Optimal Wavelet Functions in Wavelet Denoising for Multifunction Myoelectric Control

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ABSTRACT

Wavelet analysis is one of the most important methods for analyzing the surface Electromyography (sEMG) signal. The aim of this study was to investigate the wavelet function that is optimum to identify and denoise the sEMG signal for multifunction myoelectric control. This study is motivated by the fact that there is no universal mother wavelet that is suitable for all types of signal. The right wavelet function becomes to achieve the optimal performance. In this study, the optimal wavelets are evaluated in term of mean square error of two criterions, namely denoising and reconstruction. Fifty-three wavelet functions are used to perform an iterative denoising and reconstruction on different noise levels that are added in sEMG signals. In addition, various possible decomposition levels and types of wavelets in the denoising procedure are tested. The results show that the best mother wavelets for tolerance of noise in denoising are the first order of Daubechies, BioSplines, and ReverseBior but the classification results are not recommended. The fifth order of Coiflet is the best wavelet in perfect reconstruction point of view. Various families can be used except the third order of BiorSplines and Discrete Meyer are not recommended to use. Suitable number of decomposition levels is four and optimal wavelets are independent of wavelet denoising algorithms.

Keywords: Wavelet, Wavelet Function, Denoising, EMG, Electromyography, Myoelectric Control

1. INTRODUCTION

Surface electromyography signal is one of the most significant biomedical signals [1]. It is widely studied and applied in clinic. This is owing to the fact that the use of sEMG signal is very easy, fast and convenient. In other words, sEMG signal is more advantage than the other biomedical signal such as Electrooculography (EOG), and Electroencephalography (EEG) signals in because of its higher amplitude and signal to noise ratio (SNR) [2]. Feature extraction is the method that uses to model and analyze sEMG signal. It is an important stage to achieve the better performance in myoelectric control. Feature extraction can be divided into three groups [3]. Firstly, time domain group is very easy to understand and calculate such as mean absolute value and root mean square. Nevertheless, features in time domain group were limited successful because these methods assume that sEMG signal is stationary, while the sEMG signal is nonstationary. In addition, the time domain is very sensitive with various noises. Thus changing trend toward the use of information contained in frequency domain, some characteristic variables in power spectral density are presented. Mean frequency and median frequency are the most popular frequency method but it is not usefulness in multifunction myoelectric control [4]. Current advances in time-frequency analysis are crucial to understand the complexity of sEMG signal [5]. Wavelet analysis is becoming more important in time-frequency method. Most popular in sEMG application is Discrete Wavelet Transform (DWT) and Wavelet Packet Transform (WPT) [6]. The most advantages of using DWT and WPT is that features can be easily extracted and contain useful information in both of frequency content and time domain. Moreover, DWT and WPT can perform local analysis of sEMG signal and expose the trends of sEMG signal [7]. DWT and WPT decomposes original sEMG signal into some multi-resolution components according to a basis function called mother wavelet or wavelet function. The wavelet function is both translated and extended in time undertaking a two-dimensional cross correlation with the time domain sEMG signal. However, the difference between DWT and WPT is that WPT offers more range of possibilities for signal analysis than DWT.

The problem is what a high quality feature is. Three properties of feature [4] including maximum class separability, robustness, and computational complexity were used to indicate the high quality EMG feature extraction. The first property is to guarantee that the resulting percentage accuracy classification will be as high as possible. In the previous works, lots of researchers have successfully evaluated

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DWT to classify the sEMG signal that the optimal wavelet function is dependent on the kind of applications [4-8]. Moreover, varieties of noises that are originated from measure instruments are major problems in analysis of sEMG signals. The amplitude of sEMG signal is very small. It is ranging between 50 μV-100 mV [1]. The amplitude of various noises is higher than the amplitude of sEMG signal. As a result, analysis of sEMG signal is very difficult to get accurate classification. Generally, sEMG signal is corrupted with two major noises [9]. First, noises generated by biological resources such as motion artifacts. Second, noises generated by environment resources such as power-line interference. Power line interference or instability of electrode-skin contact can be removed using typical filtering procedures but the interference of white Gaussian noise (WGN) is difficult to remove using previous procedures [10]. Recent advance in wavelet denoising algorithms, an advance signal processing method, have been received considerable attention in the removal of WGN [10,11].

