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Application of Wavelet Analysis in EMG Feature Extraction for Pattern Classification

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Nowadays, analysis of electromyography (EMG) signal using wavelet transform is one of the most powerful signal processing tools. It is widely used in the EMG recognition system. In this study, we have investigated usefulness of extraction of the EMG features from multiple-level wavelet decomposition of the EMG signal. Different levels of various mother wavelets were used to obtain the useful resolution components from the EMG signal. Optimal EMG resolution component (sub-signal) was selected and then the reconstruction of the useful information signal was done. Noise and unwanted EMG parts were eliminated throughout this process. The estimated EMG signal that is an effective EMG part was extracted with the popular features, i.e. mean absolute value and root mean square, in order to improve quality of class separability. Two criteria used in the evaluation are the ratio of a Euclidean distance to a standard deviation and the scatter graph. The results show that only the EMG features extracted from reconstructed EMG signals of the first-level and the second-level detail coefficients yield the improvement of class separability in feature space. It will ensure that the result of pattern classification accuracy will be as high as possible. Optimal wavelet decomposition is obtained using the seventh order of Daubechies wavelet and the forth-level wavelet decomposition.

Keywords: Electromyography signal, EMG, feature extraction, wavelet transform, mean absolute value, root mean square, multi-resolution analysis

1. INTRODUCTION

ELECTROMYOGRAPHY (EMG) signal is one of the most important physiological signals that are widely used in clinical and engineering applications [1-2]. In order to use the EMG signal as a diagnostic tool or a control signal, feature extraction technique becomes a significant step to achieve good classification performance on EMG recognition systems. In the last decade, wavelet transform (WT) became an effective tool to extract useful information from the EMG signal [3]. A wide class of literatures has focused on the evaluation and investigation of an optimal feature extraction obtained from wavelet coefficients [4-11]. Many applications have been proposed, such as studies of combat sports and martial arts strikes [4], characterization of low back pain [5], determination of muscle fatigue for an automated system [6], estimation of knee joint angle for control of leg prostheses [7], determination of muscle contraction during human walking [8] and identification of hand motion commands for control of upper-limb prostheses [9-12]. Most of the research works have paid more attention to identifying hand motion commands. Hence, in our study, the EMG data that were recorded during six daily-life upper-limb movements from two useful forearm muscles were deployed as a representative EMG signal.

WT is a time-frequency analysis method that is successful in the analysis of non-stationary signals including the EMG signal. However, the WT yields a high-dimensional feature vector [9]. Commonly, the high dimensionality of a feature vector causes an increase in the learning parameters of a classifier [10]. Hence, reduction of dimensions of the feature vector without loss of classification accuracy is required. Moreover, the dimensionality reduction method can increase both classifier speed and classification accuracy [10-12]. For this reason, in wavelet analysis, selection of an optimal dimensionality reduction method is essential before applying the feature vector to a classifier.

Feature projection is the popular way to reduce dimensions of the feature vector. Linear and non-linear transformation methods are critical to the success of the time-frequency based feature sets during the last decade. Englehart et al. [10] extracted a feature vector through the WT and used principal component analysis (PCA), a common linear transformation method, for dimensionality reduction. Moreover, various types of the transformation method have been proposed, such as a combination between PCA and a self-organizing feature map (SOFM) [11], nonlinear discriminant analysis (NLDA), and linear discriminant analysis (LDA) [12]. Another approach that is frequently used for dimensionality reduction is the simple time domain and frequency domain extraction method [4, 7, 13-17], such as mean absolute value (MAV), energy, variance, zero crossing (ZC), mean and median frequency, and auto-regressive coefficients (AR). In this study, we used two popular and successful EMG features in both clinical and engineering applications, root mean square (RMS) and MAV [2, 18], as the representative features.

The main benefit of the WT is generation of the useful subset of the frequency components or scales of the interested signal, whereas all research works introduced above used all components or scales as a feature vector for a classifier. In this study, we have investigated the usefulness of an extraction of EMG features from some effective wavelet components or scales instead of extracting features from all wavelet components [19-20]. The useful resolution components from the EMG signal were generated and selected [17, 19]. Noise and unwanted parts were reduced effectively through the selection of the valuable frequency components [20]. In addition, to extract the successful EMG information, a suitable wavelet basis function should be addressed [21-22]. Various wavelet functions with different levels of wavelet decomposition were evaluated.

