# ECG Signal Denoising Using Wavelet Wiener Filtering

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*The paper deals with the methods of ECG signals denoising via wavelet transform. We focus on the WienerShrink method. We have studied influence of input parameters setting on the filtered signal in consideration of achieved signal-to-noise ratio (SNR) and output signal distortion. The algorithm was implemented in MATLAB and tested on signals from CSE database.*

## 1 Introduction

ECG signal has a great diagnostic importance however its delineation and evaluation is complicated by the noise. One of the most troublesome kind of noise is electromyographic (EMG) noise. The problem is that the frequency spectrum of EMG noise overlaps the ECG spectrum. It is not suitable to use linear filtering in this cases. This always leads to total smoothing and damage of the noise-free signal. It is better to use the wavelet transform to decompose the input signal into several frequency bands. Subsequent filtering is used separately in each band, where the signal energy is concentrate into a relatively small number of large wavelet coefficients (with the exception of the lowest band).

## 2 Methods

We suppose that a corrupted signal $x(n)$ is additive mixture of noise-free signal $s(n)$ and noise $w(n)$,

$$x(n) = s(n) + w(n), \tag{2.1}$$

both uncorrelated. If we transform the noisy signal $x(n)$ by the linear discrete time wavelet transform (DTWT) to the wavelet domain, we obtain wavelet coefficients

$$y_m(n) = u_m(n) + v_m(n), \tag{2.2}$$

where $u_m(n)$ are coefficients of the noise-free signal and $v_m(n)$ are coefficients of the noise, $m$ is the level of decomposition and denotes $m$-th frequency band. Our goal is to estimate the noise-free signal wavelet coefficients $u_m(n)$ from given noisy observations $y_m(n)$.

### 2.1 WienerShrink method

We are able to recover the noise-free coefficients $u_m(n)$ from $y_m(n)$ by the WienerShrink method, which is based on the Wiener filtering theory [2], [3]. The procedure is illustrated in Fig 1. There is implemented the wavelet transform WT1 in the upper path, coefficients modification in the block H (with the soft thresholding) and the inverse transform IWT1. We get the pilot estimate $\bar{s}(n)$, which approximates the noise-free signal $s(n)$. This estimate is then used to design a Wiener filter (HW), which is applied to the original noisy signal $x(n)$ in WT2 domain (lower path) via Wiener correction factor

$$\bar{g}_m(n) = \frac{\bar{u}_m^2(n)}{\bar{u}_m^2(n) + \sigma_{vm}^2}, \tag{2.3}$$

where $\overline{u}_m(n)$ are square wavelets coefficients obtained from the pilot estimate $\overline{s}(n)$ and $\sigma^2_{vm}(n)$ is the variance of noise coefficients $v_m(n)$. We process the noisy coefficients $y_m(n)$ in the block HW by this Wiener correction factor, to obtain modified coefficients ${}^{\lambda}y_m(n)$,

$$^{\lambda}y_m(n) = y_m(n)\overline{g}_m(n). \tag{2.4}$$

Output signal $y(n)$ is obtained by the inverse transform IWT2 of modified coefficients ${}^{\lambda}y_m(n)$.

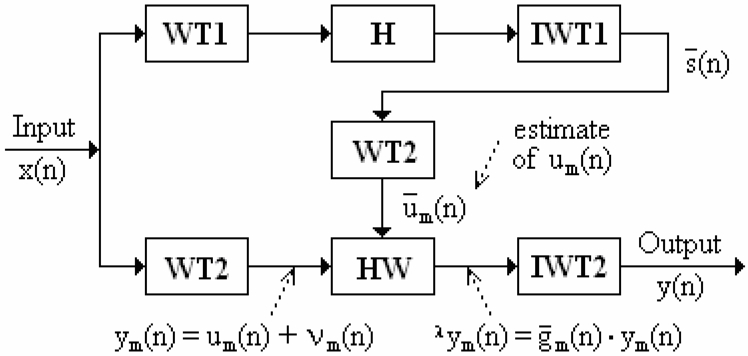



Fig 1.The block diagram of the pilot estimation method.

The goal of our research is to choose suitable transforms WT1 and WT2 and to find optimal parameters setting in the block H for increasing of output signal SNR.