In the literatures, many researcher groups are attending to employ wavelet denoising for sEMG signal in myoelectric control. Jiang and Kuo [12] compared four classical threshold estimation methods and two threshold transformation methods with simulated signal at fixed 16-dB SNR and original sEMG signal. The literature used signal-to-noise estimator for evaluation of the quality of the reconstructed signal. This estimator can estimate the quality of denoising methods for the simulated signal but it does not work for the sEMG signal. Subsequently, they concluded that the denoised sEMG is insensitive to the selection of denoising methods. The researchers apply the second order of Daubechies wavelet (db2) with six decomposition levels by the suggestion of [13]. Guo et al. [14,15] compared the same denoising methods as Jiang and Kuo but they changed real sEMG signal from mouse clicking to normal walking on the flat. The result of Guo et al. is similar to Jiang and Kuo. That is, they did not show the evaluation and quality results. The selected fifth order of Symlets wavelet (sym5) with four decomposition levels is adopted in [14,15]. Zhizeng and co-laboratory [16,17], and Kumar et al. [7] are other researcher groups that use the Symlets wavelet family in sEMG signal. Zhizeng et al. [16,17] apply the eight order and four levels (sym8) to denoise sEMG signals with hand movements. On the other hands, Kumar et al. [7] apply the fourth and fifth orders and eight levels (sym4, sym5) to determine muscle fatigue. In addition, the most popular wavelet family in sEMG analysis is the Daubechies wavelet. The various orders of Daubechies and various levels of decomposition are used such as the forth order (db4) with three and six levels, the fifth order (db5) with five levels, and the tenth order (db10) with eight levels in [18-21], respectively.

However, from the literatures, it has been shown that all of them fixed the wavelet function and the scale level. But in real world, there is no universal wavelet function that is suitable for all type of signals. This was not powerful enough to make the comparison fair with respect to the variety of wavelet function and scale level. Consequently, the selection of wavelet function becomes important stage to achieve optimal performance in signal processing for a given signal of interest. There are literatures on an optimal wavelet selection for ECG signal applications [22,23] and other applications [24] but there is no an optimal wavelet selection for sEMG signal applications. In this research, we evaluate most standard wavelet families, namely Daubechies, Symlets, Discrete Meyer, Coiflet, BiorSplines, and ReverseBior wavelets with different orders and decomposition levels. The optimal wavelet functions are critically attended to test the performance in robustness point of view and the discussion in classification criterion is proposed.

This paper presents a complete comparative study of decomposition, denoising, and reconstruction using wavelets for tolerance and removing WGN from sEMG signal. The aims of this study were to conclude: 1) the suitable wavelet functions in decomposition, denoising and reconstruction points of view 2) the optimal level of wavelet decomposition 3) the effect of wavelet denoising algorithms with the optimal wavelet functions.

The paper is organized as follows. Experiments and data acquisition are described in Section 2. Section 3 presents a description of wavelet analysis methods. Results and discussion are reported in Section 4, and finally the conclusion is drawn in Section 5.

2. EXPERIMENTS AND DATA ACQUISITION

In this section, we describe our experimental procedure for recording sEMG signals. The sEMG signals were recorded from flexor carpi radialis and extensor carpi radialis longus of a healthy male by two pairs of surface electrodes (3M red dot 2.5 cm. foam solid gel). Each electrode was separated from the other by 20 mm. The frequency range of sEMG signal is within 0-500 Hz, but the dominant energy is concentrated in the range of 10-150 Hz. A band-pass filter of 10-500 Hz bandwidth and an amplifier with 60 dB gain were used. Sampling rate was set at 1000 samples per second using a 16 bit A/D converter board (NI, USA, IN BNC-2110).

A volunteer performed six upper limb motions including hand open, hand close, wrist extension, wrist flexion, pronation, and supination as shown in Fig.1. Hand close and wrist flexion were analyzed using signals from extensor carpi radialis longus and the others motions were analyzed using signals from flexor carpi radialis because each motion has strong signal depending upon electrode position. In experiment, a subject performed six hand motions at constant force

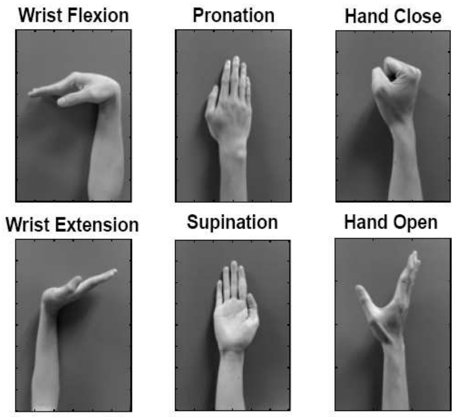


Fig.1: *Six Upper Limb Motions.*

contractions for 1 second, and switched between relaxation (4 seconds interval) and static contraction, and then repeats the pattern to 10 sessions. After recording, ten datasets of each motion were stored for processing. The sample size of sEMG signals is 256 ms for real-time constraint that response time should be less than 300 ms.

3. METHODOLOGY

The objective of wavelet denoising algorithm is to suppress the noise part of the signal $s(n)$ by discarding the WGN $e(n)$ and to recover the signal of interest $f(n)$. The model is basically of the following form:

$$s(n) = f(n) + e(n). \qquad (1)$$

The general wavelet based denoising procedures are composed of three steps:

Step 1: Decomposition. Choose a wavelet function and decomposition level J. Compute the wavelet decomposition of the sEMG signal at level J.

Step 2: Denoising wavelet's detail coefficients. For each level selects a threshold value and apply thresholding to the detail coefficients.