The scatter graph of the features in space and the statistical measurement method, namely the ratio of a Euclidean distance to a standard deviation index (RES) were used as the evaluation tools [23]. The results of this study will show the usefulness of the extraction of EMG features with some optimal frequency components that is generated from the WT method. The improvement of class separability in feature space of the EMG features is shown. As a result, this leads to the increase in recognition accuracy.

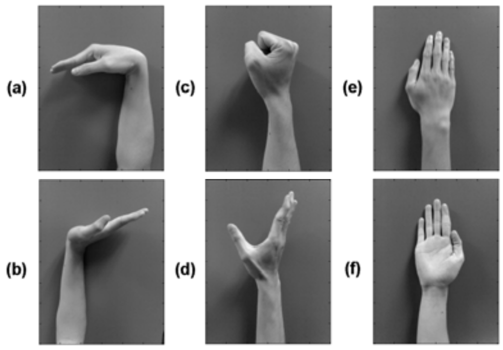


Fig.1. Six daily-life upper-limb motions (a) wrist flexion (b) wrist extension (c) hand close (d) hand open (e) forearm pronation (f) forearm supination [24].

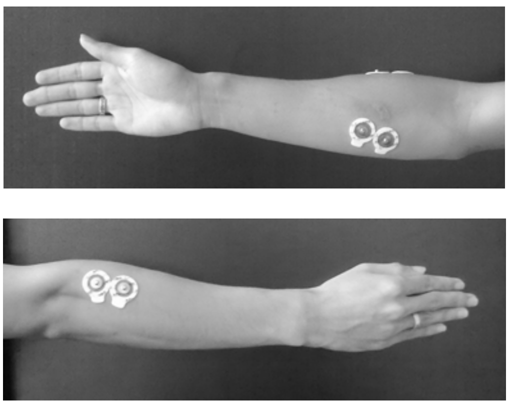


Fig.2. Two muscle placements of right forearm (top) flexor carpi radialis muscle (bottom) extensor carpi radialis longus muscle.

2. MATERIAL & METHODS

A. *EMG signal acquisition and experiments*

In this section, we describe our experimental procedure for recording the EMG data. The representative EMG signals used in this study were extracted from six daily-life upper-limb movements and two forearm muscle channels. A volunteer was asked to perform the six upper-limb motions including wrist flexion (wf), wrist extension (we), hand close (hc), hand open (ho), forearm pronation (fp), and forearm supination (fs) as shown in Fig.1. The EMG signals were recorded from two forearm muscles, flexor carpi radialis muscle (CH1) and extensor carpi radialis longus muscle (CH2), on the right forearm of the volunteer by two pairs of surface electrodes (3M red dot 25 mm foam solid gel) as shown in Fig.2. The electrodes were separated from each other by 20 mm. A band-pass filter of 10-500 Hz bandwidth and an amplifier with 60 dB gain were used. The sampling frequency was set at 1000 Hz using a 16 bit A/D converter (NI, DAQCard-6024E). In the experiment, ten datasets were collected for each motion. The window size of EMG samples was set to 256 ms for a real-time constraint of an engineering application that the response time should be less than 300 ms [10].

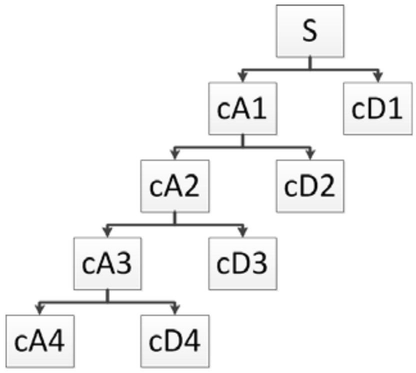


Fig.3. Discrete wavelet transform decomposition tree from the decomposition level 4.