### 2.2 Database of utilized electrocardiograms

ECG signals from the CSE database were used for our tests. The database contains 125 realistic 12-lead and 3-lead (orthogonal) records, taken as a reference for testing different algorithms. Electrocardiograms have a length of 10 seconds and were sampled by 500 Hz sampling frequency.

### 2.3 Evaluation of results

We evaluated the results according to achieved SNR. Therefore we should know the noise-free signal $s(n)$ and the noise $w(n)$ which is not possible in a real situation. We created a noise-free signals by a careful filtering of the selected electrocardiograms from the CSE database. Those signals were corrupted by an artificial noise $w(n)$.

The results were evaluated by achieved signal-to-noise ratio of output signals ($SNR_{out}$) according to equation

$$SNR_{out} = 10 \cdot \log_{10} \frac{\sum_{n=1}^{N-1} [s(n)]^2}{\sum_{n=1}^{N-1} [y(n) - s(n)]^2} \; [dB], \tag{2.5}$$

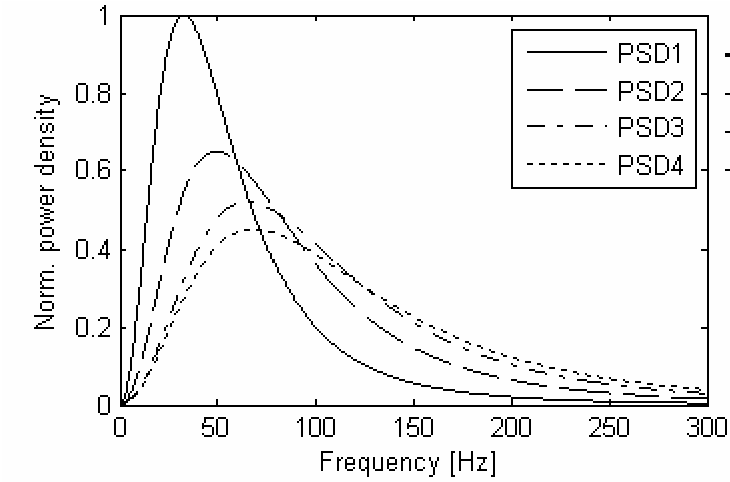
where $s(n)$ is the noise-free signal and $y(n)$ is the output (filtered) electrocardiogram.

### 2.4 Synthetic noise

Authors in [2], [3] used white gaussian noise as an artificial interference in their tests. However, white noise does not correspond to the spectral characteristics of EMG. We were inspired by the article [1], where a model of the surface EMG signal is created by filtering a white gaussian noise using a time variable shaping filter $H_m(f)$.

$$H_m(f) = A \frac{f_h^4 f^2}{\left(f^2 + f_l^2\right)\left(f^2 + f_h^2\right)^2}, \tag{2.6}$$

where $A$ is the magnitude setting constant and parameters $f_h$ and $f_l$ changes the shape of the spectral function. The power spectra made according to (2.6) for different parameters $f_h$ and $f_l$ are shown in Fig 2.




| PSD | $f_l$(Hz) | $f_h$(Hz) |
|---|---|---|
| 1 | 30 | 60 |
| 2 | 40 | 100 |
| 3 | 60 | 120 |
| 4 | 50 | 150 |

Fig 2.Examples of expected spectra obtained from the equation (2.6) for different values of the parameters $f_h$ and $f_l$.

# 3 Results

Our investigation is divided into two parts. The first part deals with finding of a suitable filter bank combination of the transforms WT1 and WT2. The second one is focused on the level setting for soft thresholding in the block H. In all tests were used dyadic wavelet transforms with four levels of decomposition. Algorithms were tested on 12 electrocardiograms from the CSE database and the result ($SNR_{out}$) is an average value from these signals. ECG signals were corrupted by optional noise level $SNR_{in}$.

## 3.1 Filter banks

We tested biorthogonal (`BiorX.X`) and orthogonal (Daubechies, `DbX`) filters as well as filters with short, middle and long impulse response (`Haar`, `Db3`, `Db5`, `Db10`, `Bior1.3`, `Boir2.4`, `Bior3.9`). Names come from the Matlab Wavelet Toolbox. Results are summarized in Tab 1.

