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EMG Spectral Analysis for Prosthetic Finger Control

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***Abstract*—Electromyography monitoring is an effective method for prosthetic limb movement control. However, existing algorithms do not offer satisfactory accuracies. In this paper, we propose an accurate method to extract features from EMG that can be used in prosthetic finger movement control. The proposed algorithm estimates power spectral density of EMG signal using an autoregressive model to extract features. The key advantage of our method is in reducing the dimensionality of EMG signal and capturing its frequency content simultaneously. The proposed method has achieved above 89% accuracy in classifying ten finger movements archived in a public database.**

***Index Terms*—Autoregressive Process, Surface Electromyography, Finger Movement, Prosthetic Control, Spectral Analysis**

I. Introduction

A. Motivation and Prior Work

In recent years, there has been an increasing interest for Electromyography (EMG) monitoring and the corresponding applications. This interest is not only for medical abnormality detection, but also is related to the control of prosthesis [1]. Specifically, finding the EMG pattern of different finger activities among upper-arm amputee has received a great deal of attention in recent years.

Researchers have utilized EMG measurements to recognize pattern of finger activity using time-domain features [2]. However, these time-dependent features are too sensitive toward sensor position variation. Spectral-domain characteristics of EMG signals are used as features to study prosthetic finger control in [3]. Authors improved the robustness of finger activity recognition by addressing the problem of variable force level variation among amputees [4]. Prosthesis finger control is performed on both individual [5] and combined [6] finger movements using surface EMG. Authors in [6] used two EMG electrodes mounted on the forearm to record the EMG data from eight subjects. They extracted a large set of features from EMG signals including: slope sign change, number of zero crossing, waveform length, Hjorth time domain parameters, sample skewness, and autoregressive model. Next, they performed Linear Discriminant Analysis (LDA) to reduce dimensionality of the feature space. Finally, a Bayesian data fusion approach was used to improve classification accuracy of different movements.

Autoregressive (AR) models have been employed in field of EMG signal processing and pattern recognition. In [7], authors used autoregressive signal features and LDA classifier to investigate EMG signals corresponding to different fingers' movement using five integrated EMG electrodes. High density EMG pattern of twelve hemiparetic stroke subjects were investigated using autoregressive features in order to improve stroke rehabilitation [8]. Another method used multichannel (12 electrodes) surface EMG for SVM-based finger movement classification using autoregressive and time domain features [9]. Two pairs of electrodes were employed to record EMG signals for activating prosthetic arm using autoregressive and spectral domain features among four healthy subjects [10]. Another technique, proposed in [11] used both time-domain and autoregressive features of intrinsic and extrinsic hand muscle EMG signals to distinguish different finger movements among both partial-hand amputee and non-amputee subjects. Authors used Artificial Neural Network (ANN) for finger movement identification using EMG signals for five finger movements [12] [13].

B. Main Contribution

We propose a modified autoregressive model for feature extraction for prosthetic finger control using surface electromyography. For this purpose, we use the established mathematical framework for studying random processes and spectral analysis for studying surface EMG. The proposed technique uses parametric power spectral density estimation to extract features from surface EMG. These features reduce the dimension of EMG signal but preserve the key information to achieve accurate classification of finger movements. The experimental results verify that our proposed methodology achieves a higher classification accuracy compared to similar techniques.

In our work, an autoregressive model is employed for power spectrum estimation of EMG signal over a window of time. Although AR was previously used to develop model-based prosthetic finger control system [7], we use it in a new context for feature extraction. More specifically, our features are the reflection coefficients of the autoregressive model. These coefficients are used as features for classification of time series EMG data. One advantage of our methodology is in its performance (faster run time due to efficiency of the AR model) that makes it suitable for real-time applications such as prosthetic finger control.

II. Spectral analysis

A. Spectrum Estimation - Background

It is shown that various finger movements affect different properties of EMG signal. Spectral analysis can serve as a

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mechanism for capturing these changes. We can consider EMG signal as a random process. Mathematically, Fourier series of a random process cannot be found using the conventional mathematical models [14]. So, we use autocorrelation model of the random process in order to calculate the spectral characteristics of the process. This model is in general represented as $R(m) = E[V(n)V(n+m)]$ for a real discrete wide-sense stationary process $V(n)$, where $E[\cdot]$ defines the expectation operator and m defines the lag variable. Note that $R(m)$ is not considered as a random function. It correlates the values of the random process at a specific lag of m. We apply Fourier transform on $R(m)$, i.e $P(f) = \mathscr{F}\{R(m)\}$, in order to extract spectral characteristics of the process. $P(f)$ indicates the energy distribution of a process over the entire frequency band which is known as *Power Spectral Density* (PSD). Calculating the inverse Fourier for $m = 0$ shows that $\sigma_V^2 = R(0) = \int_{-\frac{1}{2}}^{\frac{1}{2}} P(f)df$, where σ_V^2 is the variance of $V(n)$. Briefly, PSD indicates the effect of each frequency element in the total variance of the process.

