A Comparative Study of Wavelet Denoising for Multifunction Myoelectric Control

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***Abstract*—The aim of this study was to investigate the application of wavelet denoising in noise reduction for multifunction myoelectric control system. Six upper limb motions including hand open, hand close, wrist extension, wrist flexion, pronation, and supination. For each motion, two channels of electrodes were applied. A comparative study of four classical denoising algorithms including universal thresholding, SURE thresholding, hybrid thresholding, and minimax thresholding have been used to remove white Gaussian noise at various signal-to-noise ratios (SNRs) from EMG signals. Applications of soft and hard thresholding as well as threshold rescaling methods were considered and the whole procedures of noise reduction were applied with different wavelet functions and different decomposition levels. Evaluations of the performance of noise reduction are determined using mean squared error (MSE). The results show that Daubechies wavelet with second orders (db2) provides marginally better performance than other possibilities. Suitable number of decomposition levels is four. Universal and soft thresholding is the best of wavelet denoising algorithms from eight possible denoising processes under investigation. In addition, the threshold using a level-dependent estimation of level noise showed better than others.**

Keywords-EMG; Wavelet Denoising; Myoelectric; Prosthesis

I. INTRODUCTION

Varieties of noises originated from measure instruments are major problems in analysis of surface electromyography (sEMG) signals. Therefore, methods to eliminate or reduce the effect of noises have been one of the most important problems. 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. Wavelet denoising algorithms, an advance signal processing method, have been received considerable attention in the removal of white Gaussian noise [1-3].

Comparative studies of wavelet denoising methods have been proposed [4-7]. Jiang and Kuo [4] compared four classical threshold deviation methods and two transformations with simulated signal at 16-dB SNR and original sEMG signal. They 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 EMG is insensitive to the selection of denoising methods. Guo et al. [5] compared the same denoising methods as Jiang and Kuo but they changed real EMG 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.

This study is motivated by the fact that the available results of the comparative study of denoising methods were not effective enough. From the literatures, it has been shown that all of them fixed the wavelet function and the scale level. This was not powerful enough to make the comparison fair with respect to the variety of wavelet function and scale level. In addition, there were not publications considering about threshold rescaling methods in EMG.

This paper presents a complete comparative study of denoising algorithms using wavelets for removing white Gaussian noise from surface electromyography signal. The objectives of this study were to investigate: 1) the suitable wavelet functions and their scale level 2) the best threshold estimator method and transformation method 3) the suitable threshold rescaling method.

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

II. EXPERIMENTS AND DATA ACQUISITION

In this section, we describe our experimental procedure for recording surface myoelectric control system (sMES). The sMES was 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 EMG is within 0-500 Hz, but the dominant energy is concentrated in the range of 10–150 Hz. A band-pass filter of 10-450 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 (IN BNC-2110, National Instruments Corporation).

A subject 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.

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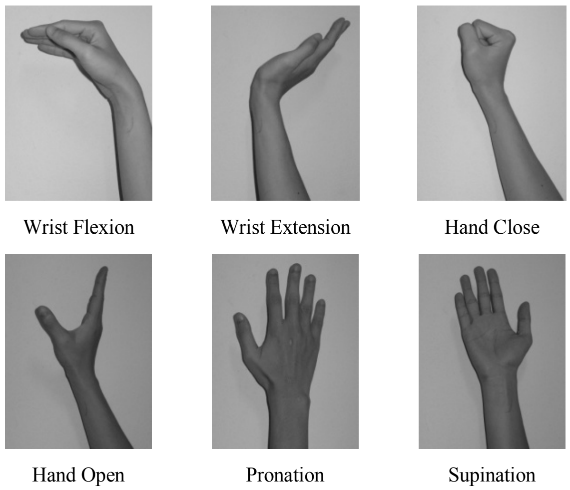


Figure 1. Estimated six hand motion.

Ten datasets were collected for each motion. The sample size of the EMG signals is 256 ms for the real-time constraint that the response time should be less than 300 ms.

III. Methodology

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

$$s(n) = f(n) + e(n). \tag{1}$$

The procedure of wavelet denoising follows three steps described below.

A. Wavelet Decomposition

The first step of wavelet denoising procedure is selection of wavelet function or mother wavelet. It is importance of choosing the right filters [8]. The right wavelet function determines perfect reconstruction and performs better analysis. We adopted five wavelet functions from the suggestion of previous research [1-7] including Daubechies wavelet with second and fifth orders (db2, db5), Symlets wavelets with fifth and eighth orders (sym5, sym8), and Coiflet wavelet with fifth order (coif5).

