ADAPTIVE WAVELET FILTERING METHODS FOR ECG DENOISING

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Abstract: In this study we applied two methods of adaptive wavelet based denoising of ECG signals corrupted by random myopotentials: Median valued thresholding (MVT) and Wiener wavelet denoising with pilot estimation of signal (WWD), both realized by dyadic redundant discrete time wavelet transform (DTWT). In MVT and the pilot estimation of the signal in WWT we used a hybrid thresholding of DTWT coefficients.

Introduction

The ECG signal is a superposition of the signal and noise. Occurrence of noise complicates a computer analysis. Linear filtering isn't suitable for wideband myopotentials suppression, because it leads to strong cut off the local extreme of QRS complexes and to disturbance the significant variation of signal precipitousness in onsets and offsets of the QRS complexes.

Discrete-time wavelet transform (DTWT) appears as a useful tool for myopotentials suppression. The filtering is based on modification of the coefficients of wavelet transform depend on estimated noise level. Important is to choice a threshold strategy. Occurrence of high artefacts cause to overthreshold values of DTWT coefficients of noise is disadvantage of using a hard thresholding. It is distinct mainly around onsets and offsets of QRS complexes. On the other hand, the main disadvantage of a soft thresholding is decreasing the values of local extremes in QRS complexes and sporadic occurrence of mentioned artefacts. Smaller decreasing of local extremes and sporadic occurrence of artefacts is property of hybrid thresholding (see later).

Wavelet domain Wiener filtering with pilot estimation of the signal gives better results than wavelet filtering with using some of mentioned type of thresholding. This method do not significantly distorts the extremes in QRS complexes and it is without artefacts by realization of suitable pilot estimation. In [5] was used the wavelet domain Wiener filtering with decimation and very simplify estimation of DTWT coefficients. In [6] was realized wavelet domain Wiener filtering with pilot estimation of signal composed by DTWT with decimation and hard thresholding. It has been led to frequent occurrence of artefacts in filtered signal.

The point of view in our experiments was on wavelet domain Wiener filtering with pilot estimation of the signal realized by shift-invariant dyadic DTWT. The pilot estimation has been realized as a wavelet filtering (shift-invariant dyadic DTWT) with hybrid thresholding.

In this study we applied two methods of adaptive wavelet based denoising of ECG signals corrupted by random (electromyographic) noise: Wiener wavelet denoising (WWD) [1] and developmentally older Median valued thresholding (MVT) first published in [2]. Principles of both methods are mentioned and obtained results are compared.

Materials and Methods

Discrete time wavelet transform

Both of the methods are based on decomposition by redundant (shift–invariant) discrete dyadic wavelet transform (shift–invariant DTWT). The three–level of decomposition can be seen on Figure 1. This structure

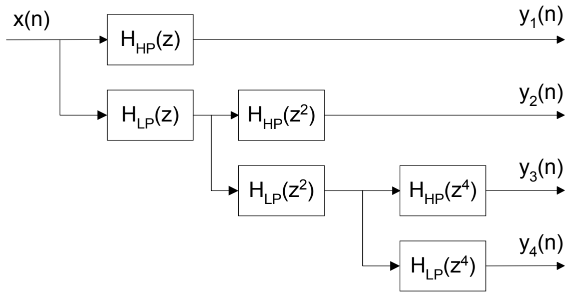

Figure 1: Three–level of shift–invariant DTWT decomposition

without decimation has one important advantage: it is invariant towards time shift of the input signal. The blocks $H_{HP}(z)$ and $H_{LP}(z)$ are highpass and lowpass decomposition filters. Banks of filters, which are generated by MATLAB, have been used in our work. Especially it was used orthogonal and biorthogonal banks of filters.

MVT method

This method is based on setting the optimal value of the threshold and thresholding by one specific threshold method. The value of the threshold shouldn't be too high, because it should cause damage the signal. However, the low threshold value causes the occurrence of the noise artefacts. For value of the threshold determination was used some of the advantages of median filter. The median filter is ineffective in case of sharp transitions. In case of wavelets coefficients, filtering have a sense in first four decomposition levels (for sampling frequency 500 Hz), where the noise is mostly represented. In those levels the QRS complexes are presented as sharp impulses. By filtering each decomposition level

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by median filter, we would give the threshold line which copy the envelope of the noise background and it would be inert to peaks of R–wave. Experiments just validated that the size of threshold is too low. For correct size of threshold determination the median filter has to be generalized. The threshold value isn't just as the middle term of the sorted sequence of length *r* but rather as any chosen k^{th} term, $k \in <1,r>$. On the Figure 2 is shown the sorted sequence of the data from 2nd level. The length *r* is equal

