EMG ACQUISITION AND HAND POSE CLASSIFICATION FOR BIONIC HANDS FROM RANDOMLY-PLACED SENSORS

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ABSTRACT

This paper presents a unique real-time motion recognition system for Electromyographic (EMG) signal acquisition and classification. It is the first approach which can classify hand poses from multi-channel EMG signals gathered from randomly placed arm sensors as accurately as current placed-sensor EMG acquisition approaches. It combines time-domain feature extraction, Linear Discriminant Analysis (LDA) feature projection and Multilayer Perceptron (MLP) classification to allow nine distinct poses to be correctly identified more than 95% of the time. This is comparable to state-of-the-art placed-sensor EMG acquisition systems. Processing times of 11.70 ms also make this a viable candidate approach for real-time EMG acquisition and processing in practical prosthesis applications.

Index Terms— Electromyographic (EMG), time-domain features, pattern recognition, linear discriminant analysis (LDA), multilayer perceptron (MLP).

1. INTRODUCTION

Electromyographic (EMG) sensing and classification is a popular method for the control of bionic hand units and a lot of research has studied techniques for discriminating between EMG signals to allow a variety of hand poses to be told apart [1–3]. This has led to a series of commercial and research products, such as the Ottobock [4], Becker [4], Steeper [4], and Sensor [4] hands and the open source underactuated robotic hand [4] which offer around nine degrees of freedom [4]. Whilst well short of the 27 degrees of freedom in the human hand, these still represent the state of the art in EMG-driven bionic hand technology.

These approaches all require skilled placement of sensors on the skin, over specific arm muscles [5]. This requires knowledge of muscle structure and expert handling for sensor placement, making these systems difficult to install. The signal processing approaches which translate the signals gathered from these sensors to movements of the hand are heavily reliant on this exact sensor placement over the muscles responsible for movement [6–9].

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Nowadays, commodity EMG acquisition systems which are easy to install and do not require any prior knowledge of sensor placement are becoming widely available [10]. These systems randomly place multiple sensors on the skin's surface. However, whilst some work has shown how this approach can enable highly primitive differentiation of poses [10] their capabilities are well short of those of placed-sensor systems [6–9].

This paper presents an EMG acquisition and classification approach which overcomes this shortcoming. Relying on commodity EMG acquisition hardware providing 8-channel EMG signals from randomly placed sensors, it shows how wrist flexion-extension, pronation-supination, ulnar flexion-radial flexion and hand open-close motions incorporating 4 degrees of freedom can be classified with 95.57% accuracy - comparable with the leading placed sensor approaches on record. It also enables classification in less than 12ms on a workstation PC, indicating it's potential to support real-time classification in practical prosthetic equipment.

Section 2 survey the state-of-the-art in EMG acquisition and classification techniques, before Section 3 presents our proposed approach for randomly-placed sensing setups, the performance of which is analysed in Section 4.

2. RELATED WORK

In recent years, researchers have studied differentiating between nine wrist-hand motions using a variety of different EMG acquisition and classification approaches [6–9, 11, 12]. These studies use a range of pattern-recognition techniques to evaluate feature vectors from EMG signals with feature projection and classification methods for discriminating distinct classes [9, 11, 12]. The approach in [6] uses the Delsys myoelectric system for EMG acquisition through placed sensors from four forearm muscles and classify the different wrist-hand motions. It uses Local Discriminant Basis (LDB) with Wavelet Packet Transform (WPT) for feature extraction along with Principal Component Analysis (PCA) and MLP for feature projection and classification. In [7], the Ottobock system is used for EMG acquisition from two forearm muscles using active placed sensors to classify three hand motions using 1D Local Binary Pattern (LBP) feature extrac-

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tion. The work in [8] uses four placed MyoScan EMG sensors over forearm muscles for EMG acquisition to classify four hand motions using the combination of time and frequency domain features with PCA and LDA for feature projection and classification. In [9], an array of eight passive electrodes are placed on the forearm, with time domain features provided to a Support Vector Machine (SVM) classifier for eight wrist-hand motions. The approach in [11] uses four placed passive electrodes on the upper forearm to extract EMG signals for eight wrist-hand motions with different time-domain features, PCA feature projection and LDA classification. This body of work shows that significant numbers of wrist-hand movements can be differentiation using a multi-channel placed-sensing approach. According to [4], time-frequency analysis using features derived from wavelet transforms, Wavelet Packet Transforms (WPTs) or fourier transforms are particularly promising. These produce feature vectors in high-dimensional space [4, 6, 13] with subsequent feature projection to classification. Generally, PCA and LDA have been used for efficient dimensionality reduction and projection in EMG signal analysis [9, 11]. For classification, Artificial Neural Network (ANN) [4], MLP [6], SVM [9] and LDA [11] has been used to enable the best results to date. However, none of these approaches have been studied when randomly-placed multi-channel EMG sensing is employed.

