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Noise Cancellation by Combining the Discrete Wavelet Transform With the Wiener Filter

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ABSTRACT
In this study by using noise-free signal estimation the reduction of noise in the image is being proposed. The dyadic stationary wavelet transform is used for both the wiener filter and in estimating the noise free signal. Finding a suitable filter bank and choosing other parameters of the wiener filter with respect to obtained signal-to-noise ratio (SNR) is our goal. Testing was being performed on the standard images corrupted with the noise. The artificial interference was created from the generated white Gaussian noise, whose power spectrum was modified according to a model of the power spectrum of the image. The adaptive setting parameters of the filtering according to the level of interference in the input signal are being used to improve the filtering performance. The average SNR of the whole test database is increased by about 10.6 dB. The better results can be provided by using the provided algorithm than the classic wavelet wiener filter
Keywords: image, dyadic stationary wavelet transform, SNR, white Gaussian noise, Wiener filter,

I. INTRODUCTION

A digital image is a numerical representation of a two dimensional image .Image acquired through modern sensors may be contaminated by a variety of noise sources. By noise we refer to stochastic variations as opposed to deterministic distortions such as shading or lack of focus. So removal of noise is considered as the important in the image processing. Linear filtering is not suitable for the suppression of the broadband noise unlike the narrow band interference because it leads to significant cropping of the edges of the pixels in the image. Noise spectrum is predominant at the higher frequencies and overlaps significantly with the image spectrum. Therefore it is difficult for automatic interpretation, following accurate detection of characteristics of the image.

Compared to linear filtering, the discrete wavelet transform can increase effectiveness of suppression of the noise in the image. WT decomposes the signal so that the highest bands contain noise and some additive components of the image and the lower bands contain more components of image. Depending on the estimated level of the interference in the transform coefficients, the signal can be filtered by appropriate adjustments in the transform coefficients. The wavelet wiener filtering is being focused in this paper. Dyadic SWT is used in the wiener filter and also in the estimation of a noise-free signal. Finding most appropriate filter bank and to recommend other parameters of the wiener filter is our goal. Selection of appropriate values of the parameters was performed to maximize the average resulting signal-to-noise ratio (SNR) for all the signals tested. We confirmed that the appropriate values of these parameters depend on the noise level or SNR. A general scheme of the filter, consisting not only of the own filter but also of the estimation of a noise-free signal, was extended with automated estimation of the SNR.

II. PREVIOUS METHODS

1. STATIONARYWAVELET TRANSFORM (SWT)

WT provides not only about the frequency characteristics of the signal but also about the time characteristics of the signal. So, WT has been a popular and effective tool for signal processing. The wavelet decomposition can be described as iterative signal composition, using filter banks of low pass and high pass filters (organized in a tree) with down sampling of their outputs. This decomposition tree structure so called dyadic transform [2],[10], in which decomposition of outputs of low pass filters is performed .

It is known fact by experience that SWT [8] will give better results than simple signal processing method. In SWT outputs of decomposition filters in all decomposition levels are not down sampled. Interpolation errors that might occur during the reconstruction part can be avoided. We used the SWT in this study.

The no of decomposition levels used and impulse characteristics used of the initial low pass and high pass filters are the important parameters

2. Wavelet Filtering Method:

The simple Wavelet Filter is based on an appropriate adjustment of wavelet coefficients in the wavelet domain [10]. With regard to the character of image wavelet coefficients, it is effective to separate the interference and the signal via thresholding. Effective thresholding requires 1) to evaluate the right value of the threshold and 2) to choose the right methods of thresholding

2.1) Threshold Level: We suppose that the corrupted signal $x(n)$ is an additive mixture of the noise-free signal $s(n)$ and the noise $w(n)$, $x(n) = s(n) + w(n)$, both uncorrelated, where n represents the discrete time ($n = 0, 1, \ldots, N-1$) and N is the length of the signal. If we transform the noisy signal $x(n)$, using the linear dyadic SWT, into the wavelet domain, we obtain the wavelet coefficients $ym(n) = um(n) + vm(n)$, where $um(n)$ are the coefficients of the noise-free signal and $vm(n)$ are the coefficients of the noise, and m is the level of decomposition which denotes the mth frequency band.

The threshold levels for the modification of the wavelet coefficients should be set separately for each decomposition level m with respect to the noise level $vm(n)$ (its standard deviation σvm). In the case of lower noise level, the threshold level is lower and the corruption of the noise-free signal is also lower. The issue of the wavelet thresholding is described in detail in [11].