Step 3: Reconstruction. Compute the reconstruction based on the original approximation coefficients of level J and the modified detail coefficients of levels from 1 to J.

To achieve and optimize the above procedures, four points must be addressed, namely selection of the suitable wavelet function, level of decomposition, threshold estimation, and threshold transformation. Most wavelet based denoising literatures highlight the thresholding techniques rather than selection of available wavelet functions [10,13-17]. The procedure of wavelet denoising follows three steps described below.

3.1 Wavelet Decomposition

The first step of wavelet denoising procedure is to select wavelet function. It is important of choosing the right filters [22,23]. The right wavelet function determines perfect reconstruction and performs better analysis. A total of 53 wavelet functions are used in evaluation of the denoising performance. The 53 wavelet functions consist of 10 Daubechies wavelets, 7 Symlets wavelets, 5 Coiflet wavelets, 15 BiorSplines wavelets, 15 ReverseBior, and Discrete Meyer wavelet. All of wavelet functions are presented in Table 1.

Table 1: *The 53 types of wavelet functions.*

Wavelet family	Wavelet function with orders
Daubechies	db1 or haar, db2, db3, db4, db5, db6, db7, db8, db9, db10
Symlets	sym2, sym3, sym4, sym5, sym6, sym7, sym8
Coiflet	coif1, coif2, coif3, coif4, coif5
BiorSplines	bior1.1, bior1.3, bior1.5, bior2.2, bior2.4, bior2.6, bior2.8, bior3.1, bior3.3, bior3.5, bior3.7, bior3.9, bior4.4, bior5.5, bior6.8
ReverseBior	rbio1.1, rbio1.3, rbio1.5, rbio2.2, rbio2.4, rbio2.6, rbio2.8, rbio3.1, rbio3.3, rbio3.5, rbio3.7, rbio3.9, rbio4.4, rbio5.5, rbio6.8
Discrete Meyer	dmey

Next step is the selection of the number of decomposition levels of signal. DWT use high-pass filter to obtain high frequency components so-called details (D) and low-pass filter to obtain low frequency components so-called approximations (A). Procedure of noise reduction is based on decreasing of noise content in high frequency components (details) of signal. The decomposition levels are varied from one (the first level of decomposition) to eight (the maximum dept of decomposition, $J = log_2 N$, where N is the length in samples of time-domain signal) [6] in this study.

3.2 Wavelet Denoising

Four classical threshold estimation methods were applied in this study, namely universal threshold, SURE threshold, hybrid threshold, and minimax threshold, to observe the effect with optimal wavelet function. Four methods were described in the following.

1. Universal thresholding method: This method was also proposed in [25]. It used a fixed form threshold, which can be expressed as

$$THR_{UNI} = \sigma\sqrt{2\log(N)}, \qquad (2)$$

where σ is noise variance. It can be estimated using median parameter which can be calculated as

$$\sigma = \frac{median(|cD_j|)}{0.6745}, \qquad (3)$$

where cDj is the detail wavelet coefficients at scale level j and 0.6475 is a normalization factor.

2. SURE thresholding method: This method used a threshold selection rule based on Stein's Unbiased Estimate of Risk. It gets an estimate of the risk for a particular threshold value THR_{SURE}, where risk is defined by Stein's unbiased estimate of risk [26]. Minimizing the risk in THR_{SURE} gives a selection of the threshold value.

3. Hybrid thresholding method: This method attempts to overcome the limitation of SURE thresholding. It is a mixture of the universal thresholding method and the SURE thresholding method. It improved the limitation of SURE thresholding method. The exact conditions of this algorithm are described in [27].

4. Minimax thresholding method: This method was also proposed in [26]. It used a fixed threshold chosen to yield minimax performance for mean square error against an ideal procedure.

Level dependent thresholding is applied in this study. σ is calculated for each decomposition level. Therefore, the threshold values are different in each level.

After threshold values are determined, thresholding can be done using hard and soft transformation. In addition, two modified threshold transformations, namely hyperbolic and non-negative garrote were applied for this study to observe the effect same as the threshold estimation. The methods were described in the following.

1. Hard Thresholding: This transform can be described as the usual process of zeroing all detail coefficients whose absolute values are lower than the threshold ($THRj$), and then keeping other detail coefficients. It can be expressed as [25]

$$cD_j = \begin{cases} cD_j & , if|cD_j| > THR_j \\ 0 & , \text{otherwise} \end{cases} . \tag{4}$$

2. Soft Thresholding: This transform is an extension of hard thresholding. First all detail coefficients whose absolute values are lower than the threshold is zeroed and then the other coefficients are shrinked towards zero. It is defined as [?,]

$$cD_j = \begin{cases} \operatorname{sgn}(cD_j)(cD_j - THR_j) & , if|cD_j| > THR_j \\ 0 & , \text{otherwise.} \end{cases} \tag{5}$$