3. CONCEPT APPROACH

We aim to develop an EMG acquisition and classification approach for commodity multi-channel EMG sensing equipment employing randomly placed sensors whilst supporting classification of as many (nine) wrist-hand movements, as accurately as current placed-sensor systems. EMG sensing is enabled by the wireless Myo Armband, which employs active surface electrodes to measure the EMG signals from the muscles *viz.* extensor carpi ulnaris, extensor digitorum, extensor carpi radialis, extensor carpi longus, flexor carpi radialis, palmaris longus, pronator teres and flexor carpi ulnaris [14].

As described in Section 2, most current approaches [4, 6, 13] use time-frequency analysis of the EMG signals. This time-frequency approach is adopted because the EMG signals eminating from the muscles over which the sensors are placed is contained within different frequency bands, and distinguishable from each other at each sensor [14]. In the case of randomly placed sensors, this is not the case - here, all sensors produce composites of the signals produced by all muscles. Hence, frequency domain analysis is inappropriate in the random-sensing case. Instead, we use a time-domain approach, composed of:

1. Augmented 7^{th} order auto-regressive feature extraction
2. LDA-based supervised feature projection
3. An MLP classifier employing three hidden layers

The LDA-based feature projection and MLP classifier are respectively motivated by the observations on the effectiveness of these approaches in [11, 13] and [6]. The overall structure of our proposed simplified EMG hand motion recognition system is shown in Fig. 1.

3.1. EMG Acquisition

The Myo Armband has 8 active surface EMG sensors which measure the electric potential of the muscles as an effect of muscle activation while performing hand motion with a sampling frequency (*fs*) of 200 Hz per channel [10]. The placement of Myo armband dependent on subject's forearm size due to the minimum circumference of the Myo *i.e.* 19.05 cm [10]. Hence, we install the armband on the upper forearm so as to consider the maximum hand surface wherein the muscles are well sorted. In our work, we have considered all possible wrist-hand motions *viz.* opening and grasping of the fingers, flexion and extension of the wrist, pronation and supination of the wrist, radial and ulnar flexion of the wrist, and relaxation.

3.2. Feature Extraction

We have proposed the use of time domain analysis with auto-regression model for feature extraction since the acquired EMG signals are composite mixtures of EMG emissions by the muscles being used ref13. A single time domain feature is not enough to extract adequate information from the signal and identify the intended motion properly [13]. Hence, we use three classes of time-domain features - Integrated EMG (IEMG), log root mean square, Kurtosis and 7^{th} order auto-regressive model features.

3.2.1. Integrated EMG

Integrated EMG is commonly used for onset detection index in EMG for measuring variation in muscle strength [13]. It is related to the EMG signal sequence firing point and is defined as a summation of absolute values of the EMG signal amplitude, which is expressed as,

$$IEMG = \sum_{t=1}^{N} \mid x\left[t\right] \mid \tag{1}$$

where $x\left[t\right]$ represents the EMG signal in the t^{th} time frame and N denotes total number of time frame of EMG signal.