Practically, $R(m)$ is not known and we need to estimate the value of $P(f)$. Usually, there are two methods to estimate the PSD: non-parametric and parametric. Non-parametric methods use periodogram to estimate $P(f)$. Considering L training samples of a realization of a random process, the periodogram calculates the PSD as $P(f) = \frac{1}{L}\left|\sum_{n=1}^{L} V(n)e^{-2\pi jnf}\right|^2$. Generally, $P(f)$ is estimated by *Fast Fourier Transform* (FFT) over L equidistant points in the spectral domain. The main problem of the periodogram power estimation is that the estimation value provides a high variance, i.e. about the square of its expectation. Even increasing the number of samples (L) does not address the problem and just increases the resolution of the process in the spectral domain. Averaging approaches are used to enhance the variance of periodogram [15].

On the contrary, parametric methods consider the random process as a parametric model in the spectral domain. In this case, the estimation of PSD is equivalent estimation of the model's parameters. In our work, parametric PSD estimation is considered for extracting spectral domain features. In other words, the estimated spectrum can be represented using a set of parameters for the assumed model. We introduce an AR model for extracting spectral characteristics of EMG data. The AR model is fitted by Burg method, which takes advantage of high accuracy and fast computation compared to other proposed parametric PSD estimation methods [15]. The next sub-section represents Burg PSD estimation.

B. Parametric PSD - Reflection Coefficients

An *autoregressive* (AR) model of a stationary random process $V(n)$ is calculated as [14]:

$$V(n) = -\sum_{i=1}^{p} a_i V(n-i) + \epsilon(n) \tag{1}$$

where $\epsilon[n]$ is a zero mean white noise process with variance of σ_ϵ^2, a_is define model parameters and p is the model order. The PSD is then extracted as:

$$P(f) = \frac{\sigma_\epsilon^2}{|A(f)|^2} \tag{2}$$

where $A(f) = 1 + \sum_{i=1}^{p} a_i e^{(-2\pi j)if}$ is calculated by simplifying Eqn. 1. In order to tune the model parameters (a_is), different methods are introduced [15]. In Burg method, Eqn. 1 is represented as:

$$\epsilon(n) = \sum_{i=0}^{p} a_i V(n-i) \tag{3}$$

where $a_0 = 1$. Eqn. 3 shows a *Finite Impulse Response* (FIR) filter. One possible method for realizing a digital FIR filter is the lattice structure in which a p-order filter is realized as p cascaded first-order lattice components. This structure can be represented as:

$$\begin{cases} f_i(n) = f_{i-1}(n) + k_i b_{i-1}(n-1) \\ b_i(n) = b_{i-1}(n) + k_i f_{i-1}(n-1) \end{cases} \tag{4}$$

where k_i is a scalar namely the *reflection coefficient* at the i^{th} stage. $f_i(n)$ and $b_i(n)$ are called *forward* and *backward* prediction errors at the i^{th} stage, respectively. A p-order filter is implemented by cascading p building components. The input to the first stage is the input (e.g. EMG) signal, $f_0(n) = b_0(n) = V(n)$ and the output of the final stage is the filter's output, $f_p(n) = \epsilon(n)$. In cases that coefficients of the AR model (a_i) are known, k_is values are calculated straightforwardly [15]. However, in the PSD estimation problem, they are unknown. Burg introduced an approach for parameter estimation of the AR process based on optimization of the forward and backward prediction errors [16].

The model order (p) is also unknown in Eqn. 1. The key challenge is selecting the right value for p. The reason is that an extremely low-order model cannot obtain spectrum's peaks and a large-order will be highly sensitive to noise and represents spurious peaks in the spectrum. In our work, the Final Prediction Error (FPE) criteria is used for model order selection [14]. Finally, by finding the order of the model, the vector of reflection coefficients are obtained as $\boldsymbol{k} = [k_1, k_2, \cdots, k_p]^t$. Historically, $\boldsymbol{k}$ is used for evaluating statistical hypothesis corresponding to the AR model [14]. In our work, vector $\boldsymbol{k}$ is used for feature extraction which is a new context and application. Vector $\boldsymbol{k}$ has unique properties that make it an excellent source to extract features for EMG signal.