3. Hyperbolic Thresholding: This transform is similar to soft thresholding. It is achieved to address the limitation of soft thresholding. It is shown as [?,]

$$cD_j = \begin{cases} \operatorname{sgn}(cD_j)\sqrt{(cD_j^2 - THR_j^2)} & , if|cD_j| > THR_j \\ 0 & , \text{otherwise.} \end{cases} \tag{6}$$

4. Non-negative Garrote thresholding: This transform is composed of hard and soft thresholding. It provides a good compromise between hard and soft thresholding. It is given by [?,]

$$cD_j = \begin{cases} \operatorname{sgn}(cD_j)(cD_j - \frac{THR_j}{cD_j}) & , if|cD_j| > THR_j \\ 0 & , \text{otherwise.} \end{cases} \tag{7}$$

The response of four threshold transformation functions is presented in Fig.2. We suppose threshold value (THR) to 0.4 and diagonal dashed line indicates the input signal. The third aim is evaluated with various wavelet denoising procedures as described above.

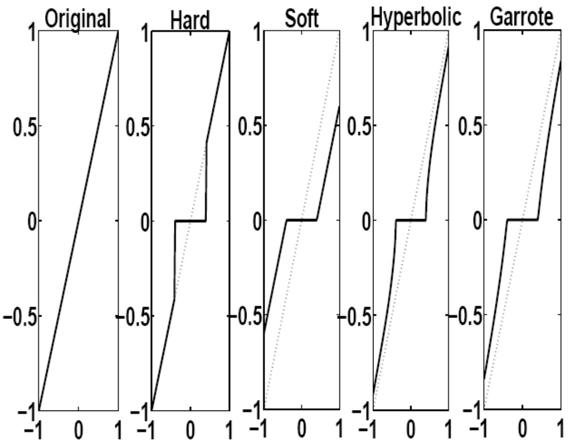


Fig.2: *The response of threshold transformation functions with 0.4 threshold value (THR).*

3.3 Wavelet Reconstruction

After denoising procedure, the reconstructed signal computes wavelet reconstruction based on the original approximation coefficients of level J and the modified detail coefficients of levels from 1 to J.

3.4 Myoelectric Control-based on Wavelet Transform

Wavelet coefficients provide information related to time-frequency variation of sEMG signal [7]. In practice, it has been found that lots of applications used wavelet coefficients to extract the useful information parameters. To extract the effective features from wavelet denoising or wavelet decomposition, we can extract features based on three types: wavelet coefficients of wavelet decomposition (Type I), modified wavelet coefficients of wavelet denoising (Type II), and modified sEMG signal of wavelet denoising (Type III). From the experiments in [11] and [30], we can conclude that the trends of robustness in Type I and II are similar. Therefore, this paper presents only results of denoising (Type II) and the robustness result of Type III is presented. Type III is considered only the suitable wavelet in denoising criterion because feature is calculated based on reconstructed sEMG signal. The classification result is not directly dependent on the selected wavelet function in wavelet denoising procedure. However, Type II should be considered in both robustness and classification criterions because the result of classification is directly dependent on the selection of optimal wavelet function. The block diagrams of three type's extractions are shown in Fig.3.

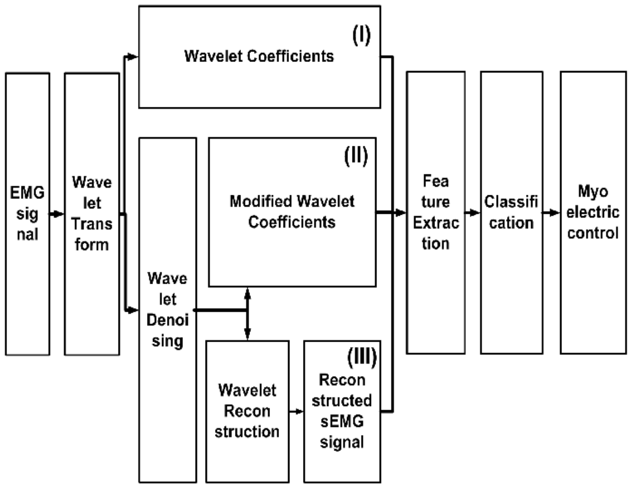


Fig.3: *Feature extraction based on wavelet transform.*

3.5 Evaluation

In this research, the robustness criterion is evaluated by mean square error (MSE). MSE of modified wavelet coefficients and reconstructed sEMG signal is used to evaluate three types of extraction (Type I-III). MSE is a standard statistical criterion that presents the same results as SNR and Root mean square (RMS) difference (compare the results of [11] and [31] as will be discuss in Section 4.2). MSE of modified wavelet coefficients (MSE_W) can be given by

$$MSE_W = \frac{\sum_{i=1}^{N}(c_i - c_{ei})^2}{N}, \tag{8}$$

where c_i represents the modified wavelet coefficients of original sEMG signal and c_{ei} is the modified wavelet coefficients of noisy sEMG signal.