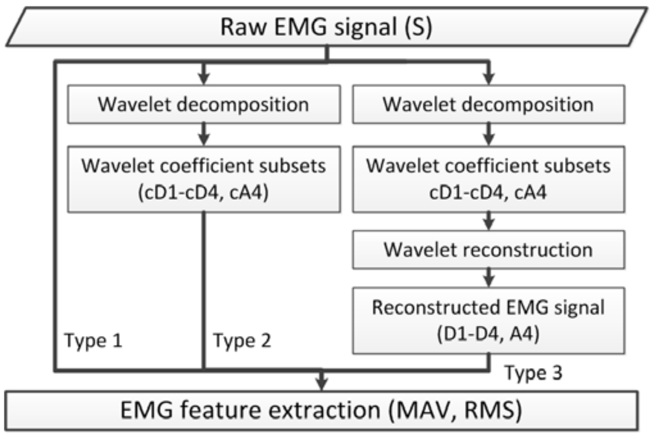


Fig.4. The procedure of an extraction of the EMG features from wavelet coefficients and reconstructed EMG signals.

B. *Wavelet transform and feature extraction methods*

Wavelet transform method is divided into two types: discrete wavelet transform (DWT) and continuous wavelet transform (CWT). DWT was selected in this study because of the concentration in real-time engineering applications [1-2]. DWT is a technique that iteratively transforms an interested signal into multi-resolution subsets of coefficients. Like the conventional time-frequency analysis, the DWT transforms the EMG signal with a suitable wavelet basis function (WF). Therefore, the WF plays a key role in the multi-resolution analysis. In this study, we investigated the usefulness of the multi-resolution analysis through studying of the EMG features with different scales and local variations and also the elimination of the undesired frequency components. In addition, the selection of an optimal WF is proposed.

The original EMG signal (S) is passed through a low-pass filter and a high-pass filter (coefficients of filters depend on WF type) to obtain an approximation coefficient subset (cA1) and a detail coefficient subset (cD1) at the first level. In order to obtain the multiple-resolution subsets, repetitious transformation is done. This process is repeated until the desired final level is obtained. In this study, four levels of decomposition are selected as shown in Fig.3. In the EMG analysis, four levels of wavelet decomposition show better performance than the other levels in a lot of literatures [19, 21]. Finally, this generates the coefficient subsets of the level 4 approximation (cA4) and the level 1, 2, 3, 4 details (cD1, cD2, cD3, and cD4), respectively. Moreover, each coefficient subset can be reconstructed to obtain an effective EMG signal part. Reconstruction of a signal is done by using the inverse wavelet transform. Generally, the inverse transform is performed by using the coefficients of all the components of the final-level decomposition, that is the fourth-level approximation and the first four levels of detail (cA4, cD1, cD2, cD3, and cD4). However, in this study, we define the reconstructed EMG signal by the inversion of subset dependence. For example, in order to obtain the estimated signal from approximation coefficient subset only, the reconstructed EMG signal (A4) is inversed by using the coefficients of the fourth-level approximation (cA4) only. Therefore, we will obtain the reconstructed EMG signals, namely A4, D4, D3, D2, and D1 that are reconstructed from cA4, cD4, cD3, cD2, and cD1, respectively. However, the optimal wavelet function is dependent on the type of interested applications. Some good wavelet functions that are suitable for EMG signal analysis are shown in one of our previous works [21]. Seven mother wavelets are selected to be evaluated in this study. There are the second and the seventh orders of Daubechies wavelet (db2 and db7), the forth and the fifth orders of Coiflet wavelet (coif4 and coif5), the fifth order of Symlets wavelet (sym5), the fifth order of BioSplines wavelet (bior5.5), and the second order of ReverseBior wavelet (rbio2.2).

After that, the wavelet coefficient subsets (cD1-cD4, cA4) and the reconstructed EMG signals (D1-D4, A4) were extracted from their features with six hand movements and two muscle channels. In this study, the popular and successful features called MAV and RMS are selected. However, in the experiments we found that the MAV and RMS features gave the same trend on the results. Moreover, MAV feature is better than RMS feature in the class separability point of view [23]. Therefore, in this paper, only results of the MAV feature were discussed in the later section. The definition of MAV feature is defined as

$$\mathrm{MAV} = \frac{1}{N}\sum_{n=1}^{N}\left|x_n\right|, \tag{1}$$

where x_n represents the n^{th} sample of the EMG signal (S) or the wavelet coefficients subsets (cD1-cD4, cA4) or the reconstructed EMG signals (D1-D4, A4) in a window segment and N denotes the length of EMG signal window-segment (N = 256 in this study). The procedure of the above explanation is shown in Fig.4. The comparison of class separability in each type is discussed to find the suitable EMG subset.

