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Optimal Wavelet Filterfor De-noising Surface Electromyographic Signal Captured From bicepsbrachii muscle

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ABSTRACT

This paper presents a study on finding an optimal wavelet filter for denoising surfaceelectromyographic signal, the surface electromyographic signal was captured from the biceps brachiimuscle of the human arm, this signal was stored in a one-dimensional matrix and conducted a series of procedures to reduce the noise.The performance has been tested based upon the nearest five wavelet filters in terms of the shape of the form of the original signal, after subjected to three noisy Gaussian environments at different signal to noise ratio. A tremendous amount of results was obtained, These results show that the fourth order Daubechies wavelet filter at the fourth decomposition levelis optimized to reduce the noise of the surface electromyographic signal that captured from bicepsbrachii muscle, where the results of the tests in a very noisy environment show that the value of the mean square error is 0.0159 and the output signal-to-noise ratio is 11.4424.

Keywords:EMG, Wavelet function, Wavelet denoising.

أمثل مصفي مويجي لتقليل ضوضاءأشارة التحفيز العضلي السطحية الملتقطة من العضلة العضدية ثنائية الرأس

الخُلاصة

هذا البحث يقدم دراسة عن ايجاد امثل مصفي مويجي لأشارة التحفيز العضلي السطحية,تم التقاط اشارة التحفيز العضلِي السطحية من العضلة العضدية ثنائية الرأس منذراعِ بشرية, خُزِنت هذه الأشارة بشكل مصفوفة احادية البعد وأُجْرِيت عليها سلسلة من اجراءات تقليل الضوضاء , تمَّ اختبار الأداء استناداًالأقرب خمس مصفيات مويجية من حيث الشكل لشكل الاشارة الاصلية وذلك بعد اخضاعها لثلاث بيئات ضوضائية كاوسية مختلفة الشدة. تم الحصول على كم هائل من النتائج التي بينت أن المصفي المويجي "دوبيشيس من الدرجة الرابعة" وعند مستوى التفكك الرابع هو الامثل في تقليل ضوضاء اشارة التحفيز العضلِي السطحية المُلتقطة من العضلة

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العضدية ثنائية الرأس حيث بينت نتائج الاختبارات في بيئة شديدة الضوضاء ان قيمة خطأ مربع المعدل هو 0.0159وان نسبة الاشارة الى الضوضاء الخارجة هي 11.4424.

INTRODUCTION

Electromyographic signals (EMG) represent the electrical activity of a muscle during contraction. In particular, the surface electromyographic (SEMG) signal, due to its non-invasiveness, is achieving increasing attention in several fields such as physiological muscle assessment, rehabilitation, and sport and geriatric medicine [1]. Varieties of noises originated from measurement instruments are major problems in the analysis of surface electromyographic (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 [2]. Wavelet denoising algorithms, an advance signal processing method, have been receiving considerable attention in the removal of white Gaussian noise [2]. This study is motivated by the fact that the available results of the comparative study of denoising methods from the previous research were not effective enough because they fixed the wavelet function and the scale level [2]. But in the real world, there is no universal wavelet filter that is suitable for all types of signals. In this paper, we evaluate the most standard wavelet families namely Daubechies, Symlets, andCoiflet with different orders and decomposition levels. The aims of this study were to conclude: the suitable wavelet functions in decomposition, denoising and reconstruction points of view, and the optimal level of wavelet decomposition.

Experiments and data acquisition

The SEMG signals were collected from a healthy male in the Planning unit of the brain and nerves in Ghazi Hariri hospital in Baghdad's medical city. For the experiment, the subject was asked to perform a series of contractions and relaxations of his bicepsbrachii muscle as shown in figure (1). The SEMG signals were recorded by two pairs of surface electrodes each electrode was separated from the other by 3 cm. The electrodes were installed with a transparent medical adhesive after being sterilized with a solution of dettol. The data were saved as binary files and opened in Matlab (R2012a) for the processing.

Methodology

The objective of wavelet denoising algorithm is to suppress the noise part of the signal s(t) by discarding the WGN n(t) and to recover the signal of interest s(t). The model is basically of the following form:[3]

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

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

Step1. Decomposition:choose a wavelet function and decomposition level J, Compute the wavelet decomposition of the SEMG signal at level J.

Step2.Denoising wavelet detail coefficients:foreach level selects a threshold value and apply thresholding to the detail coefficients.