There are many methods for estimating the optimal threshold values. Most of the methods assume white Gaussian noise and the decimated WT. They include, for example, the Universal threshold [12], Stein's unbiased risk estimate threshold (SURE) [13], [14], or Minimax threshold [15]. However, these methods are always based on the standard deviation of the noise multiplied by a derived constant value. In our study, we use the SWT, and the suppressed noise characteristics. For the calculation of the threshold value, we also use the standard deviation of the noise multiplied by an empirical constant TM (the threshold multiplier). Setting this constant is not yet entirely clear and therefore it will be tuned later. The threshold levels λm can be described by the equation

$$\lambda m = \mathrm{TM} \cdot \sigma vm \qquad (1)$$

Where σvm is the standard deviation of the noise in the mth frequency band.

In the case of setting the threshold too low, we risk the occurrence of noise artifacts. On the other hand, setting the threshold too high, we can damage the noise-free signal. In the cases where the noise dynamically changes its energy, fixed thresholds are failing. One of the possible solutions can be also to adaptively change the threshold level. This approach can be found in [16].

It is a robust estimate of the standard deviation of noise using the median; it was first introduced in [12] and used, for example, in [15], [17] and [18]

$$\sigma vm = \frac{\mathrm{median}\,(|ym|)}{0.6745} \qquad (2)$$

If we estimate the standard deviation of noise using a sliding window, we obtain the time-dependent $\sigma vm(n)$. For the same reasons that were described earlier, we multiply the calculated standard deviation by the constant TM and obtain the time varying threshold

$$\lambda m\,(n) = \mathrm{TM} \cdot \sigma vm(n) \qquad (3)$$

We need to ensure that the standard deviation of the noise calculated in a sliding window by (2) is not affected by the noise-free component of the signal. For this reason, we need to ensure that at any time the sliding window contains exactly one pixel. This is complicated in cases where the pixel rate is time variable and in that context the length of the RR interval is also varying. From the above, it follows that we should dynamically change the length of the sliding window to ensure that the calculation of the standard deviation of noise is correct.

2.2) **Thresholding Methods**: Five thresholding methods are tested in this paper they are: hard and soft thresholding [12], hyperbolic [21], nonnegative garrote [22], and semisoft (firm) thresholding [23], [24]

3. Wavelet wiener filtering method (WWF)

Consider the block diagram of WWF method in Fig.1. The estimation of the noise free coefficients *um (n)* can be done from the coefficients *ym (n)*, using the WWF method, which is based on Wiener filtering theory applied in the wavelet domain[7], [25].

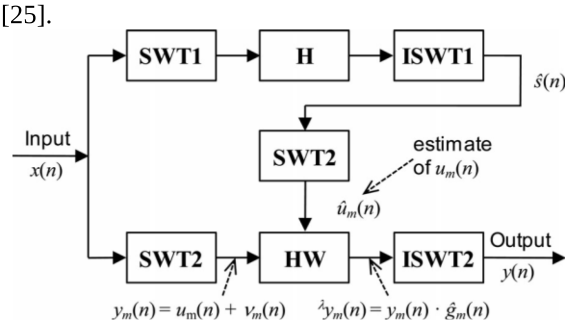

Fig. 1. Block diagram of the WWF method. The upper path is used to estimate the noise-free signal ˆ$s(n)$; the lower path implements the Wiener filter in the wavelet domain

The upper path of the scheme consists of four blocks: the wavelet transform SWT1, the modification of the coefficients in block H, the inverse wavelet transform ISWT1, and the wavelet

Transform SWT2. The first three blocks mentioned represent the classic Wavelet Filtering method described previously. The lower path of the scheme consists of three blocks: the wavelet transform SWT2, the Wiener filter in the wavelet domain HW, and the inverse wavelet transform ISWT2.

We get the estimate *s~(n)*, which approximates the noise-free signal *s(n)*, using the inverse transform ISWT1. This estimate is used to design the Wiener Filter (HW), which is applied to the original noisy signal *x*(*n*) in the SWT2 domain (lower path), via the Wiener correction factor [2], [26]

$$\hat{g}_m(n) = \frac{\hat{u}_m^2(n)}{\hat{u}_m^2(n) + \sigma_{\nu m}^2(n)} \quad (4)$$

where ˆ*u*^2*m*(*n*) are the squared wavelet coefficients obtained from the estimate ˆ*s*(*n*), and *σ*2*vm*(*n*) is the variance of the noise coefficients *vm*(*n*) in the *m*th band, estimated using (2).We process the noisy coefficients *ym*(*n*) in the HW block, using the previously described Wiener correction factor, to obtain the modified coefficients.

$$^{\lambda}y_m(n) = y_m(n) \cdot \hat{g}_m(n). \quad (5)$$

The output signal *y*(*n*) is obtained by the ISWT2 inverse transform of the modified coefficients *λym*(*n*).