Soft thresholding in the block H, threshold = $3\sigma_{vm}$

| Filters WT1/WT2 | Length of Filters [sa] | $SNR_{in}$ = 10 dB | $SNR_{in}$ = 14 dB | $SNR_{in}$ = 20 dB |
|---|---|---|---|---|
| | | $SNR_{out}$ [dB] | | |
| `Bior1.3/Bior2.4` | 6 / 10 | 20.51 | 23.95 | 28.99 |
| `Haar/Bior2.4` | 2 / 10 | 20.44 | 23.94 | 29.06 |
| `Db3/Bior2.4` | 6 / 10 | 20.23 | 23.85 | 29.02 |
| `Haar/Db3` | 2 / 6 | 20.42 | 23.80 | 28.88 |
| `Haar/Bior3.9` | 2 / 20 | 19.97 | 23.71 | 29.12 |
| `Bior1.3/Haar` | 6 / 2 | 19.76 | 22.93 | 27.55 |
| `Bior3.9/Bior3.9` | 20/ 20 | 17.66 | 21.80 | 27.92 |
| `Db10/Db10` | 20 / 20 | 17.73 | 21.24 | 26.88 |

Tab 1. Influence of filters WT1/WT2.

Distortion of filtered signals is also important (except $SNR_{out}$). Mainly, small waves are damaged, oscillation appears nearby QRS complex and causes its dilatation. Some of these typical distortions are shown in Fig 3. There are good results in parts A and B of Fig 3 where we used short and middle length filters. Q wave is not distorted and QRS complex is not expanded. The worse situation occurred when we used long length filters combination. We can observe the QRS complex expansion in the part C and genesis of oscillations in the part D.

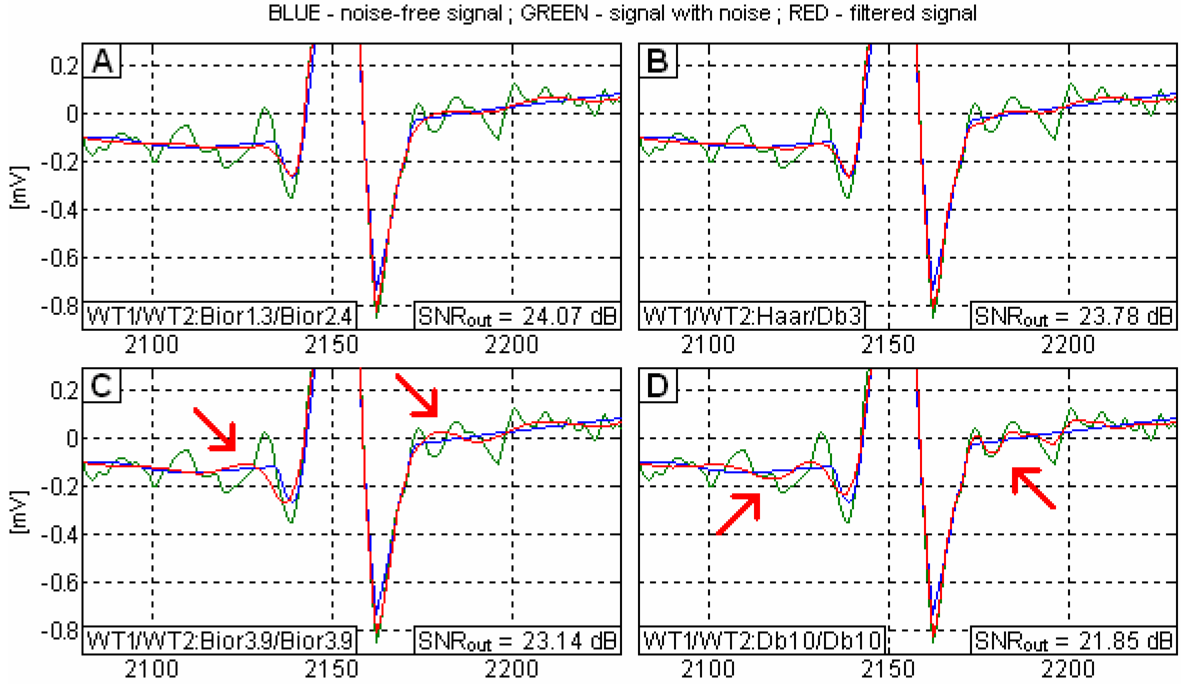



Fig 3.Filters WT1 and WT2 influence on filtered signals distortion. The used signal was W038 and lead V3. $SNR_{in}$ = 14 dB.