III. Finger-Control Methodology

Figure 1 shows the overview of our proposed approach. Two pairs of electrodes were employed to record EMG signals. Each finger movement changes the frequency contents of the EMG signals in a unique way. In this work, spectral analysis for feature extraction is employed to distinguish them. However, EMG signals are non-stationary and the spectral analysis method reviewed in Section II is valid only if we

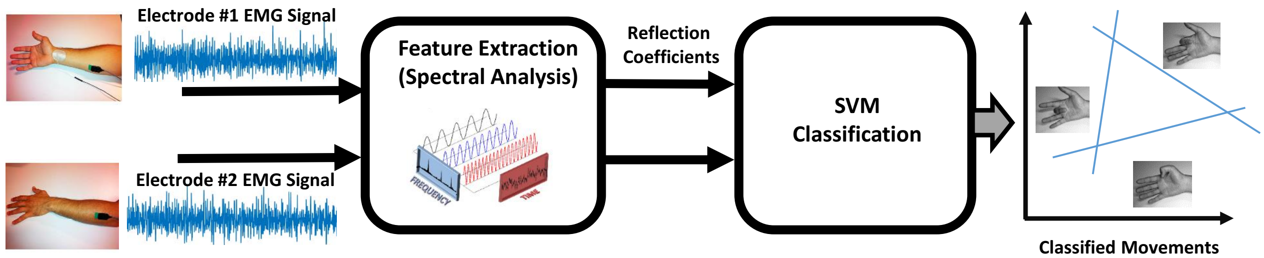

Fig. 1. The overall view of our proposed model.

assume EMG is a stationary process. To tackle this issue, spectral analysis is used only over short windows of the EMG signal for which the assumption of stationarity is proven to be valid [17]. This window length needs to be selected short enough to meet the stationarity assumption. On the other hand, a very short window increases the variance of estimating reflection coefficients. By sliding this window over time, we can monitor any changes in PSD of EMG signal. In this work, we have empirically selected window sizes in range of 150 to 500 ms.

We used a *Support Vector Machine* (SVM) for validation. i.e. classification. A binary SVM classifies data points by finding the best hyperplane that separates all data points of one group from others [18]. Extension of binary classifier to a multi-class classifier is reported using several techniques. We used *Error Correcting Output Codes* technique for this purpose [19].

IV. Experimental Results

A. EMG Dataset

The proposed method is applied to a surface EMG dataset provided by Center of Intelligent Mechatronic Systems at the University of Technology at Sydney [6]. Data is recorded at 4000 Hz for eight normally limbed subjects (6 males and 2 females) performing different finger movements using two EMG channels. A conductive adhesive electrode is attached to the wrist of each subject as a reference point. Ten categories of finger movements are performed including five individuals and five combined movements. The individual finger movements contain flexion of each of thumb, index, middle, ring, and little fingers. The combined finger movements contain pinching of Thumb-Index, Thumb-Middle, Thumb-Ring, Thumb-Little fingers, and hand-close. The total duration of contraction from rest and holding each finger posture is 5 seconds. Figure 2 (from [6]) shows the ten different finger movement. Each movement is performed in 6 trials. We used the first four trials as training data and the last two trials as test data.

B. Discussion

Our approach is able to classify all ten finger movements using a single classifier in contrast with other works that only trained the classifiers using only five finger movements. The overall methodology estimates the PSD of EMG signals from two channels over various size sliding windows using the AR model. The parameters of these models are estimated using Burg technique [16]. We use the reflection coefficients as feature vector. Then, a SVM multi-class classifier groups different finger movements among all the subjects.

For testing the proposed algorithm, the sliding window length varies from 600 to 2000 samples (150 ms to 500 ms). The overlap percentage is selected in range of 10% to 50%. In order to evaluate the performance of the proposed approach, we divided the data into 6 parts. We used 4 parts as training and used 2 parts for testing as other works reported in literature [6]. Table I tabulates the average classification accuracy among all subjects and classes for different window size and overlap percentages. The average accuracy of the classifier improves by increasing the window size. However, a too large window sizes makes the technique less practical for real-time applications. Our observations in Table I indicate that windows sizes with duration longer than 300 ms will slightly (about 1%) improve the accuracy. So, in this work, we have selected 300 ms as the size of the window. In order to show the effectiveness of our method, we compared our approach with similar works reported in the literature [6][12][13]. The comparison results are summarized in Table II.