Next step is the selection of the number of decomposition levels of signal. Discrete wavelet transforms (DWT) use high-pass filter to perform high frequency components so-called details (D) and low-pass filter to perform 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. We decomposed the signals into various scale levels. The scale levels are varied from one to ten levels.

B. Wavelet Denoising

In basic model, estimation of detail coefficient threshold was selected with estimator methods for each level from 1 to n. Four classical threshold estimation methods were applied in this study including universal threshold, SURE threshold, hybrid threshold, and minimax threshold. Four methods were described in the following.

1) Universal thresholding method: This method was also proposed in [9]. It used a fixed form threshold, which can be expressed as

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

where N is the length in samples of time-domain signal.

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, where risk is defined by Stein's unbiased estimate of risk [10]. Minimizing the risk in THR 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 tresholding method. The exact conditions of this algorithm are described in [11].

4) Minimax thresholding method: This method was also proposed in [10]. It used a fixed threshold chosen to yield minimax performance for mean square error against an ideal procedure.

After already have threshold value, thresholding can be done using hard and soft transformation. Threshold transformations were described in the following.

1) Hard thresholding: This transformation can be described as the usual process of zeroing all detail coefficients whose absolute values are lower than the threshold, which can be expressed as

$$cD_j = \begin{cases} cD_j & if \ |cD_j| > THR_j \\ 0, otherwise \end{cases} . \tag{3}$$

2) Soft thresholding: This transformation is an extension of hard thresholding, first zeroing all detail coefficients whose absolute values are lower than the threshold, and then shrinking the nonzero coefficients towards zero, which can be expressed as

$$cD_j = \begin{cases} \operatorname{sgn}(cD_j)(cD_j - THR_j), & if \ |cD_j| > THR_j \\ 0, & otherwise \end{cases} . \tag{4}$$

Combining the four threshold estimations and threshold transformations, there exist eight possible wavelet denoising procedures as shown in Table I.

In practice, the above basic model cannot be used directly. The threshold rescaling methods were considered. Three methods are described in the following.

1) Basic model: Estimation of threshold for each level.

2) Basic model with unscaled noise: Estimation of threshold uses a single estimation of level noise based on the first-level detail coefficients (cD_1). The detail coefficients provide a good estimate of standard deviation of the essential white Gaussian noise.

3) Basic model with non-white noise: Estimation of threshold uses a level-dependent estimation of level noise. This method is same kind of strategy as in the previous but it estimates standard deviation level by level.

Three threshold rescaling method were applied with eight possible wavelet denoising procedures.

TABLE I. WAVELET DENOISING PROCEDURES

Wavelet Denoising Procedures	Combination of wavelet denoising	
	Threshold Estimation	***Threshold Transformation***
SURE/Soft	SURE Thresholding	Soft Thresholding
SURE/Hard	SURE Thresholding	Hard Thresholding
Hybrid/Soft	Hybrid Thresholding	Soft Thresholding
Hybrid/Hard	Hybrid Thresholding	Hard Thresholding
Universal/Soft	Universal Thresholding	Soft Thresholding
Universal/Hard	Universal Thresholding	Hard Thresholding
Minimax/Soft	Minimax Thresholding	Soft Thresholding
Minimax/Hard	Minimax Thresholding	Hard Thresholding

C. Wavelet Reconstruction

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

D. Evaluation

The mean squared error (MSE) used to evaluate the quality of denoising signals can be given by

$$MSE = \frac{\sum_{i=1}^{N}(f - f_e)^2}{N} \tag{5}$$

where N denotes the length of the signal, f represents the wavelet coefficients of the original signal and f_e is the wavelet coefficients of the denoising signal.

The performance of the algorithms is the best when MSE are the smallest value. We calculated MSE averages for each motion with ten repeated datasets. Therefore, there are 60 datasets for each wavelet denoising processes and SNR values are varied from 20 to 0 dB as shown in Fig. 2. As a result, wavelet denoising processes contain 5 x 10 x 4 x 2 x 3 = 1200 possible combinations of wavelet functions, scale levels of wavelet, threshold estimator, threshold transformations, and threshold rescaling. We note that all of these results are the averages of the MSE for all kind of movement's signals.

IV. RESULTS AND DISCUSSION

The objectives of this study were to investigate: 1) the suitable wavelet functions and their scale level 2) the best threshold estimator method and transformation method 3) the suitable threshold rescaling method.