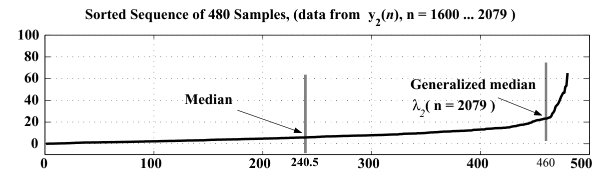

Figure 2: Sorted sequence of wavelet coefficients $y_2(n)$

to mean length of RR interval. The *k* term can be computed in dependence of decomposition level *m* as

$$k_m = r - 10 \cdot 2^{m-1}. \qquad (1)$$

Generalized median value is computed from modules of the wavelet coefficients. The constant 10 (sampling intervals) is mean of QRS complex length in first level of wavelet decomposition $y_1(n)$ (for sampling frequency 500 Hz). In a next level $y_2(n)$ is twice wider than the previous. The threshold computed via described method is adaptive to noise intensity. The threshold line can be seen on Figure 3.

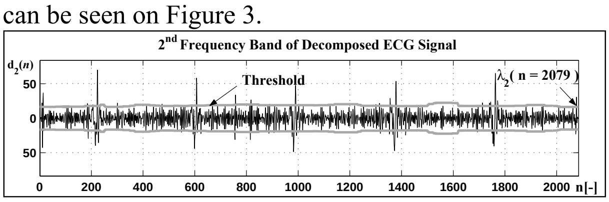

Figure 3: Computed threshold line

The threshold method was chosen between three ways: hard thresholding, soft thresholding or hybrid thresholding. First method isn't convenient in case of filtering. Soft thresholding causes the damage in wavelet coefficients, which exceed the threshold values. Hybrid thresholding was used in both MVT and WWD as a compromise between soft and hard thresholding, see below.

WWD method

Let we assume the input data $x(n)$ as a signal $s(n)$ and additive noise $w(n)$, so $x(n)=s(n)+w(n)$. DTWT coefficients of the data $x(n)$ let we mark as a $y_m(n)$ and coefficients of the signal and noise $u_m(n)$ and $v_m(n)$ respectively, where *n* is an index of the coefficient of *m*th level of decomposition. Due to linearity of DTWT is valid $y_m(n)=u_m(n)+v_m(n)$.

In several publications ([4], [5]) can be found the analogy between modification wavelet coefficients and the Wiener filtering where the coefficients $y_m(n)$ are multiplied by suitable formfactors. It has to be sought such formfactor $g_m(n)$ as modified values ${}^{\lambda}y_m(n)= y_m(n)g_m(n)=g_m(n)[u_m(n)+v_m(n)]$ for which is valid minimum square error $e_m^2(n)=({}^{\lambda}y_m(n)-u_m(n))^2 \rightarrow min$. Results give an equation for formfactor

$$g_m(n) = \frac{u_m^2(n)}{u_m^2(n)+v_m^2(n)} \approx \frac{u_m^2(n)}{u_m^2(n)+\sigma_{v_m}^2} \qquad (2)$$

where the noise values $v_m(n)$ are unknown, therefore their square were substituted by noise variance σ_{vm}^2 in m^{th} level. For $u_m^2(n) >> \sigma_{vm}^2$ will the $g_m(n) \approx 1$ and $|{}^{\lambda}y_m(n)| \approx |y_m(n)|$. On other hand for $u_m^2(n) << \sigma_{vm}^2$ will *the* $g_m(n) << 1$ and $|{}^{\lambda}y_m(n)| < |y_m(n)|$. The coefficients $u_m(n)$ are unknown, however their estimation is possible.

Hybrid thresholding

The estimation of $u_m(n)$ from $y_m(n)$ and variance of noise in form $u^2_m(n)=\max[ky_m^2(n)-\sigma_{vm}^2, 0]$ is used in [7], where is explained the choice of constant $k = 1/3$. The result leads to formfactor

$$g_m(n) = max\left[\frac{y_m^2(n) - 3\sigma_{v_m}^2}{y_m^2(n)}, 0\right] = max\left[1 - 3\frac{\sigma_{v_m}^2}{y_m^2(n)}, 0\right]. \qquad (3)$$

When we expressed the estimation ${}^{\lambda}y_m(n)$ with using (3) like ${}^{\lambda}y_m(n)=y_m(n)g_m(n)$ we can get to notion that it is the thresholding of the coefficients with the threshold

$$\lambda_m = \sqrt{3}\sigma_{v_m} \quad \Rightarrow \quad {}^{\lambda}y_m(n) = \begin{cases} y_m(n) - \dfrac{\lambda_m^2}{y_m(n)} & pro\ |y_m(n)| > \lambda_m \\ 0 & pro\ |y_m(n)| \le \lambda_m \end{cases}. \qquad (4)$$

From (4) it can be seen that it is compromise between soft and hard thresholding: it is approached to soft thresholding for values $|y_m(n)|$ approximately equal to λ_m and hard thresholding for values $|y_m(n)|$ much higher than λ_m. Therefore we named this method as hybrid thresholding.

