

# Surface Electromyography Feature Extraction Based on Wavelet Transform

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**Abstract:** Considering the vast variety of EMG signal applications such as rehabilitation of people suffering from some mobility limitations, scientists have done much research on EMG control system. In this regard, feature extraction of EMG signal has been highly valued as a significant technique to extract the desired information of EMG signal and remove unnecessary parts. In this study, Wavelet Transform (WT) has been applied as the main technique to extract Surface EMG (SEMG) features because WT is consistent with the nature of EMG as a non-stationary signal. Furthermore, two evaluation criteria, namely, RES index (the ratio of a Euclidean distance to a standard deviation) and scatter plot are recruited to investigate the efficiency of wavelet feature extraction. The results illustrated an improvement in class separability of hand movements in feature space. Accordingly, it has been shown that only the SEMG features extracted from first and second level of WT decomposition by second order of Daubechies family (db2) yielded the best class separability.

**Keywords:** Electromyography signal, EMG, feature extraction, wavelet transform, mean absolute value

## 1. Introduction

Electromyography (EMG) is a collective electrical signal acquired from muscles and includes valuable information about muscular contraction. The muscle activity is controlled by the nervous system which forms complicated properties for EMG because it is related to the anatomical and physiological characteristics of the muscles [1]. To collect EMG signal, two techniques are applied, namely, Surface Electromyography (SEMG) and needle Electromyography. Although both mentioned techniques result in EMG signal, SEMG is more popular than needle EMG since SEMG is a non-invasive technique and more convenient to use [2]. The EMG signal is applied to study skeletal muscle. The skeletal muscle tissue is attached to the bone and its contraction is responsible for supporting and moving the skeleton [3]. EMG signal has been used in various fields of study such as rehabilitation, ergonomics and sport science [4]. The SEMG has been recruited as an input to powered prosthesis control system too since it can provide a helpful and significant input to control powered prostheses. In this system, the controlled parameters of SEMG signals from a muscle or muscle group are applied to select and modulate a function of a multifunction prosthesis [5]. Accordingly, EMG analysis has fascinated many researchers and many techniques have been utilized to improve the EMG control system. Hence, the investigation of SEMG feature extraction recruiting

Wavelet Transform (WT) is presented in this paper. To reach this goal, Mean Absolute Value (MAV) of SEMG signal is designated as representative features and two evaluation criteria, namely, scatter plot and RES index [6] are determined to scrutinize the behavior of SEMG signal. As a result, an improvement of class separability in EMG feature space is obtained which leads to the increase of recognition accuracy.

The layout of this paper includes seven sections. Firstly, a brief review of EMG control system based on wavelet analysis is expressed in section two. Afterward, EMG signal acquisition is explained in section three and preprocessing stage, as an essential stage for EMG, is expressed in the fourth section. Next, feature extraction method of this study is introduced in section five. The results of this research are presented in section seven. And finally, a summary of this research is declared in seventh section.

## 2. EMG control system based on wavelet feature extraction

An EMG control system based on pattern recognition includes three significant stages, respectively, data segmentation, feature extraction and classification [7]. Therefore, feature extraction plays an important role in increasing the classification accuracy because even the best classifiers cannot perform well if they are not fed

with appropriate input. To analyze EMG signal three domains of study have been utilized in many researches, time domain, frequency domain and time frequency domain. Although the time domain has been regarded as the EMG common used field of study because of its computational simplicity, but it is not consistent with the essence of the EMG signal. EMG is a non-stationary signal while it is assumed as a stationary signal in time domain. Also, working in the frequency domain has the problem of not having access to time domain. Consequently, wavelet analysis has been applied as a strong and more compatible technique with the nature of EMG signal since wavelet has proved much capability to analyze biomedical signals. A comparative study had been done by Englehart [8] investigating the EMG feature extraction in time domain and time frequency domain. In this regard, short Time Fourier Transform (STFT), WT and WPT had been used. Finally, an improvement was reported on results of time frequency representation. Accordingly, WT outperformed STFT and WPT outperformed WT. In another research [9] the effectiveness of WT was investigated to identify the muscle fatigue. The results of this work indicated using the fourth and fifth order of Symlet family (sym4 and sym5) as mother wavelet in 8 or 9 decomposition level to determine the muscle fatigue status.