In addition, MSE of reconstructed sEMG signal (MSE_R) are used to evaluate the quality of robustness function that determines perfect reconstruction. It is calculated by

$$MSE_R = \frac{\sum_{i=1}^{N}(f_i - f_{ei})^2}{N}, \tag{9}$$

where f_i represents the original sEMG signal and f_{ei} is the estimated signal obtained from the modified wavelet coefficients or reconstructed sEMG signal.

The optimal performance of wavelet function is the best when both of MSEs are the smallest. To guarantee the best wavelet function optimized for sEMG signal, we calculate MSE averages for each motion with ten datasets. WGN with various SNR was added to the original sEMG signal as shown in Fig. 4 and is used to evaluate the performance of robustness. SNR of each datasets was varied from 20 to 0 dB. SNR is calculated by

$$SNR = 10 \log \frac{P_{Xclean}}{P_{Xnoise}}, \tag{10}$$

where P_{Xclean} is the power of the original sEMG signals and P_{Xnoise} is the power of the WGN. Power spectrum of original sEMG signal and noisy sEMG signal at 0 dB SNR is shown in Fig. 5. It shows that WGN spreads in every frequency scale.

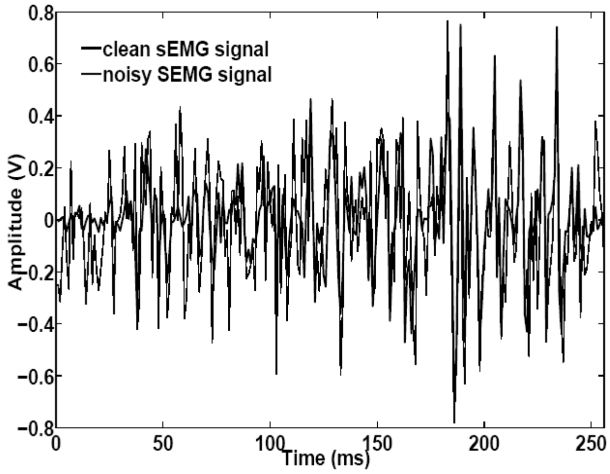


Fig.4: *Original sEMG signal and noisy sEMG signal at 0 dB SNR from extensor carpi radialis longus in wrist extension motion.*

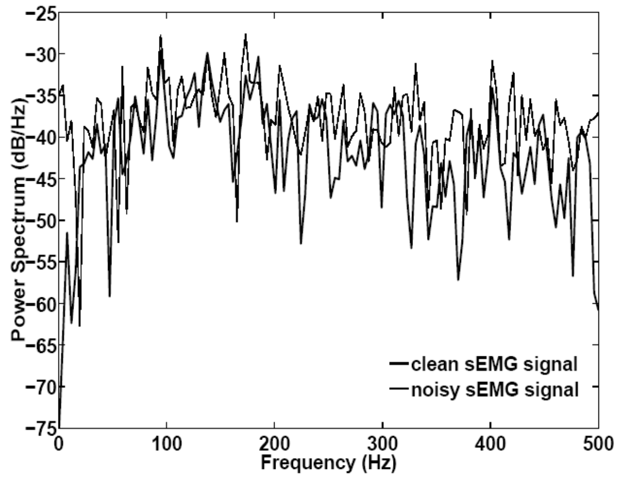


Fig.5: *Power spectrum of original sEMG signal and noisy sEMG signal at 0 dB SNR from extensor carpi radialis longus in wrist extension motion.*

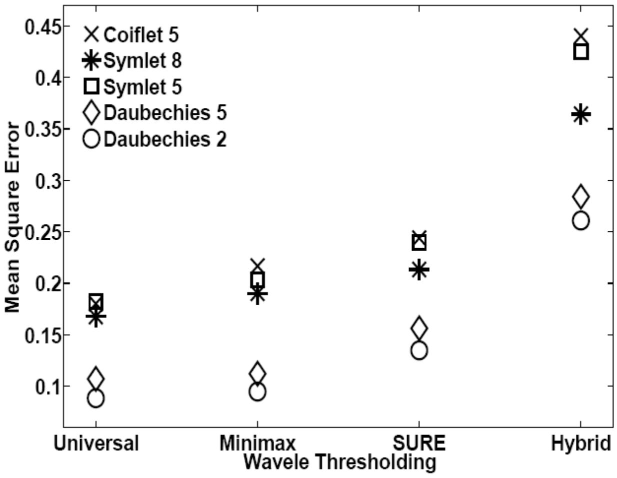


Fig.6: *MSE_W of five wavelet functions with four classical wavelet threshold estimations at 0 dB SNR.*

