An Optimal Wavelet Function Based on Wavelet Denoising for Multifunction Myoelectric Control

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***Abstract*-The aim of this study was to investigate and select the wavelet function that is optimum to denoise the surface electromyography (sEMG) signal for multifunction myoelectric control. Wavelet denoising algorithm has been used to find the optimal wavelet function for removing white Gaussian noise (WGN) at various signal-to-noise ratios (SNRs) from sEMG signals. A total of 53 wavelet functions were used in evaluation of the denoised performance. The wavelets are Daubechies, Symlets, Coiflet, BiorSplines, ReverseBior, and Discrete Meyer. Universal thresholding method has been used to estimate threshold value. Soft, hard, hyperbolic, and garrote thresholding are applied. Evaluations of the performance of these algorithms are mean squared error (MSE). The results show that the best wavelet functions for denoising are the first order of Daubechies, BioSplines, and ReverseBior wavelets (db1, bior1.1, rbio1.1). Various families can be used except the third order of decomposition of BiorSplines (bior3.1, bior3.3, bior3.5, bior3.7, bior3.9) and Discrete Meyer (dmey) are not recommended to use in wavelet denoising of sEMG signal. In addition, performance of soft thresholding is better than the others modified thresholding.**

I. INTRODUCTION

Varieties of noises generated by biological resources and environment resources 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 significant problems. Instability of electrode-skin contact or 50 Hz interference 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 algorithm, have been received considerable attention in the removal of WGN [1-5].

The general wavelet based denoising procedures are composed of three steps: decomposition, denoising wavelet's detail coefficients, and reconstruction. The comparative studies of wavelet denoising methods have been proposed [1-3]. To achieve and optimize the above procedures, four points must be addressed, namely selection of the suitable wavelet function or mother wavelet, level of decomposition, threshold estimation, and threshold transformation. Most wavelet based denoising literatures are highlight to the thresholding techniques rather than selection of available wavelet functions or mother wavelets. This study is motivated by the fact that there is no universal wavelet function that is suitable for all type of signal. Although, the selection of wavelet function become 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 [6-8] but no optimal wavelet selections for sEMG signals.

This paper presents a complete comparative study of denoising algorithms using wavelets for removing WGN from original sEMG signals. The objective of this study was to select the optimal wavelet function for sEMG signals. Furthermore, two modified thresholding methods, i.e., hyperbolic and non-negative garrote thresholding, were tested.

II. 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. Ten datasets

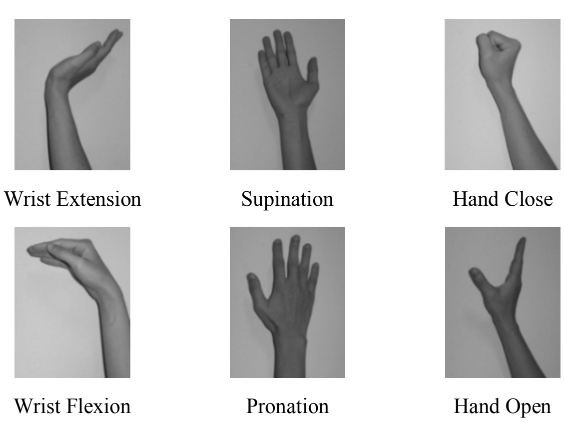

Figure 1. Six upper limb motions.

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were collected for each motion. The sample size of the sEMG 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 to select wavelet function or mother wavelet. It is important of choosing the right filters [7-8]. The right wavelet function determines perfect reconstruction and performs better analysis. A total of 53 wavelet functions are used in evaluation of the denoised 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 I.

Next step is the selection of the number of decomposition levels of signal. Discrete wavelet transforms (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. Instead of focusing on the selection of the decomposition level, we have presented in previous work that the decomposition level is 4 [9]; the MSE in each wavelet is the lowest.

B. Wavelet Denoising

Estimation of detail coefficient threshold was selected with estimator methods for each level from 1 to 4. Universal threshold estimation method was applied in this study because the suggestion of the previous research [4-5] show that the denoising results using universal thresholding method is better than the other classical methods.