Wavelet analysis has been known as a flexible technique because a vast variety of the wavelet function exists in applying wavelet techniques. Moreover, the user can design a wavelet function according to his needs. Khezri [10] proposed a mother wavelet as a new multi-wavelet function for SEMG processing to recognize hand movements. Also two intelligent classifiers, artificial neural network and fuzzy inference system were applied to decrease the effect of the classification technique on accuracy of the system. Finally, a multitude of mother wavelet was selected by evaluating some mother wavelet (MW) such as Haar, Daubechies, Coiflet, Symmlet and Biorthogonal. In other research [11], a novel method based on WPT, relative wavelet packet energy (RWPE), had been proposed to extract the features of EMG signal. This new technique showed more accuracy compare with the technique of using WPT and principal component analysis (PCA) . Rafiee [12] studied the performance of WT in feature extraction of some biomedical signals includes EMG. In this way, different mother wavelets such as Haar, Daubechies, Symlet, Coiflet, Gaussian, Morlet, Biorthogonal (totally 342 wavelet functions) had been scrutinized. Ultimately, it was proved that db44 provide the best performance for the tested signals. The noticeable point of this funding was the most similarity between db44 and the biomedical signals in shape compared to other 323 wavelet functions. However, the similarity cannot be the only criterion for finding the best wavelet function and regarding the application and the properties of signal the criteria of choosing MW are varied. Meanwhile, Daubechies family represented appropriate results in signal processing technique [12].

The effectiveness of WT on the SEMG was proved by Hussain [13] to understand the muscle fatigue during

walk by db45 as the most proper MW. Power spectrum and bispectrum analysis on EMG signal was applied through different MWs in this study. Wavelet analysis based feature extraction for EMG pattern classification usually requires using best MW to uplift the functionality of EMG classification. Some other researchers, had used db2 considering the good operation of Daubechies family in EMG feature extraction [14] and principle component analysis and sequential forward selection were utilized to reduce the dimension of feature set. Also, they exploited a multilayer perceptron neural network (MLP) and Bayesian classifier to accomplish the SEMG classification.

### 3. EMG signal acquisition

The SEMG dataset applied in this research was recorded by the University of Southampton in United Kingdom [15]. In this way, eighteen people (10 men and 8 women between 20 and 30 years old) either right or left hand, participated in the data collection. The dataset includes five movements related to three hand postures, flexion/extension, co-contraction and isometric. In other words, the dataset consists of wrist flexion/extension, finger flexion/extension, elbow flexion, co-contraction and isometric. The SEMG signals were sampled at 1500 Hz applying a Noraxon 2400T in conjunction with Noraxon Myoresearch XP Master. Also, two electrodes were used to record data from upper arm muscles, biceps and triceps brachii.

### 4. Preprocessing

Regarding the non-stationary nature of EMG signal, preprocessing is very essential to reach a proper EMG feature extraction. There have been different techniques to preprocess EMG signal before feature extraction but the windowing technique is very popular as the current method [7]. To do data windowing, two main methods adjacent and overlapping windowing exist. As these techniques can improve the accuracy of processing, in this study, all the raw SEMG data were preprocessed recruiting windowing technique in the form of adjacent windowing. In adjacent method, adjacent segments with predefined length are used while in overlapped method segments with a certain overlapping period with each other are recruited.

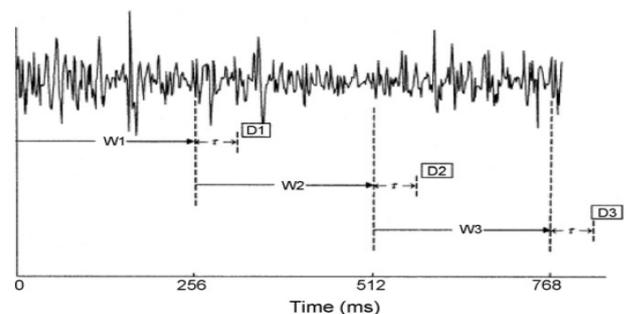


Fig. 1 Adjacent windowing technique [16]