WWD with pilot estimation of signal

Other possibility of estimation the $u_m(n)$ is method of pilot estimation ${}^{p}s(n)$ of the signal $s(n)$. After DTWT decomposition we can get the coefficients ${}^{p}u_m(n)$ of signal ${}^{p}s(n)$ [4]. Principle of wavelet domain Wiener filtering with pilot estimation is shown in the Figure 4.

Realization of pilot estimation is placed on upper branch: At first the input signal is decomposed by DTWT (WT1) into 4 levels. Than the coefficients are thresholded (block H) and reconstructed by inverse DTWT (IWT1). Output of this configuration give the pilot estimation ${}^{p}s(n)$ of the signal. Wavelet-based Wiener filtering is illustrated on the lower branch. Input signal is decomposed into 4 levels by block WT2, coefficients are modified by (2) (block HW), where the $u_m(n)$ are replaced by pilot estimation ${}^{p}u_m(n)$ obtained from decomposition of pilot signal estimation ${}^{p}s(n)$ by block WT2.

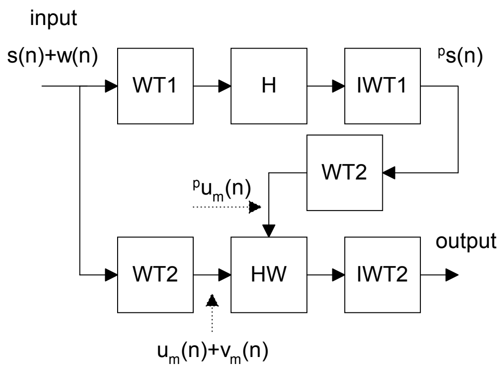

Figure 4: Wiener filtering with pilot estimation.

Output of the modification block HW is signal named $^{\lambda p}y_m(n)$. Finally the inverse IWT2 is necessary to complete reconstruction of the signal $s(n)$.

The hybrid thresholding with value of the threshold $\lambda_m=3\sigma_{vm}$ was used by pilot estimation method realization. The value of the threshold was advisedly higher against the (4) in order to prevent the artefacts creation. In case of lower threshold values it exist the risk that the Wiener filter magnify the minor noise artefacts.

Preparing for the experiments

The setting and determination of specific conditions precedes the testing and comparison of both described method.

At beginning, the signal set had to be obtained. We used the signals from CSE Multilead Atlas (sampling frequency 500 Hz). We have selected the signals only with minimal intensity of noise, because the signals from CSE library contain quantization step q=5μV, a power line interference and myopotentials. These signals were preprocessed for first were softly filtered and than were added the additive noise of known intensity. It were paid close attention to preprocessing: the result of the filtering were checked after than were put the signal into the testing set.

The additive noise is based on white noise which was frequency limited according to shape of the power spectrum of surface muscle biceps brachii EMG signal [3].

The signals were assessed according to achieved signal to noise ratio SNR_y of the output signal $y(n)$ by following equation:

$$SNR_y = 10\,log_{10}\frac{\sum_{n=0}^{N-1} s^2(n)}{\sum_{n=0}^{N-1}\left(y(n)-s(n)\right)^2}\quad [dB]. \qquad (5)$$

Where the input signal has had a zero middle value. The signal to noise ratio value of the input signal SNR_x is selected in correspondence to following tests. This value is computed same as in (5), but in denominator were only chosen dispersion of noise.

Results

Input of the tests was the chosen input signal to noise ratio of the input signal and selected wavelet filters banks. The described methods were applied to filtering of the several disposed signals (see previous sec.). The filtering was performed several times for constant SNR_x, decomposition filters bank, but for each disposed signal and some generated additive noises. The results are arranged in Table 1, where can be found

Table 1: Achieved signal to noise ratios

WWD Method							
	SNRx [dB]						
	8	10	12	14	16	18	20
Filter banks	**SNRy [dB]**	**SNRy**	**SNRy**	**SNRy**	**SNRy**	**SNRy**	**SNRy**
bior2,2' / bior2,4'	19,88	21,60	23,33	25,02	26,66	28,27	29,82
'db2' / bior2,2'	20,15	21,68	23,22	24,75	26,23	27,69	29,13
bior2,2' / 'db2'	20,25	21,77	23,29	24,78	26,23	27,65	28,99
'db2' / 'db2'	19,99	21,37	22,73	24,05	25,34	26,59	27,78
bior3,1' / 'db2'	19,23	20,85	22,45	24,04	25,57	27,00	28,32
bior2,2' / bior2,2'	19,56	20,93	22,22	23,40	24,40	25,17	25,74
bior1.5 bior1.5	16,76	17,41	17,96	18,40	18,74	18,99	20,16
bior6,8' / bior6,8'	13,73	14,28	14,74	15,10	15,36	15,55	15,68