3.2.2. Root Mean Square

The root mean square value is used to represent the non-fatiguing contraction levels of the muscle in each time analy-

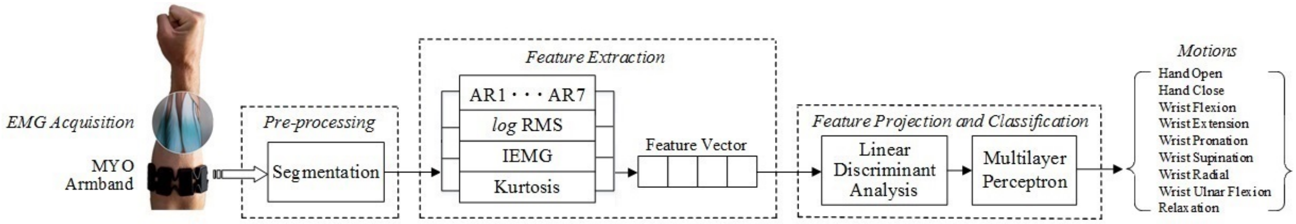

Fig. 1. Proposed EMG acquisition and motion recognition system

sis framework [13]. It is expressed as,

$$RMS = \sqrt{\frac{1}{N}\sum_{t=1}^{N} x\left[t\right]^2} \tag{2}$$

3.2.3. *Kurtosis*

Kurtosis is a measure of how outlier-prone distribution is. The distributions that are more outlier-prone than the normal distribution have kurtosis greater than 3, and those less outlier-prone have kurtosis less than 3 [15]. It is expressed as,

$$k = \frac{E\left[x-\mu\right]^4}{\sigma^4} \tag{3}$$

where μ is the mean of x, σ is the standard deviation of x, and $E[t]$ represents the expected value of the quantity t.

3.2.4. *Auto-Regressive Model*

An auto-regressive model, popularly used to represent random processes, describing each sample of the signal as a sum of linear combination of previous samples plus an error term representing the white noise [4]. It is expressed as:

$$A(t) = \sum_{p=1}^{P} a_p x\left[t-p\right] + w\left[t\right] \tag{4}$$

where $x\left[t\right]$ represents the EMG signal, a_p is each of AR coefficients, $w\left[t\right]$ is the white noise term and P is the order of the AR model (7 in our case). After fitting the auto-regressive model, the AR coefficients are used as part of our feature vector.

3.3. Feature Projection and Classification

Feature projection is an essential complement after feature extraction to remove dimensional redundancy in the features derived [6–8]. It also makes classification more reliable and efficient [11]. Mostly, LDA is used to determine the dimensionality of projected features in EMG signal analysis [6–8, 11]. LDA is a supervised feature projection technique which takes time-domain features and class labels as an input [11]. To calculate the optimal class separation, resulting in mapping the features into a lower-dimensional space [11, 16], it maximizes the between-class distance and concurrently minimizes the within-class distance which achieves maximum discrimination [11, 16]. By applying LDA to our pipeline, the extracted 10-dimensional time-domain feature vectors are projected into an 8-dimensional subspace where classification is potentially easier.

After the feature projection, the projected features are given to the input layer of MLP classifier. The MLP is configured with three hidden layers with forty-four neurons and the output layer has nine neurons, one for each of the nine hand motions to be recognised. The selection criterion was based on the convergence of the learning error from different combinations. The input of the MLP are the normalized value of the LDA output. Weights and bias were initialised before training from a uniform distribution with a mean and variance of 0 and 1, respectively. The learning process was stopped when the absolute rate of change in the average squared error per iteration was sufficiently small. In testing, the maximum output of the MLP was selected as the recognized motion for a given LDA feature vector.

4. EXPERIMENTAL RESULTS

To gauge the effectiveness of our proposed approach, experiments were conducted on ten normal subjects (seven males and three females, 26 ± 4 years) for EMG data recording. Twenty sessions of EMG recording were conducted from each subject. The first ten sessions were used for classifier training, with the remaining ten sessions used for testing. In every session, each motion was executed once for a duration of 5 sec, before the next, in a fixed order. To recognize a steady-state motion, a moving window scheme with increment window is applied. The increment window is determined based on considering the processing time of the pattern-recognition algorithm. Each window will produce a feature vector with a class label for the feature projection and classification. In our work, the length of the moving window is set to 250 msec with a 125 msec window increment, thus, allowing the proposed scheme to make two decisions within 300 msec.

