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Enhancing the stress test ECG signal for real-time QRS detector

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Abstract

The Electrocardiogram (ECG) signal, which is a record of the electrical activity of the heart, can be treated as a combination of a free-noise signal and noises. The primary source of interference in the ECG recording during exercise is broadband myopotentials (EMG), contained in a full frequency band. Because the frequency ranges of both signals (ECG and EMG) overlap, band-stop filters distort the ECG signal, especially of QRS complexes. An alternative method of removing interference may be using Adaptive Wavelet Wiener Filter (AWWF) with noise-free signal estimation. As a result of a straightforward wavelet transform, it is possible to extract noise with some components of the QRS complex in the highest frequency bands. The central part of the QRS components is in the lower frequency bands. The resulting signal can be filtered by matching the transform coefficients. Testing was performed on muscle (EMG) artifact noised signals from the MIT-BIH Noise Stress Test Database at 360 Hz sampling frequency.

Key Words: EMG, Wavelet Wiener Filtering, Stress ECG Test, MIT-BIH Database.

I. Introduction

Exercise testing can be an inexpensive and non-invasive standard diagnostic procedure performed by physicians to assess cardiovascular diseases, and the prescription of exercise and training. When performing the test, the patient's ECG signal will be monitored while their exercise level is increased gradually. There are several different methods and modes available that can provide vital information to the clinician to help patients and athletes improve their fitness or cardiovascular status. This method is based on the increase in the organism's need for oxygen and glucose exchange during physical exercise, and consequent heart beating capacity raise. As a result, it is possible to uncover potential cardiovascular problems that may not manifest at rest.

Since this testing procedure involves significant physical movement and breathing activities, multiple sources of additive noises affect the ECG analysis, and they make the cardiac monitoring difficult in practice. These sources of interference mainly include baseline wander, electrode motion artifact, and electromyogram-induced (EMG) noise. EMG is considered as the significant artifact source and is difficult to separate because its frequency spectrum overlaps the frequency spectrum of the ECG signal.

Wavelet transform (WT) based denoising methods can increase the efficiency of suppression of wide-band EMG artifact compared to linear filtering. The WT will decompose the signal into different bands so that the highest bands contain EMG artifact and several components of QRS complexes, while QRS complex components are mainly located in the lower frequency bands. Then, the resulting signal can be filtered by appropriately adjusting the transform coefficients depending on the estimated noise level. In this way, the selection of parameters such as decomposition and reconstruction filter banks, level of decomposition, and the strategy of wavelet transform coefficient adjustment will play an important role.

In [1], the authors proposed an optimal denoising approach for ECG using stationary wavelet transform (SWT). This method includes the choice of optimal mother wavelet, appropriate thresholding method, and level of decomposition. The authors in [2] presented the use of wiener filtering in the shift-invariant wavelet domain with the pilot estimation of the signal to eliminate EMG noise. This method utilizes the shift-invariant dyadic discrete-time wavelet transform (DyDWT) with four-levels of decomposition for the pilot estimation and wiener filtering blocks. In [3], the authors presented an algorithm for ECG denoising using discrete wavelet transform (DWT). This proposed method is implemented through three main steps that are forward DWT, thresholding, and inverse DWT. The ECG signal denoising algorithm including two-stage which combines wavelet shrinkage with wiener filtering in the translation-invariant wavelet domain, was presented in [4].

In this work, we focused on the wavelet Wiener filtering to eliminate EMG artifact in the ECG signal. We utilized DyDWT for both the Wiener filter and in the estimation of a noise-free signal. The goal of this work was to find the most suitable parameters for the Wiener filter based on the signal-to-noise ratio.

The remainder of this paper is organized as follows: we present the materials and proposed method in Section II. The results are presented and discussed in section III. Finally, the conclusions are presented.

II. Materials and Methods

1. Stationary Wavelet Transform

Nowadays, the wavelet transform has been a popular and useful computational tool for signal and image processing applications, because it provides signal characteristics in both the time domain and frequency domain. While analyzing non-stationary signals had been a significant challenge for various transform techniques such as Fourier Transform (FT), short-time Fourier Transform (STFT), wavelet transform techniques can effectively analyze both non-stationary and stationary signals. With the wavelet decomposition, the signal is decomposed in like-tree structure using filter banks of low-pass and high-pass filters with down-sampling of their outputs. The dyadic transform, where only decomposed outputs of the low-pass filter, is the most commonly used decomposition tree structure. In this work, we used the Stationary Wavelet Transform when it gives better filtration results [4].

2. Wavelet Filtering (WF) Method

When using the wavelet transform to remove the artifact from ECG signals, the parameters used are decomposition depth of input signal, thresholding method, threshold level, and filter banks. The selection of appropriate parameters is an essential task because the signal will be separated from interference by thresholding of wavelet coefficients.

We assume that the corrupted signal denoted $x(t)$ is an additive mixture of the noise-free signal $s(n)$ and the noise $w(n)$, both uncorrelated.

$$x(n) = s(n) + w(n) \qquad (1)$$

where n represents the discrete-time (n = *0, 1, …, N-1*), and N is the length of the signal.