Step3. 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 ofthe suitable wavelet function, level of decomposition, threshold estimation, and threshold transformation. Most wavelet based denoising literatures highlighted the thresholding techniques rather than selection of available wavelet functions. The aboveprocedures ofwavelet denoisingare described in detail as below:

Wavelet Decomposition

The first and more important step is to select wavelet function. It is important to choose the right filter because it determines the perfect reconstruction. Reference [3] had said if let the mother wavelet scaling and shifting, we could get the function $\psi_{a,\tau}(t)$:

$$\psi_{a,\tau}(t)=\frac{1}{\sqrt{a}}\,\psi\left(\frac{t-\tau}{a}\right) \quad ....(2)$$

Where

$a,\tau \in R;\ a > 0$

Where

a is the scaling gene, τ is the shifting gene, and the function $\psi_{a,\tau(t)}$is the basic wavelet function depending on aand τ We could spread any function f(t) which belonged to L2(R) space on the wavelet basis and got the continuous wavelet transform of function f(t). It was written by

$$WT_f(\tau,a)=\psi(\tau,a)=\frac{1}{\sqrt{a}}\int_R f(t)\,\psi^*\left(\frac{t-\tau}{a}\right)dt \quad ....(3)$$

We chose the scaling gene a as the discrete values according to the power of two and the shifting gene τ=1. So, we got the binary orthogonal wavelet and its wavelet basis was written by

$$\psi_{k,n}(t)=2^{-\frac{k}{2}}\psi(2^{-k}t-n)\quad k,n \in Z \quad ...\ (4)$$

According to Mallat algorithm, if Φ was scaling function and ψ(t) was the wavelet function, then, the expressions of wavelet decomposing were

$$c_{j,k}=\sum_n h0(n-k)\,c_j-1,n, \quad ....(5)$$

$$d_{j,k}=\sum_n h1(n-k)\,d_j-1,n, \quad ....(6)$$

Next step is the selection of the number of decomposition levels of the signal. Discrete wavelet transform (DWT) uses high-pass filter obtains 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 in high frequency contents (details) of the signal. The decomposition levels can be varied from one (the first level of decomposition) to J, where J=log2(N), and N is the length in samples of time-domain signal) [4].

Wavelet Denoising

There are four threshold estimation methods: universal threshold, sure threshold, hybrid threshold, and minimax.Generally, most of research worked in this field has used the universal threshold selection rule proposed by Donoho. It has been shown that its denoising capability is better than other classical methods such as sure method, Hybrid method, and minimax method as in reference [1], and [2]. Therefore in this paper we use the universal threshold method to estimate the threshold value, this method can be expressed as: [5]

$$\delta=\sigma\sqrt{2*\log(N)} \qquad \ldots(7).$$

δ: The estimated the threshold value.
N: Number of point or length of signal.
The threshold value δ is proportional to the estimated standard deviation of the signal's noise,σ, which can be estimated from the set of the wavelet coefficients in the highest scale level.After threshold values are determined, thresholdingcan be done using hard and soft transformation.

Hard thresholding

This transform can be described as the usual process of zeroing all detail coefficientthresholds, and then keeping other detail coefficients. It can be expressed as [1]:

$$c_k = \begin{Bmatrix} c_{k,} \text{ if } & |c_k| \geq \delta \\ 0, \text{ otherwise} \end{Bmatrix} \qquad \ldots(8)$$

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: [1]

$$c_k = \begin{Bmatrix} \text{sgn}(c_k)(c_k-\delta), \quad \text{if} \quad |c_k| \geq \delta \\ 0, \text{ otherwise} \end{Bmatrix} \qquad \ldots.(9)$$

Many researchers in biomedical signal processing field such as EMG and ECG signals found that the soft thresholding provides better results than hard thresholding, [1], and [2], so we used soft thresholding in our algorithm to find an optimal wavelet function for thedenoising surface electromyographic signal.

Wavelet reconstruction

This is the final step of the procedure, wherethe decomposed signal, after being denoised, is reconstructed by taking the inverse discrete wavelet transform (IDWT).

Evaluation criteria

In order to find the robustness of denoising algorithm WGN was added with three levels of signal to noise ratio (1db, 5db, and 10db) to the original SEMG signal. Mean square error (MSE) and output signal to noise ratio (SNRo) criteria were selected to find the performance of the denoisingalgorithm.The MSE, and SNRo can be calculated using equations (10), and (11) respectively [6]:

$$\text{MSE (w,l)}=\sum_{i=1}^{N}\frac{1}{N}\left(x(i)-x^{-}(i)\right)^{2} \qquad \text{…..(10)}$$

$$\text{SNRo}=10\log\left(\frac{\sum_{i=1}^{N}\left(x(i)\right)^{2}}{\sum_{i=1}^{N}\left(x(i)-x^{-}(i)\right)^{2}}\right) \qquad \text{…...(11)}$$

W:wavelet function.
L: is the decomposition level.
$x(i)$:original SEMG signal.
$x^{-}(i)$:denoised SEMG signal.
SNRo: output signal to noise ratio.
The performance of wavelet denoising algorithm is better when the MSE is smaller and SNRo is larger.