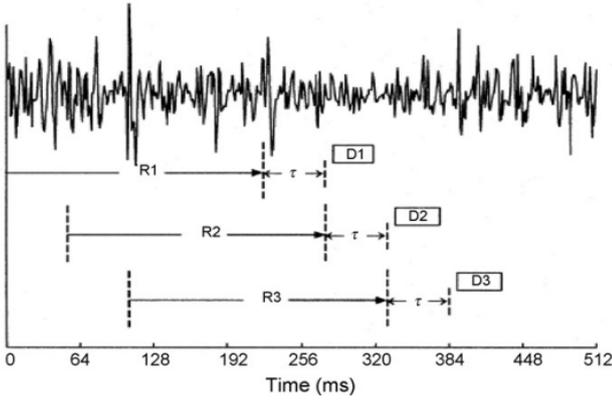


Fig. 2 Overlapped windowing technique [16]

### 5. Feature Extraction

Feature extraction plays a very significant role in EMG classification because even the best classifiers cannot perform well if they are not fed with proper features. In another word, useful information that are hidden in EMG signal are extracted in feature extraction and in this way, unwanted parts of the signal are removed. In our study, WT has been applied to find the desired features which have been defined as Mean Absolute Value (MAV) of SEMG. Since WT lead us to different frequency components through using appropriate function as mother wavelet, getting the most significant information of EMG signal spend less time and computation. The entire procedure of this study to extract features is shown as below in a block diagram in Fig.3. Fig. 3 SEMG feature extraction procedure of this study

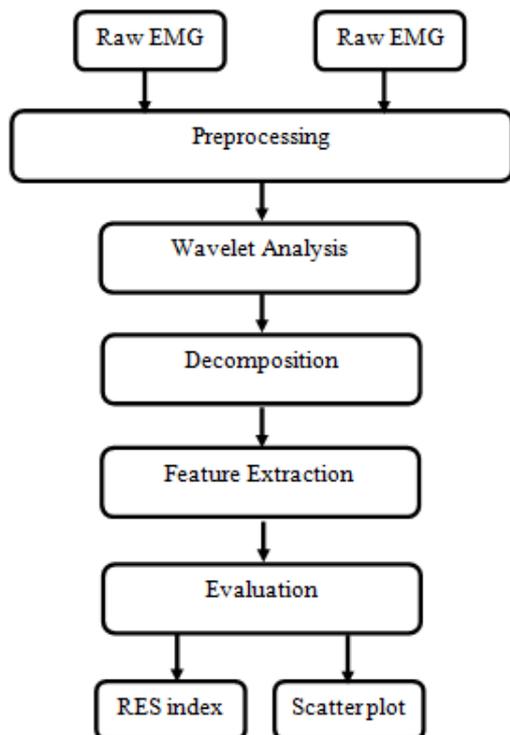


Fig. 3 SEMG feature extraction procedure of this study As it is illustrated, the signals are decomposed after SEMG signal preprocessing. Afterwards, MAV of signal is calculated as feature space and ultimately, the results of feature extraction are scrutinized by two evaluation criteria, RES indices and scatter plot. Since these methods had performed well to analyze the behavior of EMG signal in some other research [6], [17] they were chosen to evaluate SEMG in this paper. Scatter plot plays the role of a qualitative technique to investigate the separability of different hand postures and RES index, as a statistical measurement technique, represents a quantitative method to confirm the performance of the scatter plot. RES index appeared in the equation (1), uses the ratio of Euclidean distance,  $ED$ , to standard deviation,  $\bar{\sigma}$ , to analyze the performance of the EMG signal. Hence, greater RES value signifies more separability between different data sets.

$$RES\ index = \frac{ED}{\bar{\sigma}} \tag{1}$$

$$ED = \frac{2}{K(K-1)} \sum_{p=1}^{K-1} \sum_{q=p+1}^K \sqrt{(\bar{x}_p^2 - \bar{x}_q^2)^2 + (\bar{y}_p^2 - \bar{y}_q^2)^2} \tag{2}$$

$$\bar{\sigma} = \frac{1}{1K} \sum_{i=1}^i \sum_{k=1}^K S_i^k \tag{3}$$

In equation (2),  $ED$  is the distance between coordinates of a pair of clusters  $p$  and  $q$  in  $n$ -dimensional Euclidean space. In our case study,  $p$  and  $q$  are movements number (wrist flexion/extension=1, finger flexion/extension=2, elbow flexion=3, co-contraction=4, isometric=5) and  $K$  is the number of total movements that equals to five. Also, the formula of the dispersion of clusters  $p$  and  $q$  known as  $\bar{\sigma}$  is shown in equation (3). The  $S_i^k$  parameter is the standard deviation of MAV features. Lastly, it is worth mentioning the wavelet function which is selected in this study as mother wavelet is the second order of Daubechies family (db2) and the number of decomposition level is defined as four levels.