If the noisy signal $x(n)$ is transformed into the wavelet domain using the dyadic

SWT, we can obtain wavelet coefficients.

$$y_m(n) = u_m(n) + v_m(n) \qquad (2)$$

where $u_m(n)$ are coefficients of the noise-free signal and $v_m(n)$ denote the coefficients of the noise, m is the level of decomposition and denotes m-th frequency band. We need to recover coefficients of the noise-free signal $u_m(n)$ from $y_m(n)$. The idea of Wiener filtering of each wavelet coefficient can solve it.

To the modification of the wavelet coefficients to be more efficient, the threshold sizes should be set separately for each decomposition level m. For the calculation of the threshold value, the standard deviation of the noise is multiplied by an empirical constant K and described by the equation.

$$\lambda_m = K.\sigma_{vm} \qquad (3)$$

where σ_{vm} is the standard deviation of noise in the m-th frequency band, and it can be estimated using the median [5], [6].

$$\sigma_{vm} = \frac{median(y_m)}{0.6745} \qquad (4)$$

If the standard deviation of the noise is estimated using a sliding window, we can obtain the time-dependent $\sigma_{vm}(n)$, and the threshold value becomes,

$$\lambda_m(n) = K.\sigma_{vm}(n) \qquad (5)$$

3. Wavelet Wiener Filtering (WWF) Method

By input signal preprocessing using wavelet transform and thresholding we obtain an estimation of coefficients $u_m(n)$. This strategy is showed in Figure 1.

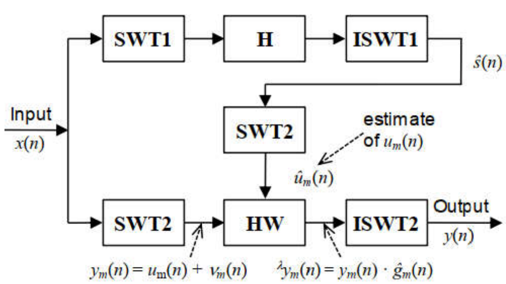

Figure 1. The block diagram of the Wavelet Wiener Filtering method.

The upper path of the scheme consists of four blocks: the wavelet transforms SWT1, modification of coefficients in the block H, the inverse wavelet transforms ISWT1, and the wavelet transform SWT2. The lower path of the scheme consists of three blocks: the wavelet transforms SWT2, the Wiener filter in the wavelet domain HW, and the inverse wavelet transforms ISWT2.

Because the signal can be easily separated from noise in the wavelet domain, the noisy signal, $x(n)$, will first be transformed into the wavelet domain by the SWT1 block. Threshold level, $\lambda_m(n)$, will then be estimated for thresholding to separate the free-noise signal and noise. The estimation $\hat{s}(n)$, which approximate noise-free signal $s(n)$ is obtained by using the ISWT1 block. This estimate is used to design the Wiener filter (HW), which is applied to the original corrupted signal $x(n)$ in SWT2 transformed domain (lower path) via Wiener correction factor [1], [7].

$$\hat{g}_m(n) = \frac{\hat{u}_m^2(n)}{\hat{u}_m^2(n)+\sigma_{vm}^2(n)} \qquad (6)$$

where $\hat{u}_m^2(n)$ are the squared wavelet coefficients obtained from the pilot estimation $\hat{s}(n)$, and $\sigma_{vm}^2(n)$ is the variance of the noise coefficients $v_m(n)$ in the m-th frequency band. We get final signal $y(n)$ by inverse transform IWT2 of modified coefficients ${}^{\lambda}y_m(n)$.

$${}^{\lambda}y_m(n) = y_m(n).\hat{g}_m(n) \qquad (7)$$

4. Adaptive Wavelet Wiener Filtering (AWWF) Method

In order to use the wavelet Wiener filter effectively, it is necessary to choose the exact parameters of the filter. The most important ones are the decomposition depth, the thresholding method, the empirical constant K, and the wavelet filter banks used in the SWT3 and SWT4 blocks. It is evident that if the noise levels in the input signal changes, the parameters need to change accordingly to get the best results.

To adapt to the change of noise, the input signal is divided into segments with an approximately constant level of noise. Besides, the WWF is also improved by adding the block for noise estimate (NE). This block has two inputs: the first input is the noisy signal $x(n)$, and the other is the estimate of the free-noise signal $y(n)$ obtained by the WWF method. The estimate of the input noise is the difference between these two signals, and the signal-to-noise ratio (SNR) can thus be calculated. The NE block is responsible for monitoring SNR changes at the beginning of each segment to choose the appropriate parameters for the filter at each segment. The filtered segments will then be reconnected.

The parameters in blocks SWT3, H3, ISWT3, SWT4, and ISWT4 are set up using an estimated SNR_{est} value.