C. Evaluation criteria

In evaluating performance of the EMG features, class separability viewpoint is a central criterion. The good quality in class separability viewpoint means that the result of misclassification will be as low as possible. In other words, maximum separation between classes is obtained and minimum of the variation in subject experiment is reached. In this study, we used two evaluation criteria, called the scatter graph and the RES index (statistical measurement method). Generally, the selection of EMG features can be deployed based on either classifier method or statistical measurement index. However, a drawback of an evaluation using classifier is that the evaluation results are dependent on types of the classifier [25]. Hence, in this study, we have proposed the selection of EMG features based on statistical index.

The definition of RES index [23] that was used in this study is as follows. The MAV features in the matrix form can be expressed as

$$M_{i,j}^{k} = \begin{bmatrix} m_{1,1}^{k} & m_{1,2}^{k} & \dots & m_{1,10}^{k} \\ m_{2,1}^{k} & m_{2,2}^{k} & \dots & m_{2,10}^{k} \end{bmatrix}, \tag{2}$$

where m is the MAV value, i is the channel number ($1 \le i \le$ I, I=2), j is the trial number ($1 \le j \le$ J, J=10), and k is the motion number ($1 \le k \le$ K, K=6). Note that the MAV values from each channel of all motions were normalized to be in the range of 0 and 1 which can be expressed as

$$m_{norm} = \frac{m - \min(m)}{\max(m) - \min(m)}. \tag{3}$$

The average of MAV values of each channel can be given by

$$\overline{\mathbf{X}}_{i}^{k} = \begin{bmatrix} \overline{x}_{1}^{k} \\ \overline{x}_{2}^{k} \end{bmatrix}, \tag{4}$$

where

$$\overline{x}_{i}^{k} = \frac{1}{\mathrm{J}}\sum_{j=1}^{\mathrm{J}} x_{i,j}^{k}. \tag{5}$$

The standard deviation of MAV values of each channel can be defined as

$$\mathbf{S}_{i}^{k} = \begin{bmatrix} s_{1}^{k} \\ s_{2}^{k} \end{bmatrix}, \tag{6}$$

where

$$s_i^k = \sqrt{\frac{\sum_{j=1}^{J}(x_{i,j}^k - \overline{x}_i^k)^2}{J}} \ . \tag{7}$$

The definition of RES index can be expressed as

$$\text{RES index} = \frac{\overline{ED}}{\overline{\sigma}}, \tag{8}$$

where

$$\overline{ED} = \frac{2}{K(K-1)} \sum_{p=1}^{K-1} \sum_{q=p+1}^{K} \sqrt{(\overline{x}_1^p - \overline{x}_1^q)^2 + (\overline{x}_2^p - \overline{x}_2^q)^2} \ , \tag{9}$$

$$\overline{\sigma} = \frac{1}{IK} \sum_{i=1}^{I} \sum_{k=1}^{K} s_i^k \ , \tag{10}$$

and p and q are motion numbers (1=wf, 2=we, 3=hc, 4=ho, 5=fp, and 6=fs). In addition, the *ED* is the distance between co-ordinates of a pair of clusters p and q in n-dimensional Euclidean space, and σ is the dispersions of clusters p and q. This index uses the Euclidean distance as a distance function and uses the standard deviation as a dispersion measure.

3. Results and Discussion

A. EMG signal and wavelet decomposition

Example signals computed from three approaches that are described in Fig.4 are shown in Fig.5.The db7 wavelet with 4 levels of wavelet decomposition was used in the example. In Fig.5(a), the signals obtained from the raw EMG signal (Type I) and the reconstructed EMG signals at different multi-resolution levels (Type III) are presented and the signals between the raw EMG signal (Type I) and the wavelet coefficient subsets at different multi-resolution levels (Type II) are presented in Fig.5(b). Generally, in most types of natural signal, the low frequency components (i.e. the cA4 and the A4) are the most important part [26]. They can be used as the identity of its signal, whereas high frequency components (the cD1-cD4, the D1-D4) can be assumed as noises.

However, for the EMG signal, we can observe from Fig.5(a) and 5(b) that the low frequency component (cA4 and A4) contains indirect correspondence and contains the irrelevant low resolution background; whereas we found that the signals at the first and the second decomposition levels (cD1 and cD2) and reconstruction levels (D1 and D2) are similar to the original signal (S). It remains the trend (appropriate to the low frequency contents) of the EMG information and removes the fluctuation (unwanted the high frequency components) of interference. So the signals (cD1, cD2, D1, and D2) are the effective EMG information parts.