### 6. Results and Discussion

#### 6.1 Data segmentation

To begin the analysis of SEMG, raw signal has been scrutinized in time domain firstly. In this way, MAV features of raw signal are calculated and the value of RES and scatter plot are obtained too. As it is obvious in the Fig. 4(a), the raw signals of different hand movements are very noisy and there is not any coherency between the data points of each group. Moreover, the outlier points of each movement group are observed which confirm the presence of noise in SEMG signal. Hence, applying a technique to reduce the noise and making the signal ready

for following signal processing is essential. Consequently, data segmentation, adjacent and overlapped windowing are used which are demonstrated, respectively, in Fig. 4(b) and 4(c).

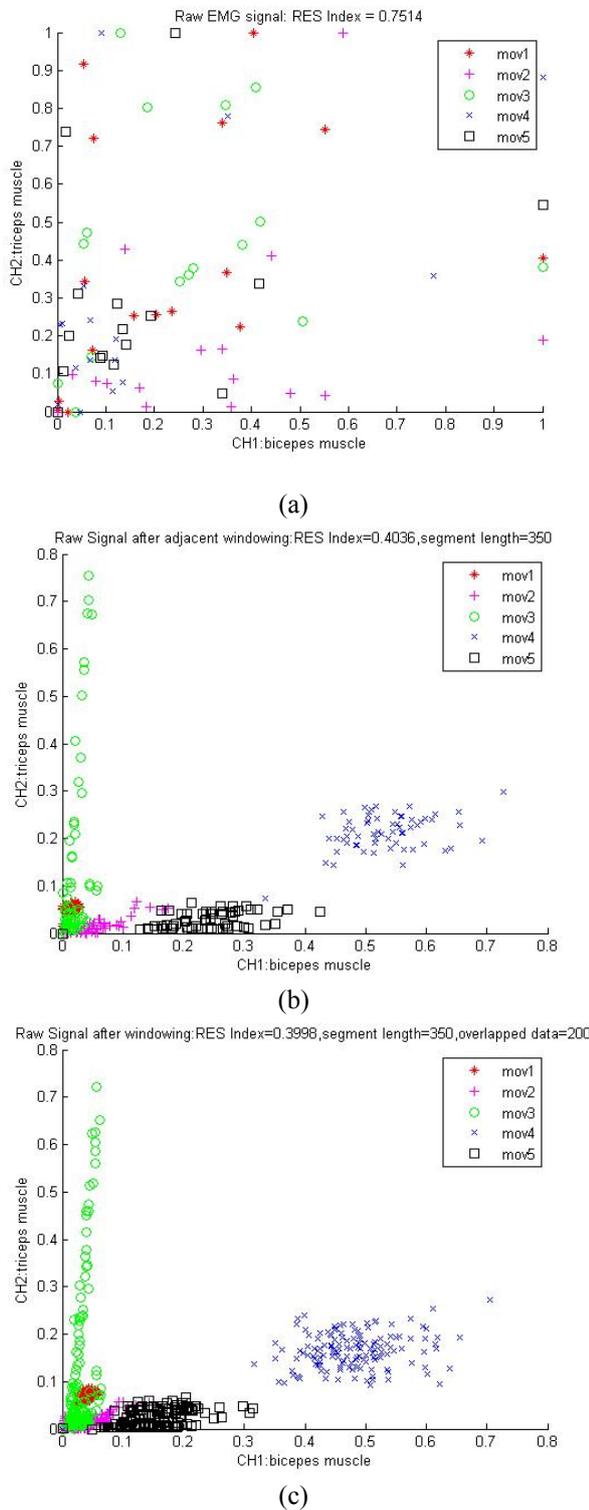


Fig. 4 Raw SEMG signal without preprocessing (a), after adjacent windowing (b), after overlapped windowing (c)

Comparing the unprocessed signal with the preprocessed signals indicates the windowing technique

as a helpful and strong method for EMG signal preprocessing. As a result, it is concluded that adjacent windowing Fig. 4(b) is more proper than overlapped windowing Fig. 4(c) because in the separability point of view, the overlap of five hand movement classes is less in adjacent windowing. Also, the value of the RES index in adjacent technique is higher than the value of overlapped technique. Moreover, it is concluded that the size of the window is very significant in data windowing and can affect the quality of result. In this study, different window sizes were used to find the optimum length. Eventually, the length of 350 data points equals to 232 ms has demonstrated the best performance. According to Englehart [18] for an engineering application the response time should be less than 300 ms.

