different channels change across the different movement and was therefore more capable of further reducing the classification error rates. This in turn proves our main point of extending the feature extraction process to look at the temporal and spatial evolution of the EMG signals from different channels when performing different hand movements.

IV. CONCLUSION

A new feature extraction method for EMG pattern recognition was presented based on time domain descriptors that utilized spatial and temporal correlations. The method proposed to extract a set of features that are equivalent to the power spectrum moments directly from the time-domain by utilizing Fourier relations and Parseval's theorem. In the proposed method, the TSD descriptors were extracted from each analysis window and a nonlinearly mapped version of it along each channel to reflect the temporal component and then along differences of the various channel combinations to reflect the spatial component. The resulting algorithm gave significant reductions in classification error rates on various EMG datasets collected from six transradial amputee subjects. Our results revealed that there were no significant differences between the error rates achieved by using the classifiers of LDA and *k*NN.

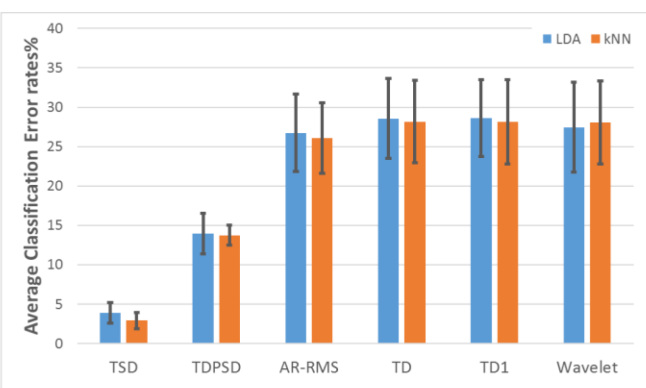

Figure 3. Average classification error rates across all amputees, with bars representing standard deviation.

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