Authors in [6] extracted Time Domain (TD) features plus AR and Hjorth features of EMG signals and used the KNN and SVM classifiers to identify ten finger movements. They employed a fusion technique for majority voting among different classifiers. Reference [12] used the AR and Root Mean Square (RMS) of amplitude of EMG samples as features. They ran an ANN classifier to identify finger movements in two separate groups of five movements. Authors in [13] extracted TD, Hjorth and RMS features from EMG signals and performed an ANN model to distinguish only five finger movements. Compared to approaches proposed in [12] and [13], our technique is able to identify five more movements with a very competitive accuracy performance. As Table IIshows, compared to other approaches, our technique provides a very competitive accuracy. More importantly, our technique is expected to do better for real-time applications as it outperforms others in terms of computational complexity. This is because we did not use any additional mechanism such as voting, dimension reduction or fusion.

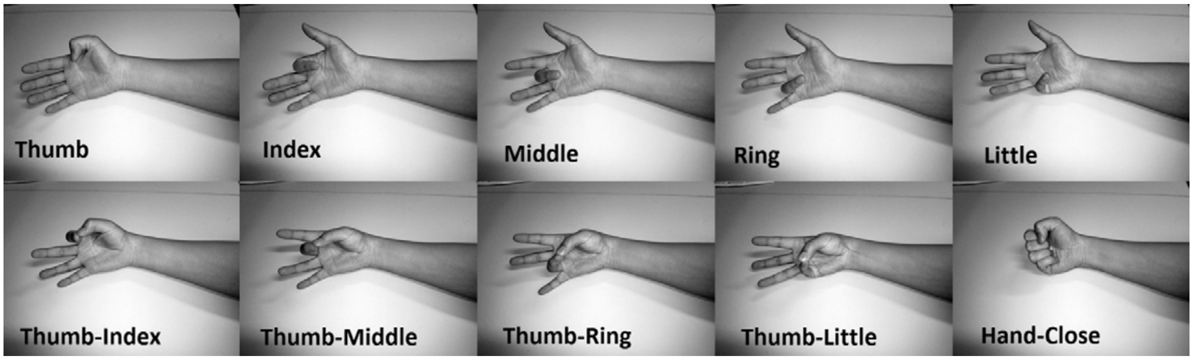

Fig. 2. Different finger movements: Top row: individual fingers; Bottom row: combined fingers (from [6]).

TABLE I
AVERAGE CLASSIFICATION ACCURACY (%) FOR DIFFERENT WINDOW SIZES AND OVERLAPS.

Window Size		Window Overlap				
# of samples	Time (ms)	10%	20%	30%	40%	50%
600	150	84.1	84.5	85.0	83.9	84.8
700	175	85.2	84.6	86.3	85.3	85.2
800	200	85.6	85.7	86.9	86.4	86.1
900	225	86.7	85.2	86.1	86.2	87.1
1000	250	86.6	87.3	87.2	88.5	87.7
1100	275	86.4	88.6	88.2	87.3	88.7
1200	300	88.4	87.5	88.2	88.5	89.0
1300	325	89.2	88.5	89.0	87.8	89.2
1400	350	88.3	88.2	87.7	89.3	89.5
1500	375	88.3	89.3	88.0	87.8	88.5
1600	400	88.8	88.5	90.4	88.7	89.4
1700	425	90.2	88.8	90.0	89.6	90.0
1800	450	89.5	89.6	89.2	89.0	89.5
1900	475	89.5	89.8	80.0	89.5	90.2
2000	500	89.2	88.5	89.5	89.2	90.2

TABLE II
COMPARING VARIOUS METHODS FOR THE SAME EMG DATABASE.

Approaches	Features	Classification	Window Size	# Classes	Avg. Accuracy [%]
[6]	TD+AR+Hjorth	KNN-SVM+Fusion	50-150 ms	10	90.0
[12]	AR + RMS	ANN+NMF	256 ms	5	92.0
[13]	TD+Hjorth+RMS	ANN	NA	5	96.7
Ours	Reflection Coefficients	SVM	300 ms	10	89.0

V. CONCLUSION

EMG analysis is a popular method for prosthetic finger movement control. We propose a new method for classifying different finger movements. This approach reduces the dimensionality of the EMG signal and simultaneously captures its frequency properties. The experimental results are promising showing 89% accuracy for 10 classes among 8 subjects. Overall, the proposed method provides competitive accuracy with much less computational complexity and thus suitable for real-time applications such as prosthetic finger control.

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