### 6.2 Wavelet decomposition

After the preprocessing stage, wavelet transforms have been used to extract the MAV features. Accordingly, daubechies family was selected as the mother wavelet and the best performance between the nine members of this family (db2-db10) has been presented by the second order of this family (db2) in this study. Therefore, db2 was selected as suitable MW in this study. The evaluation criteria for finding the best MW are RES indices and scatter plot. Also, four levels of decomposition showed better performance than other levels in lots of research [19], [20], [17]. The Fig. 5 shows the wavelet decomposition tree in four levels. To find the best features, approximation coefficients (ca4) and detail coefficients (cd1-cd4) have been scrutinized after WT decomposition.

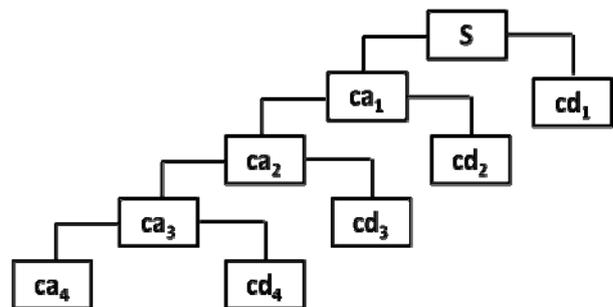


Fig. 5 WT decomposition tree in four levels

The results of this investigation are demonstrated in Fig. 6(a-e). As the scatter plots illustrates, the best performance of wavelet decomposition is in first and second levels (cd1 and cd2), Fig 6(a) and 6(b) because the separability of data points seems in the highest position while in the next levels, third and fourth (cd3, cd4), Fig. 6(c), Fig. 6(d) and Fig. 6(e) the distance between different groups of hand movements are so low that a mixture of different movement classes are easily observed. Moreover, the highest amount of RES index belongs to cd1 while a decreasing trend is followed in