Results and discussion

The critical point in wavelet denoising is the selection of right wavelet function which depend on the application and characteristics of the signal. Differentwavelet filters were investigated to optimize wavelet denoising procedures. Five wavelet filters (as shown in figure (2)): fourth order Daubechies (db4), fifth order Daubechies (db5), fifth order Symlet (sym5), eighth order Symlet (sym8), and fifth order Coiflet (Coif5) are used to denoise the noise in SEMG signal, where all these functions (filters) have orthogonal property and their shapes are very close to the original surface electromyographic signal. Since, in practice, the value of signal to noise ratio (SNR) is unknown due to the acquisition of signal under real time applications, we add varying amounts of WGN in three trails (1db, 5db, and 10db) (this procedure also used in reference [7] when they worked a study to find optimal wavelet denoising for phonocardiograms (PCGs))to simulate very noisy, noisy, and medium noise environments. The threshold value was 2.773. We obtain huge of results as shown in the tables (1-5). The results show that the fourth order Daubechies filter (db4) provides marginally better performance than other possibilities and the suitable number of decomposition level is four for very noisy, noisy environments. On the other hand, the third and fourth decomposition levels are better than other possibilities (the difference between third and fourth level is not significant) for medium noise environments. Also from our experiment results we find when decomposition levels are more than six, the MSE rapidly increases while, SNRo rapidly decreases. Therefore, in tables (1-5) only first seven levels are shown. We suggest that db4 with four decomposition levels to be used to denoise the noise in original surface electromyographic signal that captured from human arm. Figure (3) shows the original signal before, and after denoising procedures.

Conclusions

Noises contaminated in the SEMG signals are an unavoidable problem during recording data; whereas noises are a main problem in the analysis of the SEMG signal both in clinical and engineering applications. The objective of this paper was to select the suitable wavelet function (filter)of discrete wavelet transform (DWT) and optimal decomposition level. The results show that Daubechies wavelet with fourth order (db4) provides marginally better performance than other possibilities. This is due to the fact that the Daubechies with fourth order most matchingthe SEMG signal's shape. The Suitable number of decomposition levels is four.

(a): Relaxation state. (b): Contraction state.

Figure (1): Recording SEMG signal.

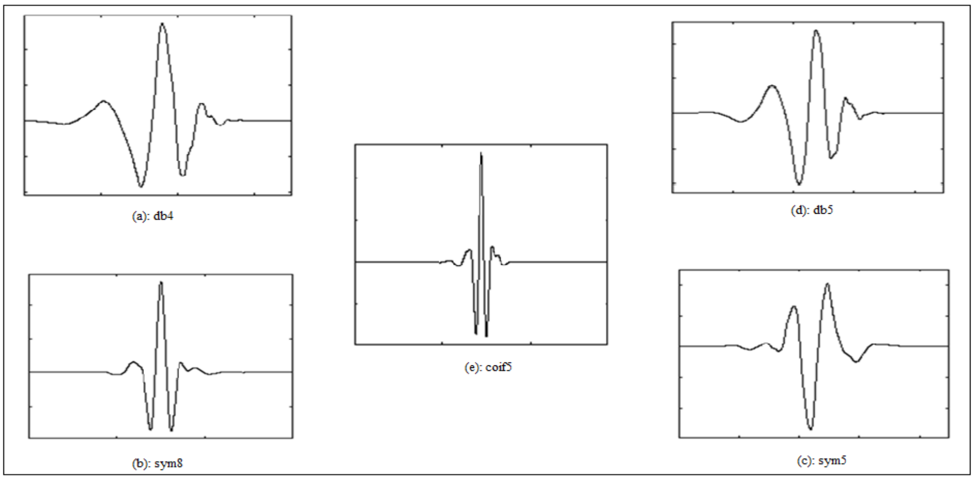

Figure (2): Shapes of the selected wavelet filters.

Table (1): Results of db4 wavelet filter.