### 3.2 Threshold level setting

The model of a noise-free signal is created in the block H (see Fig 1). The noise is removed from the input signal by using soft thresholding. The threshold level should be dependent on amount of a noise (its variance $\sigma_{vm}$ in each band *m*) included in the signal. The level of threshold $\lambda_m$ can be changed by constant *K*,

$$\lambda_m = K\sigma_{wm}, \tag{2.7}$$

for each band *m*. We tested the influence of the threshold level on the filtered signal. $SNR_{out}$ is an average value from 12 electrocardiograms. Results are summarized in Fig 4.

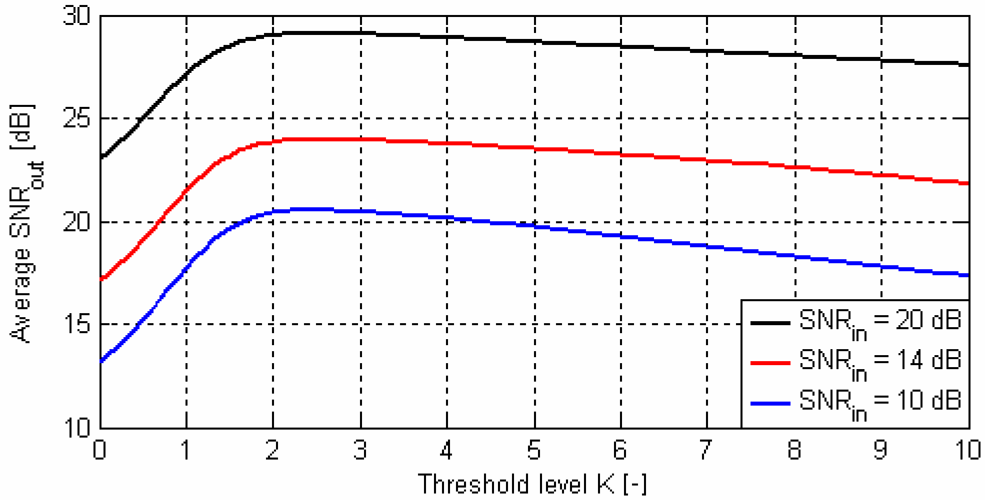



Fig 4.Influence of the threshold level on filtered signal.

It is obvious from Fig 4, that the best results are obtained with the threshold level around $3\sigma_{vm}$. Lower thresholds cause presence of noise and higher distort small waves in a pilot estimate.

## 4 Discussion

We can avoid significant wave distortion of filtered signals by the choice of appropriate filter banks. The results achieved by different filter combinations are summarized in Tab 1. However, one number ($SNR_{out}$) can not describe the signal distortion and its effects on a signal delineation. Not only the Tab 1, but the complete table with all filter combinations and their graphical representations helped us formulate the next recommendations:

- In the transform WT1, filters with long impulse response should not be used – genesis of the oscillation nearby QRS complexes.
- In the transform WT2, `Haar` filter or short impulse response biorthogonal filters should not be used – damage of small waves and distortion of P and T waves.
- Long impulse response filters combination should not be used – genesis of the oscillation and QRS complex expansion.
- It is suitable to use short filter in transform WT1 and middle length filter in transform WT2. Right combination could be `Haar/Db3` or `Bior1.3/Bior2.4`, unsatisfactory combination is `Db10/Db10` or `Bior1.3/Haar`.

Threshold level setting for the soft thresholding in Block H is obvious from Fig 4. The maximum of $SNR_{out}$ is for $K$ between 2 and 3 for all tested noise levels $SNR_{in}$. With the lower threshold levels, more coefficients of the noise remains in the pilot estimate. With the higher threshold levels, more noise-free coefficients are shrunk which distorts mainly small waves in ECG signal. The good compromise for this level setting is $K = 3$.

## 5 Conclusion

The advantage of the filters based on the wavelet transform is that these filters adapt their thresholds to the noise level. Linear filtering leads to lower magnitudes of QRS complex peaks.

For future research would be advisable to establish a method of evaluation for ECG waves distortion by automatic delineation system. It would lead to objective evaluation of used filters in the transforms WT1 and WT2.

## Acknowledgement

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