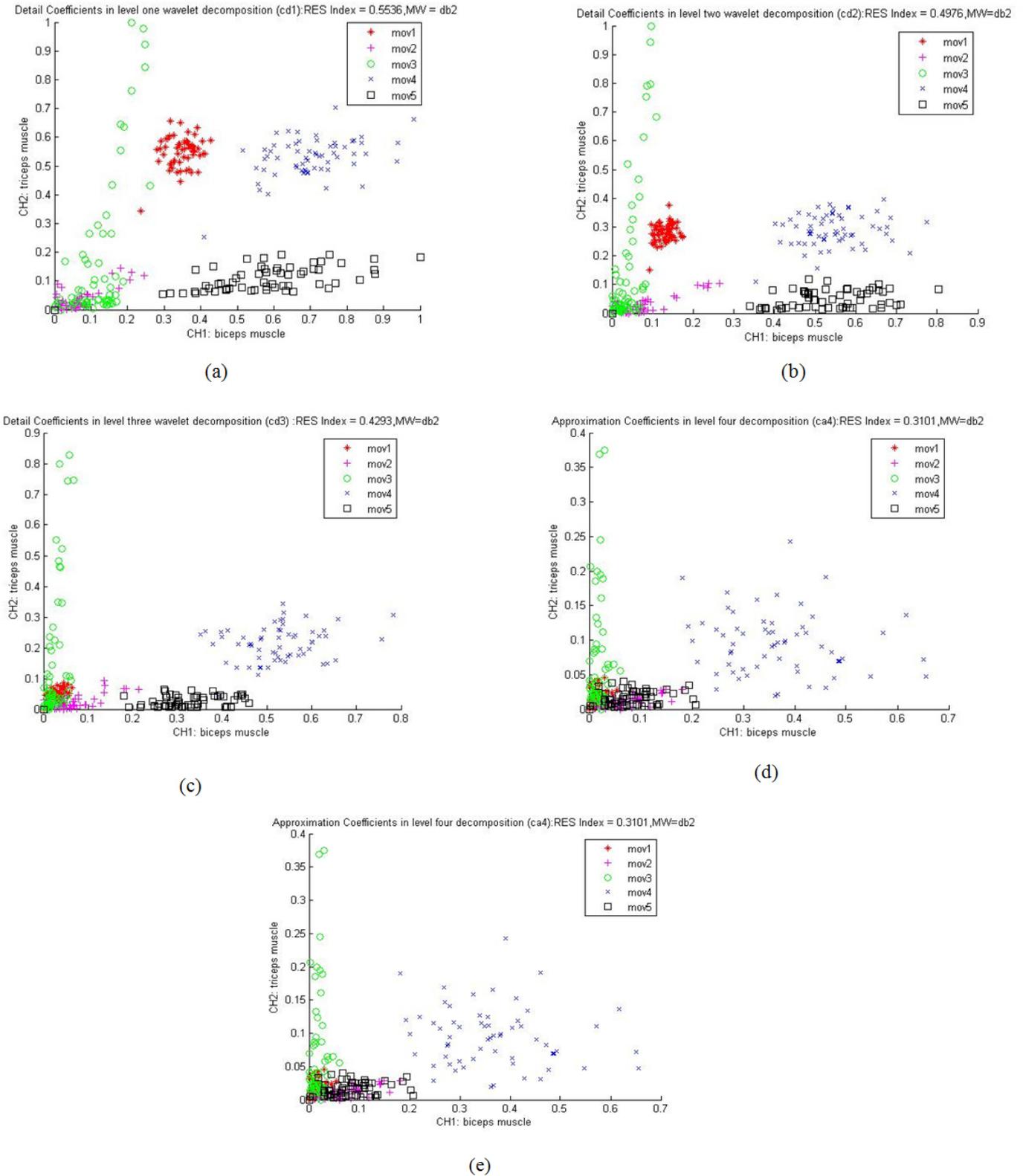


Fig. 6 The scatter plots of MAV features obtained from (a) level 1 wavelet coefficients (cd1), (b) level 2 wavelet coefficients (cd2), (c) level 3 wavelet coefficients (cd3), (d) level 4 detail wavelet coefficients (cd4) and level 4 approximation wavelet coefficients (ca4) with two muscle channels, biceps and triceps and four hand movements.

separability comparing to cd3, cd4 and ca4. In addition, the procedure of RES index values confirms the scatter plot result because as the level of decomposition increases and in separability viewpoint, the distance between data points is decreased, the values of RES are decreased. This trend is illustrated in a bar plot as Fig. 7 while it is obvious that highest amount of distance between different hand position exist in cd1.

Fig. 7 Bar plot of RES index of MAV feature from raw signal after adjacent windowing (s1), overlapped windowing (s2), different wavelet coefficients (cd1-cd4, ca4) using db2 as mother wavelet.

Hence, it is concluded that the best subsets of SEMG signal for WT reconstruction which contain valuable information are cd1 and cd2. Likewise, the best wavelet function in WT decomposition was db2 in this study. Consequently, it is possible to reconstruct the signal of the mentioned subsets include less noise and unwanted parts. In this way, unnecessary parts of signal are removed by using wavelet analysis easily. The only challenge of this study was the overlapping of some hand movements in feature extraction that needs more investigation as the future work. The WT reconstruction and classification of these new data points are in process too. It is expected to observe more improvement in classification accuracy and computational time since by applying proper preprocessing technique and efficient feature extraction, noticeable noise has been reduced.

## 7. Summary

The utility of wavelet transform to extract SEMG features has been investigated in this study. Accordingly, it is concluded that reconstructing only EMG signal that are derived of detail coefficients (cd1 and cd2) instead of the whole wavelet coefficients can yield more efficient signal. Furthermore, the suitable mother wavelet between Daubechies family (db2-db10) is introduced as db2. Comparing the scatter graphs of raw signal with wavelet coefficients has signified an improvement in EMG feature extraction separability of various hand posture classes. Finally, it is deduced that MAV can represent a popular feature of EMG signal and scatter plot and RES index play the role of suitable criteria for EMG evaluation to save more computational time in feature extraction.

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