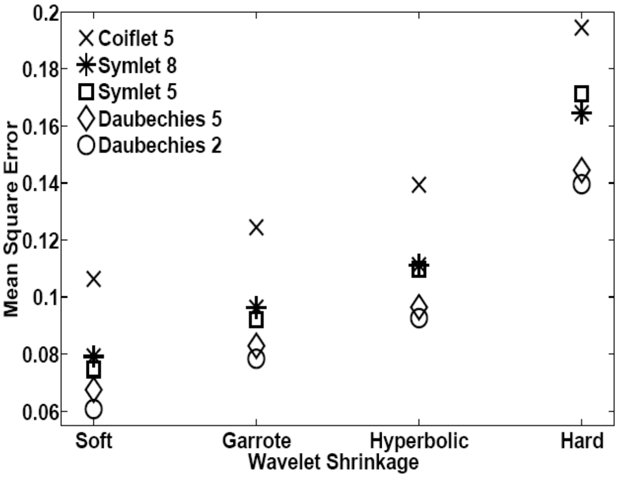
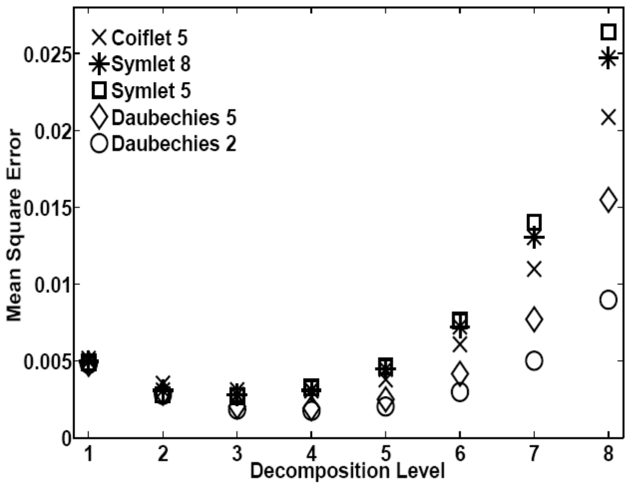
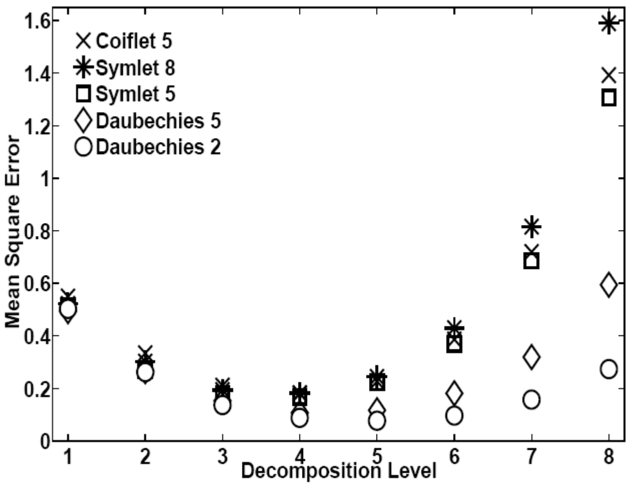


Fig.7: *MSE_W of five wavelet functions with four classical wavelet threshold transformations at 0 dB SNR.*



(a)



(b)

Fig.8: *MSE_W of five wavelet functions with eight decomposition levels. (a) 20 dB SNR.(b) 0 dB SNR.*

4. RESULTS AND DISCUSSION

4.1 Optimal Wavelet Based on Decomposition and Denoising (Type I and II)

The critical point in wavelet denoising is the selection of right wavelet function which depend on the application and characteristics of signal. Different wavelet functions were investigated to optimize wavelet denoising procedure. Firstly, the effects of variety wavelet denoising algorithms with the optimal wavelet function are discussed. In Fig. 6, we found that MSE_W of each wavelet is not dependent on the different type of wavelet estimation. Also MSE_W of each wavelet does not change when wavelet transformation is changed as shown in Fig. 7. These results answer the third aim. Secondly, Fig. 8 (a) and Fig. 8 (b) present the effects of scale levels for each wavelet functions. We found that the third level has the best performance, close by the forth level for low noises (20-10 dB SNR). On the other hand, the fourth levels are better than other scales for high noise (10-0 dB SNR). From experimental above, effect of decomposition level with optimal wavelet is a little bit. Hence, the decomposition level 4 is suggested (the second aim).