TABLE I
WAVELET DENOISING PROCEDURES

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

Universal thresholding method uses a fixed form threshold, which can be expressed as [10]

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

where N is the length in samples of time-domain signal and σ is noise variance. It can be estimated using median parameter which can be calculated as

$$\sigma = \frac{median\left(\left|cD_j\right|\right)}{0.6745} \quad , \tag{3}$$

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

Level dependent thresholding is applied in this study. σ is calculated for every 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 thresholding, namely hyperbolic and non-negative garrote were applied for sEMG signals. 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 *(THR_j)*, and then keeping other detail coefficients. It can be expressed as [10]

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

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 [10]

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

3) Hyperbolic Thresholding: This transform is similar to soft thresholding. It is achieved to address the limitation of soft thresholding. It is shown as [11]

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

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 [12]

$$cD_j = \begin{cases} \operatorname{sgn}(cD_j)(cD_j - \dfrac{THR_j^2}{cD_j}), & if\ |cD_j| > THR_j \\ 0 & , otherwise \end{cases} . \tag{7}$$

The response of four thresholding transformation functions is presented in Fig. 2. We suppose thresholding value (*THR*) to 0.4 and diagonal dashed line indicates the input signal.

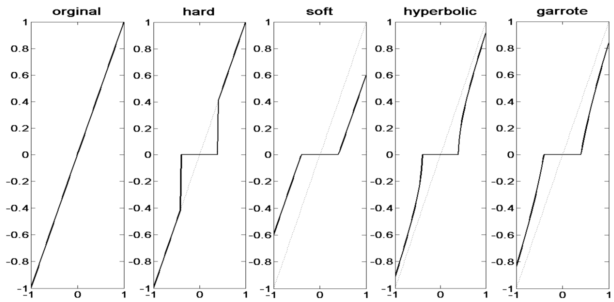


Figure 2. The response of thresholding transformation functions with 0.4 thresholding value (*THR*)

Combining the threshold estimations and threshold transformations, there exist four possible wavelet denoising procedures.

C. Evaluation

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

$$MSE = \frac{\sum_{i=1}^{N}(f - f_e)^2}{N} , \quad (8)$$

where f represents wavelet coefficients of original sEMG signal and f_e is wavelet coefficients of denoising sEMG signal.

The performance of the algorithms is the best when *MSE* is smallest. To guarantee the best wavelet function is optimize to denoise sEMG signals. We calculate *MSE* averages for each motion with ten datasets. Therefore, there are 60 datasets for each wavelet denoising processes and each datasets was varied from 20-0 dB SNR and WGN was added 5 times for each dataset as shown in Fig. 3. As a result, wavelet denoising processes contain 53×4 = 212 possible combinations of wavelet functions and threshold transformations. We note that all of these results are the averages of the *MSE* for all kind of movement's signals. Power spectrum of original sEMG signal and noisy sEMG signal at 0 dB SNR is shown in Fig. 4. It shows that WGN spreads in every frequency scale.

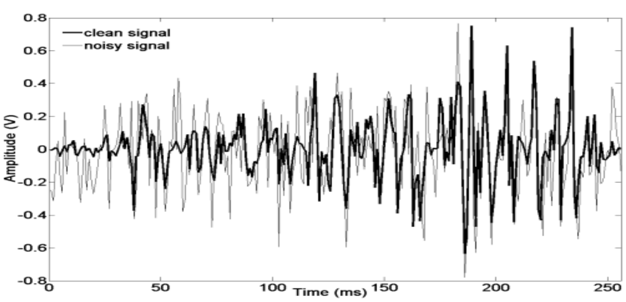


Figure 3. Original sEMG signal and noisy sEMG signal at 0 dB SNR from extensor carpi radialis longus in wrist extension motion.

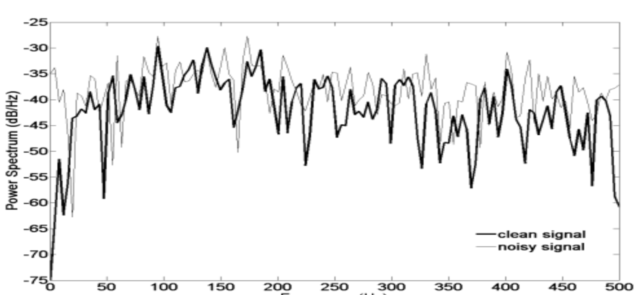


Figure 4. Power spectrum of original sEMG signal and noisy sEMG signal at 0 dB SNR from extensor carpi radialis longus in wrist extension motion.

IV. Results and Discussion

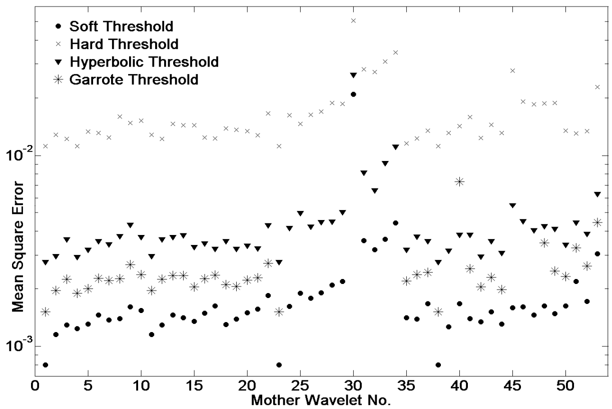
The critical point in wavelet denoising is selection of the right wavelet function which depend on the application and the characteristics of signal. Different wavelet functions or mother wavelets were investigated to optimize wavelet denoising procedure. The results of *MSE* are presented in Fig. 5 that show the ability to reconstruct the sEMG signal. Fig. 5(a-c) shows the *MSE* at 20 dB, 10 dB, and 0 dB that presents the low, medium, and high noise, respectively.