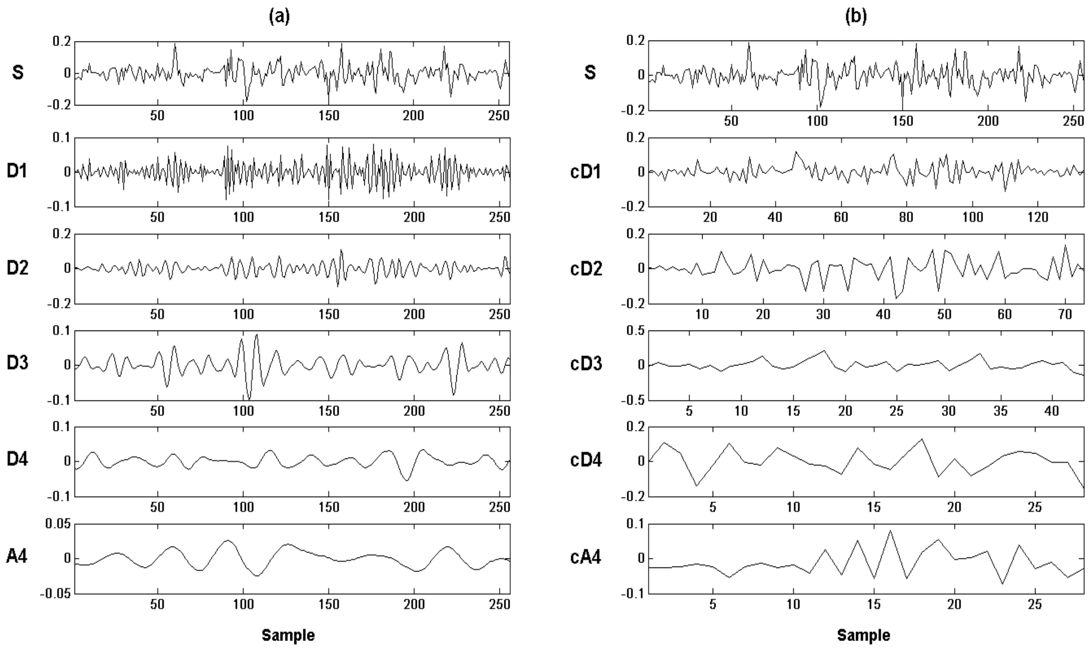


Fig.5. Example of the EMG signal using wavelet multi-resolution analysis with db7 wavelet and 4 levels decomposition and reconstruction (a) raw EMG signal (S) and the reconstructed EMG signals (D1-D4, A4) of hc from CH1 (b) EMG signal (S) and the wavelet coefficient subsets (cD1-cD4, cA4) of hc from CH1.