Wavelet filter:db4								
AWGN with SNR=1db			AWGN with SNR=5db			AWGN with SNR=10db		
Number of decomposition level	MSE	SNR(o) (db)	Number of decomposition level	MSE	SNR(o) (db)	Number of decomposition level	MSE	SNR(o) (db)
1	0.0934	3.7538	1	0.0373	7.7429	1	0.0119	12.7038
2	0.0472	6.7147	2	0.0190	10.6750	2	0.0062	15.5356
3	0.0247	9.5316	3	0.0103	13.3151	3	0.0037	17.7577
4	0.0159	11.4424	4	0.0079	14.4598	4	0.0043	17.1234
5	0.0229	9.8572	5	0.0153	11.6167	5	0.0099	13.5068
6	0.0605	5.6370	6	0.0490	6.5549	6	0.0431	7.1173
7	0.1247	2.4989	7	0.1143	2.8791	7	0.1095	3.0630

Table (2): Results of db5 wavelet filter.

Wavelet filter:db5								
AWGN with SNR=1db			AWGN with SNR=5db			AWGN with SNR=10db		
Number of decomposition level	MSE	SNR(o) (db)	Number of decomposition level	MSE	SNR(o) (db)	Number of decomposition level	MSE	SNR(o) (db)
1	0.0941	3.7239	1	0.0375	7.7105	1	0.0120	12.6734
2	0.0473	6.7117	2	0.0190	10.6478	2	0.0062	15.5418
3	0.0247	9.5355	3	0.0103	13.2957	3	0.0038	17.7437
4	0.0164	11.3027	4	0.0083	14.2579	4	0.0039	17.6922
5	0.0237	9.7040	5	0.0145	10.8225	5	0.0091	13.8885
6	0.0502	6.4549	6	0.0399	6.8955	6	0.0305	8.6111
7	0.1031	3.3264	7	0.0922	4.7916	7	0.0836	4.2381

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Table (3): Results of sym5 wavelet filter.

Wavelet filter:sym5								
AWGN with SNR=1db			AWGN with SNR=5db			AWGN with SNR=10db		
Number of decomposition level	MSE	SNR(o) (db)	Number of decomposition level	MSE	SNR(o) (db)	Number of decomposition level	MSE	SNR(o) (db)
1	0.0929	3.7782	1	0.0371	7.7669	1	0.0118	12.7263
2	0.0475	6.6903	2	0.0191	10.6513	2	0.0062	15.5141
3	0.0246	9.5563	3	0.0102	10.6513	3	0.0039	17.6822
4	0.0168	11.2072	4	0.0085	14.1630	4	0.0040	17.4042
5	0.0304	8.6363	5	0.0190	10.6593	5	0.0111	12.9881
6	0.0629	5.4694	6	0.0470	6.7334	6	0.0367	7.8127
7	0.0893	3.9518	7	0.0757	4.6656	7	0.0695	5.0398

Table (4): Results of sym8 wavelet filter.

Wavelet filter:sym8								
AWGN with SNR=1db			AWGN with SNR=5db			AWGN with SNR=10db		
Number of decomposition level	MSE	SNR(o) (db)	Number of decomposition level	MSE	SNR(o) (db)	Number of decomposition level	MSE	SNR(o) (db)
1	0.0941	3.7210	1	0.0376	7.7101	1	0.0120	12.6714
2	0.0478	6.5799	2	0.0196	10.5408	2	0.0064	15.4031
3	0.0252	9.4471	3	0.0106	13.2087	3	0.0040	17.6299
4	0.0170	11.1478	4	0.0087	14.0638	4	0.0043	17.1049
5	0.0352	7.9914	5	0.0238	9.6897	5	0.0132	12.2645
6	0.0861	4.1075	6	0.0633	5.4441	6	0.0479	6.6552
7	0.1299	2.3220	7	0.1092	3.0757	7	0.0927	3.7866

Table (5): Results of coif5 wavelet filter.

Wavelet filter:coif5								
AWGN with SNR=1db			AWGN with SNR=5db			AWGN with SNR=10db		
Number of decomposition level	MSE	SNR(o) (db)	Number of decomposition level	MSE	SNR(o) (db)	Number of decomposition level	MSE	SNR(o) (db)
1	0.0941	3.7215	1	0.0376	7.7128	1	0.0120	12.6714
2	0.0476	6.6852	2	0.0191	10.6741	2	0.0062	15.5162
3	0.0250	9.4864	3	0.0104	13.3459	3	0.0040	17.6299
4	0.0174	11.0574	4	0.0085	14.1630	4	0.0043	17.1444
5	0.0275	9.0681	5	0.0183	11.8518	5	0.0091	12.6453
6	0.0605	5.6394	6	0.0453	7.4512	6	0.0305	8.0835
7	0.0883	3.9984	7	0.0736	3.8120	7	0.0836	4.9054