The evaluation of thresholding transformation functions shows that soft thresholding is the best performance. Non-negative Garrote and hyperbolic thresholding have slightly larger error compared to soft thresholding. It is shown that modified thresholding do not improve the performance. The *MSE* of hard thresholding is the largest as it was expected to perform poorly.

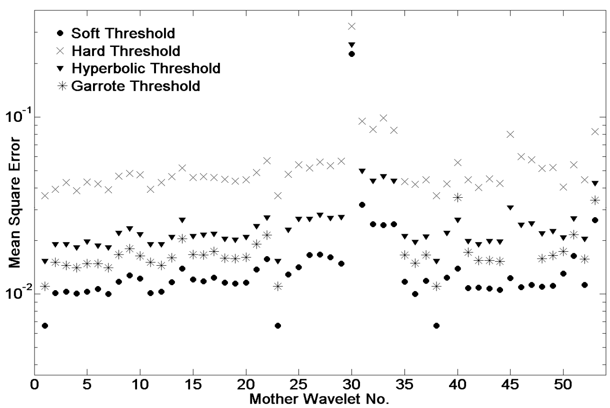
It can be seen in Fig. 5(a), (b), and (c) that results of wavelet functions in each SNR level provide the similar trend. As SNR increases, the *MSE* of each wavelet function increases. The wavelet functions db1, bior1.1, and rbio1.1 give the smallest *MSE*. It also produces the best denoising signals. The averages *MSE* are 0.0008021, 0.006635, and 0.04717 at SNR value of 20, 10, 0 dB, respectively. However, the second and higher orders are not exactly the same functions. Db2, db7, sym2, bior5.5, and rbio2.2 provide marginally better performance than other candidates. In addition, 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 used for wavelet denoising.

The wavelet bior3.1 provides the maximum *MSE* value. Its *MSE* is twenty-five times the minimum *MSE*. The third order of decomposition of BiorSplines (Bior3.3, bior3.5, bior3.7, and bior3.9) and Discrete Meyer (dmey) give poor performance. Its *MSE* is four times the minimum *MSE*. Moreover, in high noise, the second order of decomposition of BiorSplines (bior2.2-bior2.8) and rbio5.5 are not good. Therefore, these functions are not recommended to use in wavelet denoising of sEMG signal.

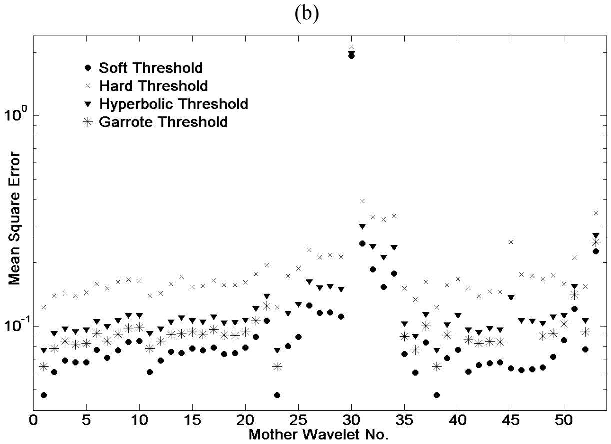
Based on demonstrated results, it can be seen that wavelet functions with complex shape and high frequency of decomposition are not optimized for wavelet denoising of sEMG signal. On the other hand, the simple shape and low frequency of wavelet functions are optimized for morphological sEMG signal. Fig. 6(a-b) shows respectively the scaling functions and wavelet functions in time domain of bior3.1 and dmey, which was found to be poor performance in EMG wavelet denoising. Fig. 6(c-d) shows respectively the scaling functions and wavelet functions in time domain of db1 and sym2.