The performance of the system is tested with the same 10 subjects and the extracted time-domain features then tested

Table 1. Classification results for different motions

Motion	Classification Accuracy (%)			
	Time-domain		Time-freq	
	LDA	PCA	LDA	PCA
Hand open	97.50	90.60	76.00	54.20
Hand close	97.70	43.40	80.50	41.60
Wrist flexion	97.60	38.50	77.30	38.90
Wrist extension	95.10	36.30	70.50	35.40
Wrist pronation	90.80	32.70	61.90	30.30
Wrist supination	94.90	47.50	72.40	36.50
Wrist ulnar flexion	91.30	36.80	64.70	32.60
Wrist radial flexion	96.80	48.10	75.10	37.80
Relaxation	98.40	78.90	76.80	65.90
Total	**95.57**	**50.31**	**72.80**	**41.47**

in the trained MLP classifier. Initially, the system performance is calculated considering only AR feature set (FS1) with LDA feature projection and MLP classifier which results in 90.48% average classification accuracy for 10 sessions of the test dataset. Further experiments, adding a single new time-domain feature are conducted, and the classification results are evaluated. FS2 comprise of AR and IEMG, FS3 of AR, IEMG and kurtosis, and FS4 including AR, IEMG, kurtosis and Log RMS features. The best classification result, for FS4, was found to be 95.57% . The classification accuracy for different feature sets is illustrated in Fig. 2.

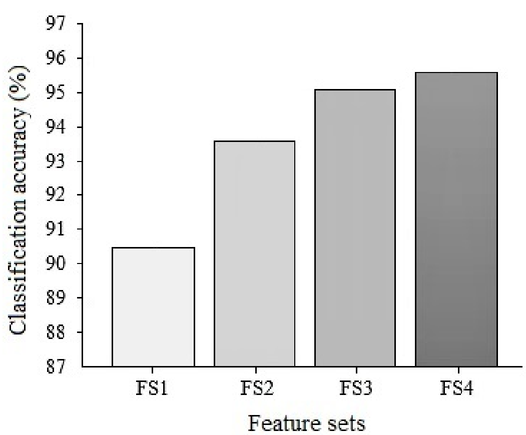

Fig. 2. Classification results of different feature sets

To verify the effectiveness of our choice of time-domain analysis (FS4), we compared the results with the leading time-frequency feature extraction method on record (WPT) [6, 17] considering both possible LDA and PCA feature projection with MLP classification technique. Table 1 presents the classification results for nine wrist-hand motions using time-domain and time-frequency features with LDA and PCA feature projection techniques keeping MLP feature classification constant.

The overall classification accuracy using our proposed time-domain approach with LDA is calculated as 95.57%. This compares very favourably with the leading placed-sensor approaches on record [6–9], which classify the same nine movements with accuracy between $92.50\% - 97.65\%$. When PCA is used in placed of LDA for feature projection, performance reduces to 50.31% on average, justifying the use of LDA. Similarly, when time-frequency features are employed, specifically WPT in this case, performance reduces to 72.80% in the case of LDA-based classification and 41.47% when PCA is used, justifying our approach of adopting time-domain analysis.

The experiments were executed in MATLAB R2016a platform on a 3.6 GHz Core i7 PC. Thus, to implement real-time pattern recognition system, the processing time should be less than the window increment, which is 125 ms in our case. Table 2 describes the average processing time taken by various feature analysis techniques in our pattern recognition system. Hence, it shows that the overall processing time of our pattern recognition system is 11.70 ms which is less then window increment time and thus, can be considered for real-time EMG system implementation.

Table 2. Processing time for pattern recognition system

Processes	Processing time (ms)
Feature extraction	6.20
Feature projection	2.60
Feature classification	2.10
Others	0.80
Total	**11.70**

5. CONCLUSION

In this paper, we have proposed a novel approach for EMG acquisition and feature extraction to detect active wrist-hand motions. The use of Myo Armband for EMG acquisition placed randomly on the forearm without any expert handling make the system wirelessly accessible and reduce the development cost to one tenth. The robust feature set is the combination of auto-regression and three set of time-domain feature coefficients. The MLP classifier with LDA feature projection was used to detect intended wrist-hand motion. From experiments of time-domain feature selection, it was shown that the classification result highly depends on selected feature set, in a manner that complements the system processing time. The proposed EMG pattern-recognition approach for different wrist-hand motions gives 95.57% classification accuracy which is an excellent compromise between computational performance and accuracy when compared with complex time-frequency approach. The overall processing time of system was calculated to be 11.70 ms in our prototype, making it possible to use in real time applications. Moreover, it has benefits of using simplified time-domain analysis making it conventional in real-time hardware implementation with high computational efficiency.

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