Finally, the evaluation of the robustness in Type I and Type II are described in Fig. 9. $MSEW$ in Fig. 8 (a-c) are plotting in log-lin type of a semi-log graph, defined by a logarithmic scale on the y axis, and a linear scale on the x axis. The figures present the results of MSE_W at 20 dB, 10 dB, and 0 dB SNR as consider as the low, medium, and high noise, respectively. The results of wavelet functions in each SNR level are the same trend. As SNR increases, the MSE_W of each wavelet function increases. The smallest MSE_W is db1, bior1.1, and rbio1.1. The MSE_W averages are 0.00407, 0.01242, 0.04090, 0.12739, and 0.41242 at SNR value of 20, 15, 10, 5, 0 dB, respectively. It also produces the best robust wavelets. The db2, db7, sym2, bior5.5, and rbio2.2 provide marginally better performance than other candidates. Furthermore, the various orders of Daubechies (db1-db10), Symlets (sym2-sym8), BiorSplines (bior1.1-bior1.5, bior4.4, bior5.5, and bio6.8), Coiflet (coif1-coif2), and ReverseBior (rbio1.1-rbio3.9, rbio6.8) can be tolerated with WGN. The most terrible wavelet function is bior3.1. Its MSE_W is as much as seven of the minimum MSE_W. The third order of decomposition of BiorSplines (Bior3.3, bior3.5, bior3.7, and bior3.9) and Discrete Meyer (dmey) are worse performance. Its MSE_W is as much as two of the minimum MSE_W. Moreover, in high noise, the second order of decomposition of BiorSplines (bior2.2-bior2.8) and the fifth order of decomposition of ReverseBior (rbio5.5) are not good. Therefore, these functions are not recommended to use for providing EMG features.

If we consider only optimal wavelets for denoising, we can conclude that db1, bior1.1, and rbio1.1 are best. The db2, db7, sym2, bior5.5, and rbio2.2 are prospective to have good performance. It means these wavelets suitable for extracted feature in Type I. Results are in agreement with our previous work [11] and the results of Hussain et al. [31]. In [11], we compare five wavelet functions from the literatures review in sEMG denoising, namely db2, db5, sym5, sym8, and coif5, with MSE_W measure. The results show that db2 is better than other functions. In [31], the researchers evaluate eight mother wavelets that commonly used in biomedical signals include the Daubechies db2, db4, db5, db6, and db8 wavelets and the orthogonal Meyer wavelet (dmey). The results show db2 is the best using SNR value and RMS difference measures. The second order of Daubechies is the optimal wavelets in both of [11] and [31]. However, the results of [11] and [31] are compared with a few wavelets that db1, bior1.1 and rbior1.1 are not contained.

Furthermore, Type II extraction must be considered the classification results to find the optimal wavelet. We did not report the classification results in this work because the suitable wavelet functions depended on the classifier type (neural network, fuzzy logic, neuro-fuzzy classifier, probabilistic classifier etc). However, the effective wavelet functions for classification are proposed by Englehart [8]. Various types of wavelet function are used in classification tasks (Type I). Wavelet coefficients are subjected to dimensionality reduction and the classification errors are reported. Within the Daubechies, Coiflet, and Symlet families, the best performance is 18, 4 and 8, respectively. Interesting trend is the improvement of classification performance tends to increasing of wavelet's order. Thus, for Type II, the balance between class separability and robustness should be considered. Db7, sym5 or coif 4 are some compromise wavelets.

4.2 Optimal Wavelet Based on Reconstruction (Type III)

Table 2: *Mean square error of reconstructed signals ($MSE_R(\times 10^{-3})$) at various SNRs.*

SNR	Most wavelets	coif5	dmey
20 dB	4.073816376	4.073816374	4.073840024
15 dB	12.42650749	12.42650748	12.42657928
10 dB	40.90699400	40.90699300	40.90723200
5 dB	127.3962764	127.3962762	127.3970231
0 dB	412.4266599	412.4266591	412.4290643

In the view point of perfect reconstruction signal, the results of $MSER$ show that the fifth order of Coiflet (coif5) is the best wavelet function. Its MSE_R at low noise, 20 dB SNR, is less than the other candidates about 2×10^{-12}. The MSE_R of other wavelet functions is approximately $4.073816376 \times 10^{-3}$ at 20 dB SNR. In addition, dmey is the worst wavelet in reconstruction that MSE_R is more than the others about 3×10^{-8}. By comparing MSE_R in every noise levels, results of wavelet functions in each SNR level is the same trend. Table 2 shows the MSE_R of most wavelet functions, coif5 and dmey. From the above experimental results, we can conclude that most wavelet functions have the same performance of reconstructed signal.

From the experimental results in Section 4.1 and 4.2, the interesting result is the wavelet functions that have the complex shape and high frequency of decomposition wavelet. It is not optimized for robustness. For example Fig. 10 (a-b) shows the scaling functions and wavelet functions in time domain of bior3.1 respectively which was found to be worse performance in robustness. The simple shape and low frequency of wavelet functions are optimized for morphological sEMG signal. For example Fig. 8 (c-d) shows respectively the scaling functions and wavelet functions in time domain of db2. Moreover, the results of WPT are not reported because it has the same trends with WT. We can observe the behavior of optimal wavelet function of WPT from the WT's trends.

5. CONCLUSIONS

Wavelet analysis is a significant tool to analyze the surface Electromyography signal. The objective of this paper was to select suitable wavelet function of DWT and WPT that is robust to varieties of noises. We can summarize the optimal mother wavelets into three points:

1. For Type I extraction, the best wavelet functions are db1, bior1.1, rbio1.1. The db2, db7, sym2,

bior5.5, and rbio2.2 provide marginally better performance than other candidates.