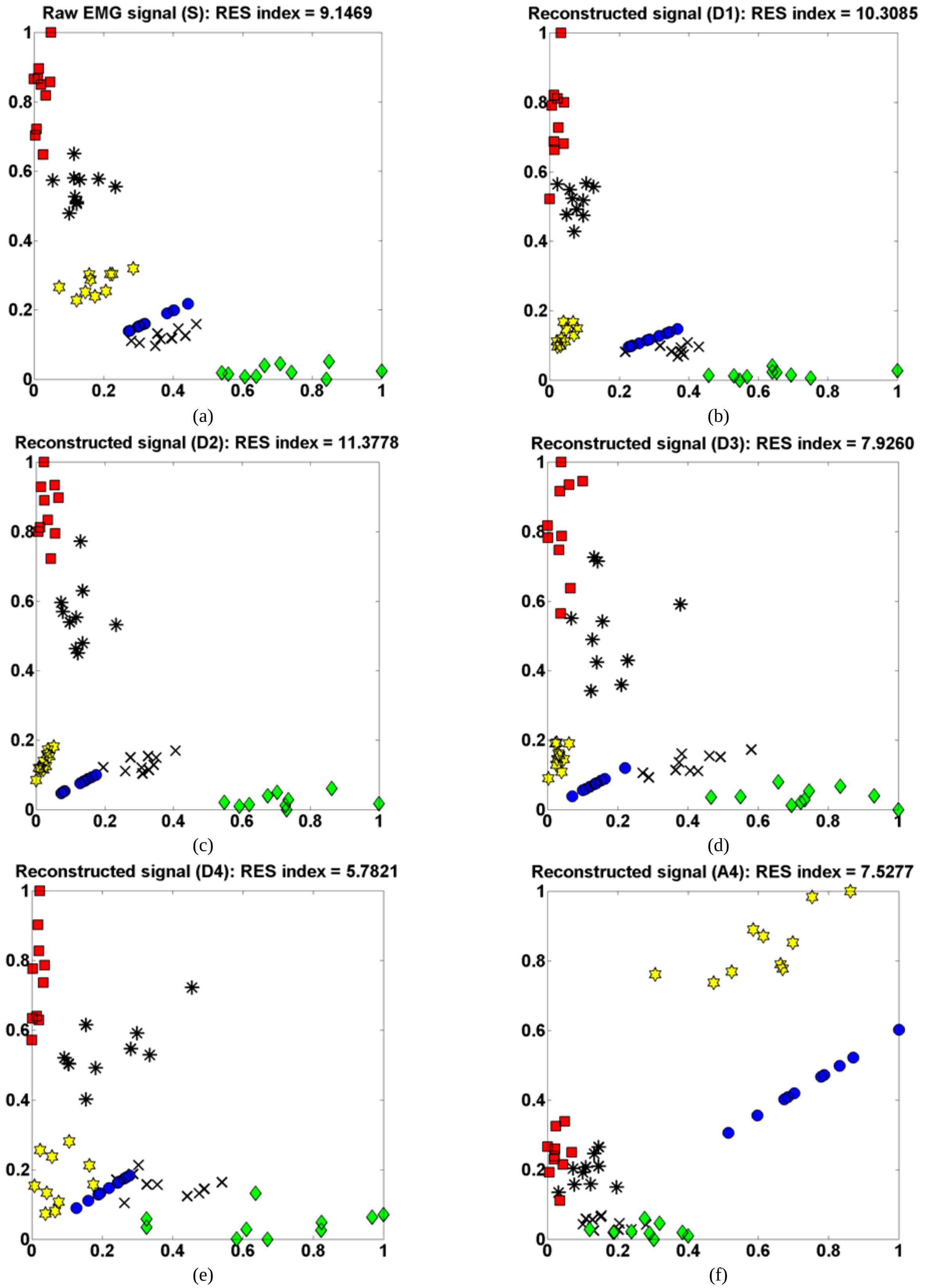
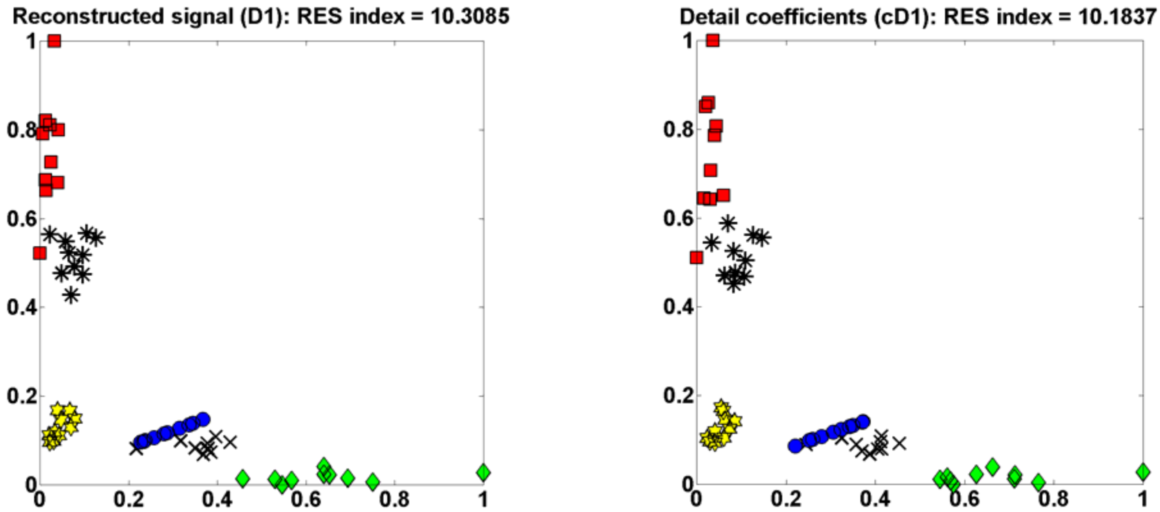