Fig. 3 shows the effects of scale levels for each wavelet functions at 10 dB SNR. When wavelet has scale levels more than six, MSE value rapidly increases. Therefore, Fig. 4(a) and Fig. 4(b) show only first six scales. We found that the third levels are better than the others scale for low noises (20-10 dB SNR). On the other hand, the fourth levels are better than the others scale for high noise (10-0 dB SNR). Subsequently, within the best thresholding approach (the results are shown in second objective), the second-order Daubechies wavelet (db2) provides marginally better performance than other possibilities and suitable number of decomposition levels is four.

Results for the second and the third objectives are presented in Fig. 5. Fig. 5(a) shows eight possible combinations of threshold estimation and threshold transformation with different threshold rescaling method. Basic model with unscaled noise and basic model with non-white noise showed different results, which is due to different wavelet denoising procedures. However, the best result is the combination of universal thresholding, soft transformation and threshold rescaling with non-white noise. The minimum *MSE* average is 0.001392 at SNR value of 20 dB and 0.072319 at SNR value of 0 dB. Interesting results of threshold rescaling method are basic model. Their values are all the same. Because the threshold values are estimated from threshold estimator, their values are over the maximum amplitudes in each detail coefficients. It means that denoising signals have only signal from approximation coefficients.

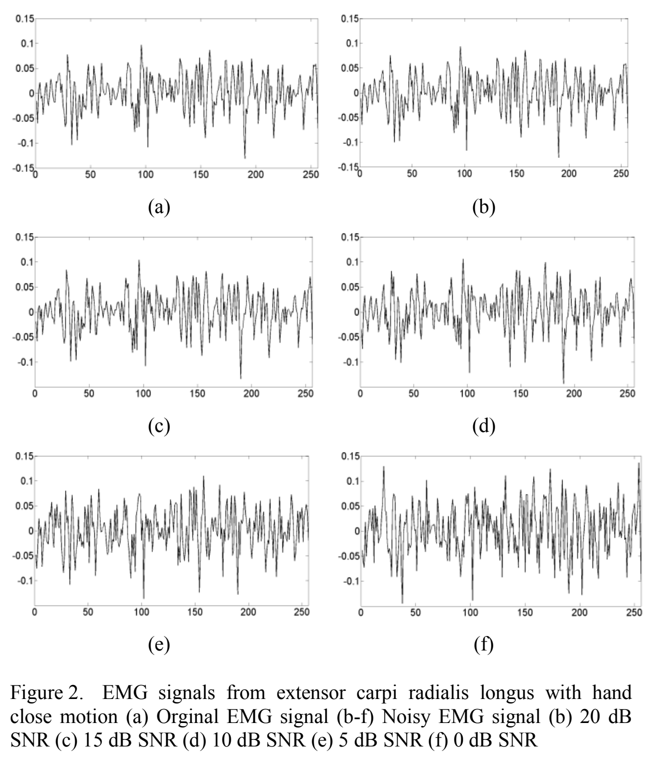


Figure 2. EMG signals from extensor carpi radialis longus with hand close motion (a) Orginal EMG signal (b-f) Noisy EMG signal (b) 20 dB SNR (c) 15 dB SNR (d) 10 dB SNR (e) 5 dB SNR (f) 0 dB SNR

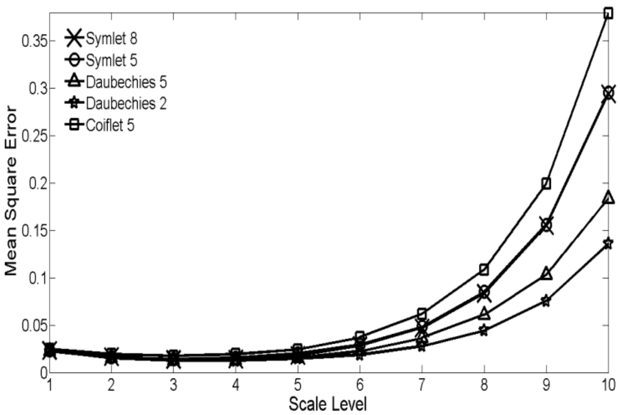
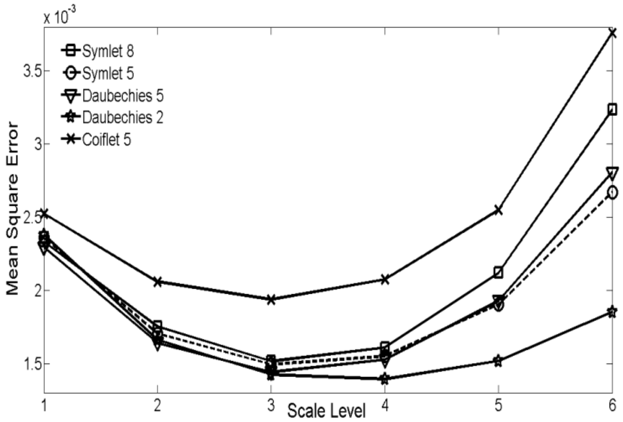
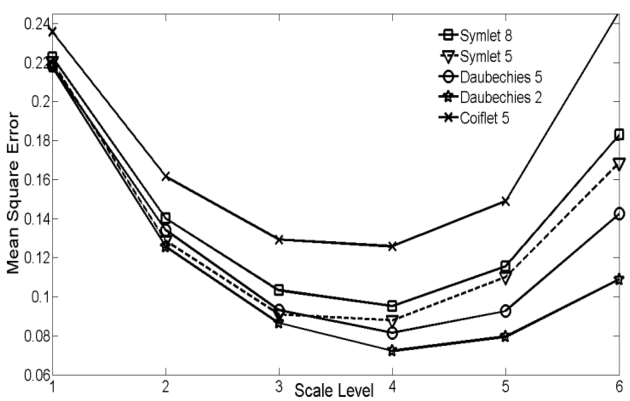