MWT Method							
	SNRx [dB]						
	8	10	12	14	16	18	20
Filter banks	**SNRy [dB]**	**SNRy**	**SNRy**	**SNRy**	**SNRy**	**SNRy**	**SNRy**
bior1,5'	19,60	20,96	22,26	23,46	24,49	25,26	25,83
bior2,4'	18,63	20,19	21,67	23,03	24,27	25,35	26,17
'db2'	19,15	20,56	21,85	22,97	23,92	24,69	25,28
bior2,2'	17,88	19,45	20,96	22,39	23,74	24,91	25,78
bior6,8'	18,30	19,53	20,69	21,72	22,58	23,24	23,75
bior3,1'	14,48	16,00	17,57	19,14	20,63	21,97	23,14

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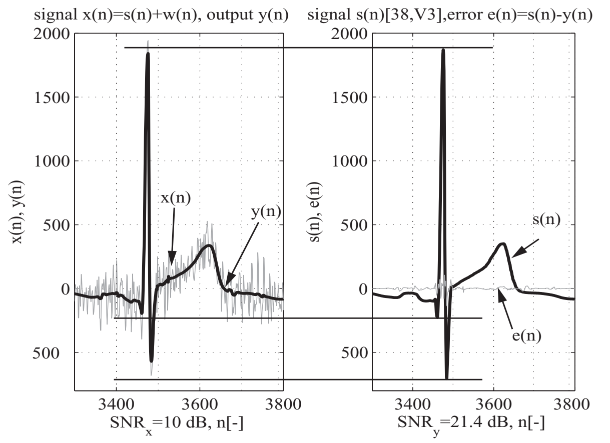

Figure 5: MVT method, input SNRx=10dB, bior1.5

the mean of achieved signal to noise ratios.

In case of WWD method, the best results give combination of filters banks `bior2.2/bior2.4`, `db2/bior2.2`, `bior2.2/db2` and `db2/db2`. Satisfying results give `bior3.1/db2` in a more intensive noising of input signal, but from for approx. 14dB the results are comparable with previous category. The other results are worse. In the case of using the filter banks `bior6.8/bior6.8` `db5/db5` with long impulse responses were in output signal visible typical oscillations placed before and behind the QRS complexes.

The results of MWT method isn't reach such values as WWD method. However generally isn't too dependent on the choice of the filters bank. The best results of this method were achieved with `bior1.5`, `bior2.4`, `db2`, `bior2.8`, and `bior2.2` filters banks. This results is equal to WWD method with following filters banks: `bior2.2/haar`, `haar/db4` or `db2/bior3.1` and in case of filtering very noisy data (SNR_x≈11dB) with `bior3.1/db2`. The filters with long impulse response don't give good results. Interesting progression of SNR_y can be found in `bior3.5` and `bior3.7` particularly `bior3.1`, where in case of very noise input data the results is worse, but in case of higher SNR_x is the results much better, equal to `db4` or `db5/db5` in WWD method.

Discussion and conclusion

We displayed part of the ECGs after denoising to-discuss the described methods (Figure 5,Figure 6). Input SNR_x was 10dB. In MVT method was achieved output SNR_y=21,4dB. The disadvantage of this method is: When the wavelet coefficients exceed the value of the threshold, it'll show it in output signal. Because this method is using only thresholding, the output signal has smaller peaks of Q,R and S wave in comparing with original signal *s(n)*.

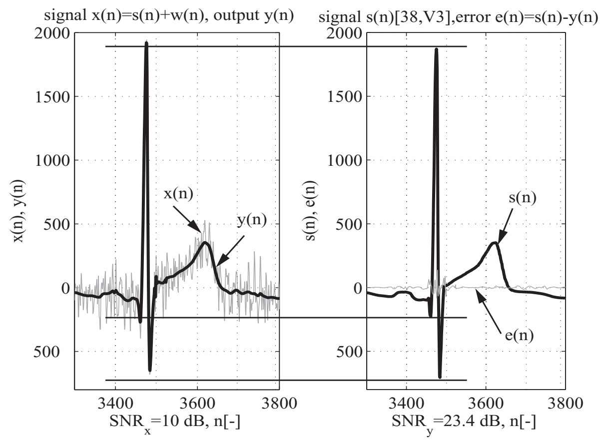

Figure 6: WWD method, input SNRx=10dB, bior2.2/bior2.4

The similarly disadvantage is In case of WWD method. When the values of some wavelet coefficients exceed the value of the threshold in part of pilot estimation, the Wiener filter this value more amplify. On Figure 6 can be seen that in some cases, the values of specific waves in ECG signal are larger than in original signal *s(n)*.

These methods MVT and WWD are suitable for wavelet filtering of the ECG signals.

Aknowledgements

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