Fig.6. The scatter plots of MAV feature calculated from (a) raw EMG signal (S) (b) reconstructed EMG signal from cD1 (D1) (c) reconstructed EMG signal from cD2 (D2) (d) reconstructed EMG signal from cD3 (D3) (e) reconstructed EMG signal from cD4 (D4) (f) reconstructed EMG signal from cA4 (A4) - with six hand movements and two muscle channels (CH1 – X axis, CH2 – Y axis).

× hc ✱ ho ■ we ◆ wf ● fp ✩ fs



(a) (b)

Fig.7. The comparison between the scatter plots of MAV feature calculated from (a) reconstructed EMG signal from wavelet's detail coefficient level 1 (D1) and (b) wavelet's detail coefficient subset at level 1 (cD1) (CH1 – X axis, CH2 – Y axis).

× hc ✳ ho ■ we ◆ wf ● fp ✡ fs

B. Scatter graphs

To demonstrate the performance of the EMG feature extraction computed from each sub-signal, which is described in the above section in class separability point of view, the scatter graphs between the MAV features extracted from two muscle channels and six upper-limb movements were shown to present the distance between two scatter groups and the variation of features in the same group. Fig.6(a) shows the scatter plot of the MAV extracted from the raw EMG signal (S), which indicates the clear separation in data points from each motion with a small degree of variation in the same group. In Fig.6(b-c), scatter plots of the MAV extracted from the reconstructed EMG signals (D1 and D2) show clearly separation and compactness. It means that the EMG feature vector obtained from these signals can yield a good classification result from the classifier. In Fig.6(d-e), scatter plots of the MAV features obtained from the reconstructed EMG signals (D3 and D4) show that the patterns of each motion have a little more fluctuation compared with the patterns of feature obtained from the original EMG signal (S) and the reconstructed EMG signals (D1 and D2). In addition, scatter plot of the MAV feature computed from the reconstructed EMG signal (A4) has a poor class separability compared with the others.

Furthermore, comparison of class separability of the MAV features extracted from the reconstructed EMG signal and extracted from the wavelet's coefficient subset is shown in Fig.7. We found that the trend of classification performance in each level of both types is similar. However, the classification performance of reconstructed EMG signals from wavelet's coefficient is always slightly superior to the classification performance of wavelet's coefficient subsets.

C. RES index

To confirm the class separability performance, we used the RES index to indicate the quality of separation. It is used as a quantitative confirmation for the observation of the scatter graphs. In Fig.8, it confirmed that RES indices of the MAV from the detail coefficients of the first level and the second level (cD1, cD2, D1, and D2) achieved the improvement in class separability in feature space compared with the RES indices of the MAV from the original signal (S). Moreover, better performance in classification of EMG feature extracted from the reconstructed EMG signals (D1 and D2) over the EMG feature extracted from the wavelet coefficient subsets (cD1 and cD2) is shown. On the other hand, the classification performances of other cases (cD3, cD4, cA4, D3, D4 and A4) are inferior to that of the original signal (S).

The results that we have discussed above are based on a fixed wavelet filter. Through Figs.9 and 10, comparisons of seven wavelet functions in order to find the optimal one have been shown. In Fig.9, RES indices from the reconstructed EMG signal D1 show that the rbio2.2 wavelet is the best mother wavelet. It is better than the others by about 0.6, and in Fig.10, the RES indices from the reconstructed EMG signal D2 show that the db7 wavelet is the best wavelet function.

We found that the classification performance obtained from wavelet decomposition level 2, D2, is greater than the classification performance obtained from wavelet decomposition level 1, D1. Thus, we can summarize that the best classification performance can be obtained by using the reconstructed EMG signal from the wavelet's detail coefficient level 2, D2, with the db7 wavelet and the forth decomposition levels.