Figure 3. MSE average of universal thresholding and soft transformation for different wavelet functions and scale levels at 10 dB SNR



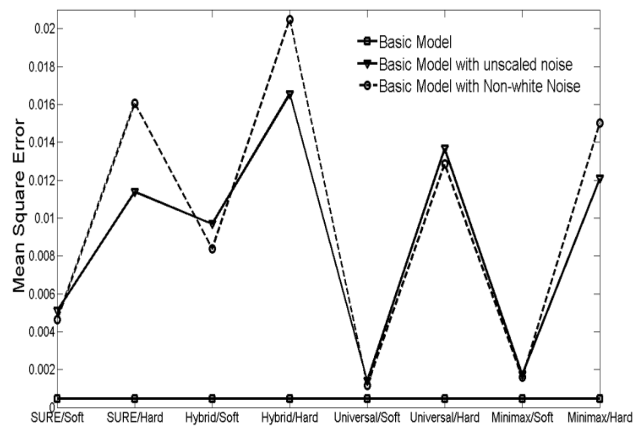
(a)



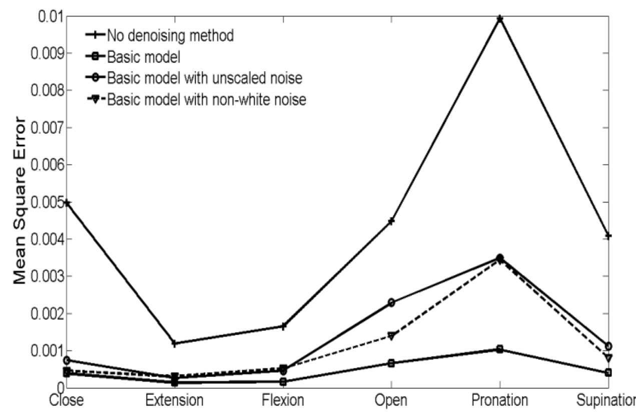
(b)

Figure 4. MSE average of universal thresholding and soft transformation for different wavelet functions (a) At 20 dB and scale level 1-6 (b) At 0 dB and scale level 1-6.

Fig. 5(b) shows the comparison of the denoising methods and traditional wavelet transform. Wavelet denoising procedures show the superior performance than traditional wavelet transform. In addition, basic model with



(a)



(b)

Figure 5. (a) MSE average of the second-order Daubechies wavelet at level 4 for different wavelet denoising methods and threshold rescaling methods (b) MSE average of the universal thresholding and soft transformation with wavelet denoising method and traditional wavelet transform.

non-white noise is comfirmed by the plots of universal thresholding and soft transformation.

V. CONCLUSION

The aim of this study was to investigate the application of wavelet denoising in noise reduction for multifunction myoelectric control system. Six upper limb motions and two electrodes channels were applied. The results show that Daubechies wavelet with second orders (db2) provides marginally better performance than other possibilities. This is due to the fact that the Daubechies with second orders most matches EMG signals shape. All results are averaged from useful six upper limb motions. Suitable number of decomposition levels is four. Universal and soft thresholding is the best of wavelet denoising algorithms from eight possible denoising procedures. Moreover, the estimation of threshold using basic model with non-white noise showed better than others.

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