III. Proposed algorithm:

Adaptive wavelet wiener filtering method (AWWF)

There are many parameters which are to be set manually in the WWF method. The decomposition level of WT, the thresholding method in the wavelet domain, the threshold multiplier and the wavelet filter banks used in SWT1 and SWT2 transforms are the most important ones. The great influence on the filtering results will be based on appropriate setting of the input parameters. But it is not clear which parameters should be used for ECG signal denoising. Moreover, it is obvious that for different noise levels present in the input signal different settings of the input parameters are suitable. Therefore, a robust filtering algorithm should be changing its parameters depending on the actual amount of noise.

We improved theWWFmethod by adding the block for noise estimate (NE), as can be seen in Fig. 2.

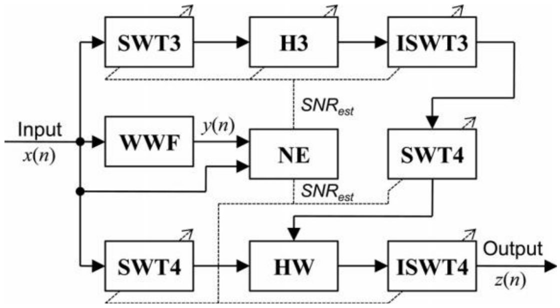

Fig.2. Block diagram of the AWWF method. The most important block is NE, where the SNR is estimated. According to this estimate all the relevant parameters are set.

This block needs two inputs: the first is the noisy signal *x* (*n*) and the second is the estimate of the noise-free signal *y* (*n*) obtained by the WWF method with universal parameters. The difference of these two signals gives an estimate of the input noise and we can calculate the SNR. The parameters in blocks SWT3, H3, ISWT3, SWT4 and ISWT4 are set up using the estimated SNRest value.

The remaining problem is that we do not know yet the correct setting of the individual blocks. Therefore, it was necessary to find these parameters individually for different levels of Interference

3.1) Modification of long term records:

It is clear from the above that with a sudden change in the SNR within the image it is suitable to change the filter settings in order to maximize the filtering performance. The probability of such changes is obviously higher for long-term signals, e.g., the Holter signals.

The proposed AWWF algorithm has an important block i.e., NE block which monitors the time dependence of SNR within the image and using set of thresholds, the changes are detected. Therefore with an approximately constant level of noise, the signal is divided in to two segments. The AWWF method uses for each segment the appropriate parameters and the filtered segments are again reconnected.

IV. Parameter setting for AWWF

The five most important parameters are: the level of the decomposition for values from 2 to 6, the thresholding method (Hard, Hyperbolic, *N* Garrote, Semisoft, Soft), the threshold multiplier for values from 1 to 20, the set of filter banks for transforms SWT3 and SWT4 (we tested 53 filter banks, which are present in the MATLAB Wavelet Toolbox); these are given in the below table I

TABLE I
BASIC GROUPS OF THE INVESTIGATED PARAMETERS

Dec. level	*Thresh.*	*TM*	*WT3*	*WT4*
2	**Hard**	1	haar	haar
3	Hyperbolic	1.5	**db4**	db4
4	Garrote	2	sym2	sym2
5	Semi-soft	⁝	⁝	⁝
6	Soft	**20**	dmey	**dmey**
5	5	15	53	53

Dec. level – decomposition level, *Thresh.* – thresholding method, *TM* – threshold multiplier

V. Algorithm for finding suitable parameters value:

Our aim was to maximize the average SNR improvement. The problem is not easy, because some parameters are continuous, some are discrete and some are highly discontinuous. We tried to use genetic algorithms for the optimization, similar to what was done in [5], but the results obtained were not relevant. We decided to use our own approach. We gradually changed the parameters in all groups and observed the SNR improvement. The step-by-step process is as follows.

1) Set the SNRin. The whole algorithm is performed successively for SNRin from −5 to 55 dB in steps of 5 dB.
2) Set up groups of investigated parameters (see Table I). At the beginning, there are always all the parameter values we are interested in (a total of 131 values). According to the number of parameters, we set the number of currently tested signals (NTS). The smaller the number of parameters, the more signals can be used with the same time requirement.
3) Randomly select the first combination of the parameters from Table I (highlighted in bold).
4) Generate a random EMG noise according to (7).
5) Gradually change the decomposition level from 2 to 6 choose the decomposition level at which we achieved the highest average SNR improvement, and gradually do the same with the thresholding method, the threshold multiplier and both WF banks. Finally, we get the first iteration (see the second line in Table II).
6) Repeat steps 4) and 5) and get other iterations until any of the following conditions is satisfied: a) five identical successive iterations; b) seven identical iterations everywhere (used in Table II); and c) ten identical parameters in each column