(a)



(b)

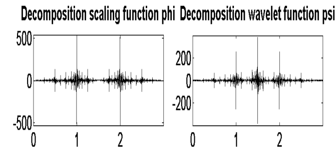


(c)

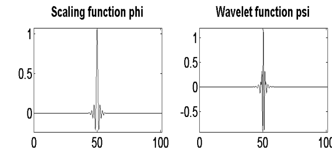
Figure 5. Mean Square Error (MSE) of all 212 possible combinations of wavelet functions and threshold transformations (mother wavelet numbers refer to the wavelets in Table I, i.e. #1-Daubechies order 1, #2-Daubechies order 2, …, #11-Symlets order 2, …,#18-Coiflet order 1, …, #53-Discrete Meyer) (a) At 20 dB SNR (b) At 10 dB SNR (c) At 0 dB SNR.

V. CONCLUSION

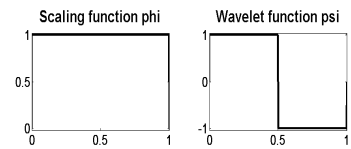
The aim of this study was to investigate and select the wavelet function that is optimum to denoise surface electromyography signals for multifunction myoelectric control. The results show that db2, db7, sym2, bior5.5, rbio2.2 provides marginally better performance than other candidates. The best wavelet functions are db1, bior1.1, rbio1.1. The minimum *MSE* average is 8.021×10^{-3} at SNR value of 20 dB. Bior3.1, Bior3.3, bior3.5, bior3.7,



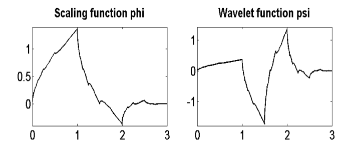
(a)



(b)



(c)



(d)

Figure 6. Scaling functions and wavelet functions in time domain of (a) bior3.1 (b) dmey (c) db1 (d) sym2

bior3.9, and dmey are not recommended. Furthermore, soft thresholding has still better performance than others modified thresholding. 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. In practice, we can adapt wavelet function to be suitable for each application.

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REFERENCES

[1] C.F. Jiang and S.L. Kuo, “A Comparative Study of Wavelet Denoising of Surface Electromyographic Signals,” in *Proc. IEEE 29th Annu. Int. Conf. IEEE EMBS*, Lyon, 2007, pp.1868-1871.

[2] Z. Qingju and L. Zhizeng, “Wavelet De-Noising of Electromyography,” in *Proc. 2006 IEEE Int. Conf. Mechatron. and Autom.*, Luoyang, 2006, pp.1553-1558.

[3] X. Guo, P. Yang, Y. Li, and W.L. Yan, “The SEMG Analysis for the Lower Limb Prosthesis Using Wavelet Transformation,” in *Proc. IEEE 26th Annu. Int. Conf. IEEE EMBS*, San Francisco, CA, 2004, pp.341-344.

[4] S.A. Chouakri, F. Bereksi-Reguig, S. Ahmaïdi, and O. Fokapu, “Wavelet Denoising of the Electrocardiogram Signal Based on the Corrupted Noise Estimation,” *IEEE Comput. in Cardiology*, vol. 32, pp.1021-1024, 2005.

[5] P.M. Agante and J.P. Marques de Sá, “ECG Noise Filtering Using Wavelets with Soft-thresholding Methods,” *IEEE Comput. in Cardiology*, vol. 26, pp.535-538, 1999.

[6] M.d.M. Elena, J.M. Quero, and I. Borrego, “Optimal Selection of Wavelet Coefficients for Electrocardiograph Compression,” *ETRI Journal*, vol. 29, pp.530-532, August, 2007.

[7] H.G. Rodney Tan, A.C. Tan, P.Y. Khong, and V.H. Mok, “Best Wavelet Function Identification System for ECG Signal Denoise Application,” in *Proc. IEEE Int. Conf. Intell. and Adv. Syst.*, pp.631-634.

[8] M. Kania, M. Fereniec, R. Maniewski, “Wavelet Denoising for Multi-lead High Resolution ECG Signals,” *Measurement Science Review*, vol. 7, section 2, no. 4, 2007.

[9] A. Phinyomark, C. Limsakul, and P. Phukpattaranont, “A Comparative Study of Wavelet Denoising for Multifunction Myoelectric Control,” in *Proc. 2009 Int. Conf. Comput. and Autom. Eng.*, Bangkok, Thailand, 2009, pp.21-25.

[10] D. Donoho and I. M. Johnstone, “Ideal Spatial Adaptation by Wavelet Shrinkage,” Department of Statistics, Stanford University, USA. April 1993

[11] B. Vidakovic, *Statistical Modeling by Wavelets*, 1st ed. Toronto, ON, Canada: Wiley, 1999.

[12] H-Y. Gao, “Wavelet Shrinkage Denoising Using the Non-Negative Garrote,” Journal of Computational and Graphical Statistics, vol. 7, No. 4, pp. 469-488.