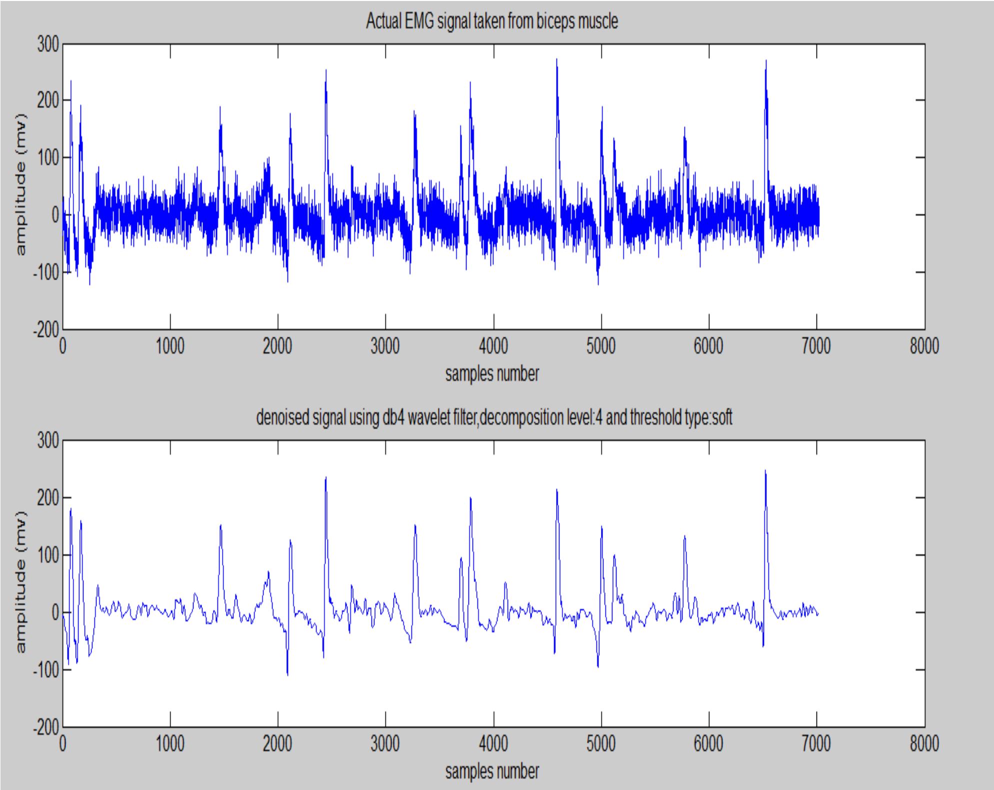

Figure (3): difference between actual, and thedenoised SEMG signal.

References

[1]. C. F. Jiang, and S. L. Kuo, "A Comparative Study of Wavelet Denoising of Surface Electromyographic Signals", Annual International Conference, IEEE, Pages: 1868- 1871, August, 2007.

[2]. A. Phinyomark, C. Limsakul, and P. Phukpattaranont "A Comparative Study of Wavelet Denoising for Multifunction Myoelectric Control", International Conference on Computer and AutomationEngineering (ICCAE), IEEE, Pages: 21-25, 2009.

[3]. Z. Qingju, and L. Zhizeng, "Wavelet Denoising of Electromyography", International Conference on Mechatronics and Automation, IEEE, Pages: 1553-1558, June, 2006.

[4]. K. Englehart, B. Hudgins "A robust, real time control scheme for multifunction myoelectric control", Transactions on Biomedical Engineering, IEEE, Vol.50, pages: 848-854, July, 2003.

[5]. G. Georgieva, andK.Tcheshmedjiev"Denoising of Electrocardiogram Data with Methodsof Wavelet Transform", International Conference on Computer Systems and Technologies, University of Ruse, ISSN 1314-9687, Pages: 9 - 16, June, 2013.

[6]. G. Umamaheswara, M. Muralidher, and S. Varadarajan, "ECG Denoising Using Improved Thresholding Based on Wavelet Transform", International Journal of Computer Science and Network Security (IJCSNS), Vol.9, No.9, Pages: 221-225, September, 2009.

[7]. S. R. Messer, J. Agzarian, and D. Abbott, "Optimal Wavelet Denoising for Phonocardiograms", Microelectronics Journal, ELSEVIER, Vol.32, Issue.12, Pages: 931-941, December, 2001.