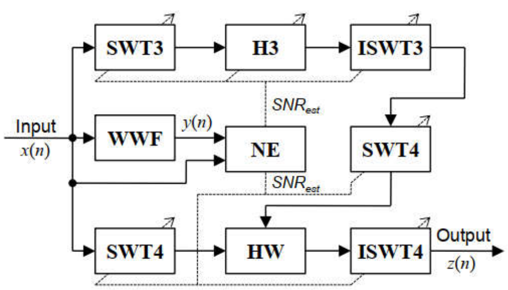

Fig. 2. The block diagram of the Adaptive Wavelet Wiener Filtering Method.

5. *Rules for evaluating results*

The results were assessed according to achieved signal to noise ratio SNR_{out} [dB] of the output signal $z(n)$ by the following equation,

$$SNR_{out} = 10log_{10}\left(\frac{\sum_{n=0}^{N-1}[s(n)]^2}{\sum_{n=0}^{N-1}[z(n)-s(n)]^2}\right) \quad (8)$$

where $s(n)$ is the free-noise signal.

From Eq. (8) it is apparent that we need to know the free-noise signal $s(n)$ to calculate the SNR_{out}, which is not possible in real situations. Because free-noise signals are not available, we selected several segments of signals of the MIT-BIH Noise Stress Test Database [8]. These signals were corrupted by a noise, which calibrated amounts of noise from record 'em'. The signal-to-noise ratios (SNRs) during the noisy segments of these records are listed in the flowing Table 1.

Table 1. The records in the MIT-BIH Noise Stress Test Database [8].

Record	SNR (dB)	Record	SNR (dB)
118e24	24	119e24	24
118e18	18	119e18	18
118e12	12	119e12	12
118e06	6	119e06	6
118e00	0	119e00	0
118e_6	-6	119e_6	-6

III. Simulation results

1. *Thresholding of pilot estimation*

The choice of thresholding in block H has an essential influence on the result. It is vital to remove the maximum of the noise. We tested three different methods for pilot estimation: hard, soft and hybrid. Table 2 summarizes the achieved results.

Table 2. Influence of different thresholding methods on results

Filters: SWT3/SWT4: db4/bior1.3

SNR_{in} [dB]	SNR_{out} [dB]		
	Pilot estimation thresholding		
	Hard	Soft	Hybrid
-6	34.3933	33.3418	33.3377
0	34.3492	33.3670	33.3012
6	34.6166	33.6817	31.3878
12	36.2835	35.4364	34.1689
18	37.6831	37.0186	35.2549
24	38.2241	37.5143	35.9313

We can see from SNR_{out}, that better results are achieved using hard or soft thresholding. Results are worse when we apply hybrid thresholding.

2. *Choice of filters for SWT3 and SWT4*

Our next investigation will be focused on the choice of the filters for SWT3, and SWT4 transforms. We have experimented with wavelet families in the library of Matlab

2017b. The best results are received as described in Table 3.

Table 3. Influence of different filters SWT3/SWT4 on results.

Hard thresholding in the pilot estimation

SWT3/SWT4	SNR_{in}	
	24 dB	**18 dB**
haar/boir1.3	37.4013	36.5682
db4/sym2	37.4619	36.9358
db4/bior1.3	38.2241	37.6831
db4/coif1	37.4740	36.9106
sym2/bior1.3	38.1714	37.6207
sym2/coif1	37.3964	36.7957
rbio1.3/coif1	37.5431	36.9949

According to SNR_{out}, we can say that the combination of filters used for SWT3 and SWT4 transforms yields the best result, db4/bior1.3. So, we have chosen db4/bior1.3 for STW3/SWT4 transforms and the hard thresholding approach to design filter.

The filtered results for the segments taken from [8] are summarized in Table 4. Where SNR_{in} is the signal-to-noise ratio of the input signal, SNR_{out} denotes signal-to-noise ratio of the filtered signal, and SNR_z denotes improvement signal-to-noise ratio, $SNR_z = SNR_{out} - SNR_{in}$. Our effort is to make the SNR_z the highest possible.

Table 4. The result achieved with the filter AWWF

SNR_{in} [dB]	SNR_{out} [dB]	SNR_z [dB]
-6	32.9	38.9
0	32.8	32.8
6	31.1	25.1
12	33.8	21.8
18	34.9	16.9
24	35.6	11.6

Besides, we also compared the results achieved when using the AWWF filter with other filters like WWF and WF. The comparison results are given in Table 5.

Table 5. Comparison results between filters AWWF, WWF and WF

Filter	SNR_{avg} [dB]
AWWF	24.51
WWF	20.73
WF	18.72

From the data table, we can see that the AWWF filtering method gives the best results, followed by WWF and WF with improved SNR of 24.51 dB, 20.73 dB, and 18.72 dB, respectively.

IV. Conclusion

In this study, we used the Adaptive Wavelet Wiener Filter for improving stress test ECG signals. From the obtained results, we can see that the proposed algorithm provides better filtering results than several other tested algorithms. The setting of suitable parameter values to the estimated noise level has a positive effect on the performance of the filtering algorithm.

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