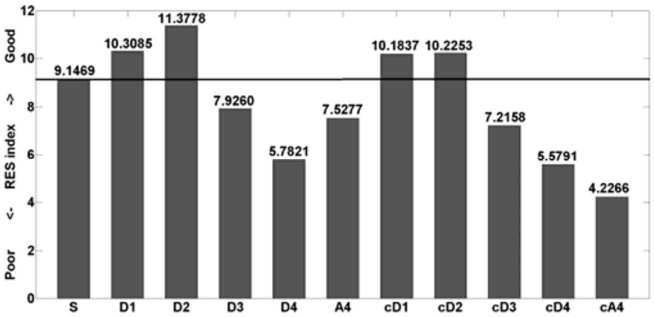


Fig.8. Bar plot of RES index of MAV feature with raw signal (S), different coefficient subsets (cD1-cD4, cA4) and different reconstructed EMG signals (D1-D4, A4) using db7 wavelet.

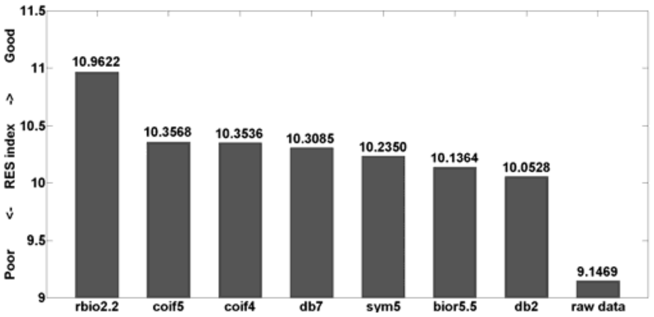


Fig.9. Bar plot of RES index of MAV feature from seven mother wavelets based on the reconstructed signal of details level 1 (D1).

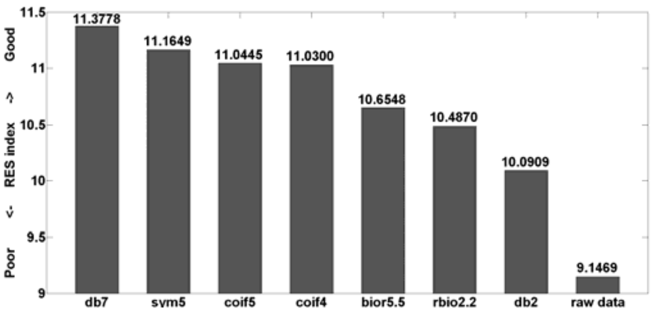


Fig.10. Bar plot of RES index of MAV feature from seven mother wavelets based on the reconstructed signal of details level 2 (D2).

D. Usefulness of feature extracted from sub-signal

As we have mentioned in the introduction section, the main benefit of the WT method is the generation of a useful subset of the frequency components, but previous research studies have used all subsets of the frequency components as a feature vector for a classifier. In this study, we have proposed to use some effective subsets instead of using all subsets. The useful resolution components from the EMG signal were generated and selected through the experiments and we found that from the forth decomposition levels, the reconstructed EMG signals from the first level and the second level of detail coefficients are suitable for an extraction of EMG features. On the other hand, other subsets contain noise and unwanted EMG parts, thus extraction of EMG feature from those subsets does not improve the classification ability. Hence, in the future works, we recommend to extract the EMG feature from the reconstructed EMG signals from the first level and the second level of detail coefficients instead of using all wavelet subsets. It does not only improve the classification accuracy but also decreases the computational time due to a reduction in sub-signals.

In future works, evaluation of the estimated EMG signals from the detail coefficient (D1 and D2) with other kinds of the dimensionality reduction method should be employed, such as linear and nonlinear transformation methods (e.g. PCA, SOFM, NLDA, LDA) and time domain and frequency domain feature methods (e.g. energy, ZC, AR). In addition, to confirm the recognition result, the classification accuracy obtained from the classifiers should be done.

4. CONCLUSIONS

The usefulness of the successful EMG features extracted from multiple-level decompositions of the EMG signal has been investigated in this paper. The optimal EMG resolution components were selected. As a result, the beneficial EMG information was obtained with a noise-free environment. By evaluations with the RES index, the results show that only EMG signals that were estimated from the detail coefficients of the first level and the second level yield the improving of the class separability. It ensures that the result of the classification accuracy will be as high as possible. The suitable mother wavelet and decomposition level are the seventh order of Daubechies wavelet and the fourth decomposition levels, respectively. The investigation results of this paper can be widely used in a wide class of clinical and engineering applications.

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