Table II

7) Return to step 3) and repeat it three times, with another randomly selected combination of the parameters. The parameters in Table I will essentially create a five dimensional parametric space. If we start the iteration process more than once, each time from another place in this space, and always find the same maximum, the probability we have found the global maximum will increase.
8) The next step is the elimination of the parameters with allow or no presence in the iterations (see Table II). If we get rid of clearly unsuitable parameters, we can use more signals for further testing in the same computational cost. Determine the relative counts of each parameter in each
Column.
9) Return to step 2). Now we have fewer parameters and can use more signals. Repeat this procedure until we cannot exclude any further parameter in step 8), or until only one parameter is left in each column
10) We get the set of advisable parameters for a particular value of SNR (see Table III). We return to step 1) and repeat the procedure for other desired levels of the input noise to complete Table III.

Table III

Iteration	*Dec. level*	*Thresh.*	*TM*	*WT3*	*WT4*
0.	6	Hard	20	db4	dmey
1.	4	Hard	4	sym2	bior4.4
2.	4	Hyperb.	4	rbio1.3	sym4
3.	4	Garrote	3.5	db4	coif2
4.	**4**	**Garrote**	**3.5**	**db4**	**sym4**
5.	**4**	**Garrote**	**3.5**	**db4**	**sym4**
6.	**4**	**Garrote**	**3.5**	**db4**	**sym4**
7.	4	Hyperb.	4	db4	sym4
8.	4	Hyperb.	4	sym5	sym4
9.	**4**	**Garrote**	**3.5**	**db4**	**sym4**
10.	4	Semisoft	3.5	db4	sym4
11.	**4**	**Garrote**	**3.5**	**db4**	**sym4**
12.	**4**	**Garrote**	**3.5**	**db4**	**sym4**
13.	**4**	**Garrote**	**3.5**	**db4**	**sym4**
End with condition 2)					

Dec. level – decomposition level, *Thresh.* – thresholding method, *TM* – threshold multiplier

***SNR$_{in}$* [dB]**	**Parameters**				
	Dec. level	*Thresh.*	*TM*	*SWT3*	*SWT4*
-5	4	Garrote	3.6	rbio3.3	rbio4.4
0, 5, 10	4	Garrote	3.4	rbio1.3	rbio4.4
15, 20	4	Garrote	3.1	db4	sym4
25, 30, 35	**3**	**Garrote**	**2.8**	**bior4.4**	**sym4**
40, 45	3	Garrote	2.5	bior3.9	sym4
50, 55	2	Garrote	2.3	sym6	bior3.3

Dec. level – decomposition level, *Thresh.* – thresholding method, *TM* – threshold multiplier

VI. RESULTS

Table IV

Sigma(σ)	20	30	40	50
Pre-PSNR	22.11	18.58	16.08	14.15
Post-PSNR	31.53	29.70	28.41	27.43

Pre-PSNR is the peak signal-to-noise ratio before applying AWWF algorithm and post PSNR is the peak signal-to-noise ratio after applying the AWWF algorithm. In the above table we observe there is improvement in the PSNR after applying the AWWF algorithm.

Input image:

Image corrupted with noise:

Output image:

VII. Comparison:

Consider the list of the methods that are tabulated below

Table V

Method	LF	WF	WWF	AWWF
Mean Imp. [dB]	-4.5	6.4	6.6	10.6
STD Imp. [dB]	8.2	3.6	3.8	2.2
Computational cost [sec]	0.003	9.543	0.040	0.310

Imp. – improvement, STD – standard deviation

In table IV we can see the summary of the results. In the above table we found that the AWWF method provides the better results than the existing algorithms.

VIII. Conclusion

The proposed AWWF algorithm provides better filtering results than another tested algorithm based on simple wavelet Wiener filtering. It is evident from the results that the setting of suitable parameters value and their adaptation to the estimated noise level have a positive effect on the performance of the filtering algorithm. Our new algorithm is adaptive in two ways. The first adaptation lies in the division of the signal into individual segments, each with an approximately constant level of noise. These segments are filtered using parameters appropriate for the given noise level. These parameters are the decomposition level, filter banks, thresholding method, and threshold value. The second adaptation is within individual segments. It lies in adaptive setting of the threshold value based on the standard deviation of the noise at decomposition levels. It serves effective noise suppression at the less significant changes in the noise power. Due to these adaptive characteristics, our filter can deal with the dynamically changing noise.

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