2. For Type II extraction, the balance between class separability and robustness should be considered. Db7, sym5 or coif 4 are some compromise wavelets. In practice, we can adapt wavelet function to be suitable for each application.

3. For Type III extraction, coif5 provides the best reconstruction for sEMG signal.

4. Bior3.1, bior3.3, bior3.5, bior3.7, bior3.9, and dmey are not recommended to use in each Type I-III.

5. DWT and WPT have the same trends of optimal wavelet functions.

The advantage of this result is possibility to receive good quality EMG wavelet functions that investigate the best correlation with sEMG signal and suitable for multifunction myoelectric control system. Future work is recommended to find the new wavelet functions, such as Morlet and Mexican Hat, to be tested and used the optimal robust wavelet function with some characteristics parameters to extract useful information features as inputs to the EMG pattern recognition.

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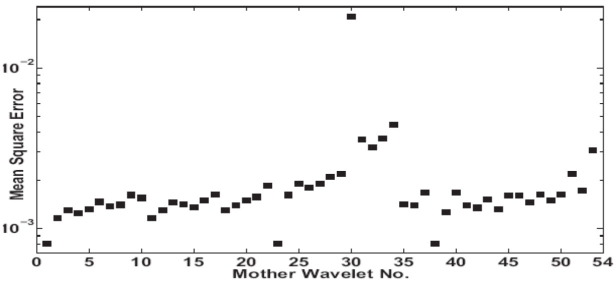

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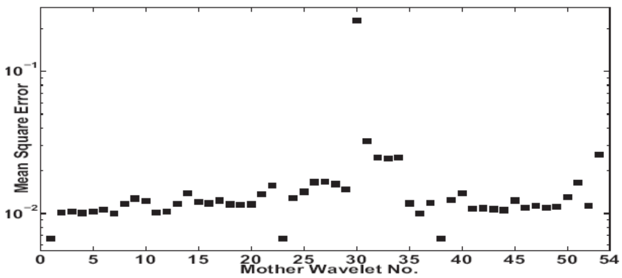

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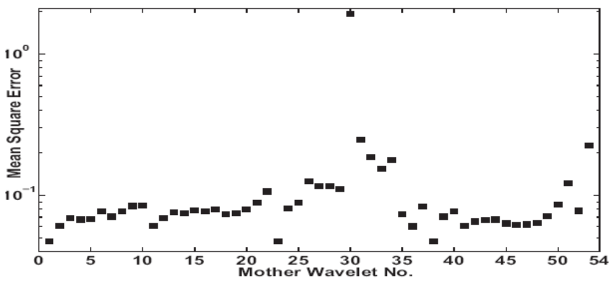
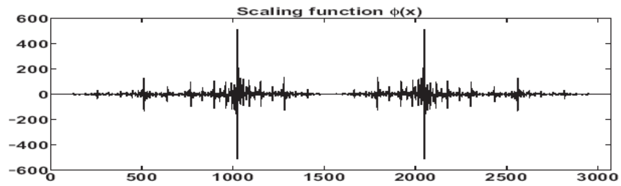
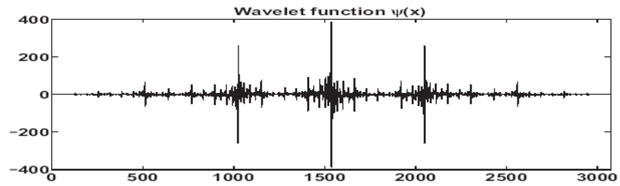


(c)

Fig.9: *MSE_W of all 212 possible combinations of wavelet functions and threshold transformations (mother wavelet numbers refer to the wavelets in Table I, i.e. ♯ 1-Daubechies order 1, ♯ 2-Daubechies order 2,. . ., ♯ 11-Symlets order 2,. . .,♯ 18-Coiflet order 1,. . ., ♯ 53-Discrete Meyer) (a) at 20 dB SNR. (b) at 10 dB SNR. (c) at 0 dB SNR.*



(a)



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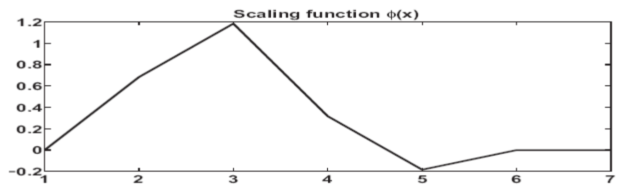

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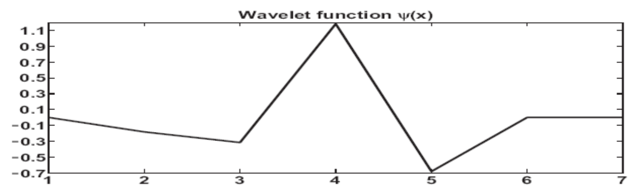

(d)

Fig.10: *Scaling functions and wavelet functions in time domain of (a-b) bior3.1. (c-d) db2.*