ECG Signal Enhancement Using Wavelet Transform

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Abstract: - ECG is an important tool for the primary diagnosis of heart disease; it shows the electrophysiology of the heart and the ischemic changes that may occur like the myocardial infarction, conduction defects, and arrhythmia. The ECG signal must be clearly represented and filtered to remove all noise and artifacts from the signal. In this paper a new approach to filter the ECG signal from noise is proposed using Wavelet Transform WT. Different ECG signals are used and the method evaluated using MATLAB' software. The aim of this paper is to adapt the discrete wavelet transform (DWT) to enhance the (ECG) signal. The presented method showed good results comparing to conventional methods particularly in ECG signal case. This method has better performance than Donoho's discrete wavelet thresholding coefficients and FIR filter.

Key-Words: - ECG signal; Filtration; Wavelet Transform; noise and artifacts.

1 Introduction

The ECG signal has a pseudo-periodic nature and it is known as non-stationary signals. The development of digital computer and at the same time the electrograph was the culmination of scientific efforts aimed at improving the physiological phenomenon and man's welfare [1,2,12].

The ECG signal pass important and main steps during the last fifty years to become automated diagnosis system replacing the simple visual inspection [3]. Filtration of ECG signals is very important, so as to, get the parameters of ECG signal (used for recognizing much variability's of heart activity) clear without noise [4,13].

Cleaned ECG signal gives full detailed information about the electrophysiology of the heart diseases and ischemic changes that may occur. As mentioned above, in order to support clinical decision-making, reasoning tool to the (ECG) signal must be clearly represented and filtered, to remove out all noises and artifacts from the signal. So, it needs a hard work to denoising [5,6,14].

The wavelet transform is one of efficient and experimented techniques that can be used for this purpose as a decomposition of signal in the time frequency scale plane.

There are several techniques available to reduce the noise of ECG signal like FIR or IIR digital filters, adaptive method and wavelet transform thresholding method.

However, for non-stationary signals it is not adequate to use digital filters or adaptive method because of loss in information. Digital filters and adaptive methods can be applied to signal whose statistical characteristics are stationary in many cases. Recently the wavelet transform has been proven useful tool for non-stationary signal analysis [1, 2,15].

One of signal processing step in wavelet transform is to remove some coefficients of produced wavelet subsignals using thresholding [2]. The filtration method that applies thresholding to reduce the noise content of the non-stationary signal has been introduced by Donoho as a powerful noise reduction method [7, 8,16]. The method works with a wide class of one or two-dimensional signals and gives a well and satisfied results.

Several methods to enhance (ECG) signal have been presented in literature. The most widely used is the least mean square adaptive algorithm (LMS). But this algorithm is not able to track the rapidly varying non-stationary signal such (ECG) signal within each heart beat, this causes excessive low pass filter of mean parameters such (QRS) complex. In this paper, we use the DWT to enhance the Signal-to-Noise Ration (SNR) of the ECG signal.

In general, the Mallat's algorithm convolutes the signal (wavelet subsignal-mother and its scaled version) with Band Pass Filter (BPF) to enhance the SNR without any losses or distortion in the original morphology of the ECG signal. [1,2].

There are two main types of thresholding: Hard thresholding by which all the coefficients below a fixed threshold T that depends on noise variance are discarded

$$H_{j,k} = \begin{cases} 1 & if\ w_{i,k} > T \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

Soft thresholding by which all the coefficients below are discarded and all the coefficients above a fixed threshold T are shrunk, where $w_{i,k}$ is the wavelet coefficient and $H_{i,k}$ is wavelet based filter.

Enhancement filter is a wavelet based filter without discarding wavelet coefficient of (ECG) signal, which can carry clinical information: using combination of wavelet filters.

Fig. 1 shows typical, simple and small wavelet which has an energy concentrated in time to give an efficient tool for analysis of transient as nonstationary or time-varying phenomena.

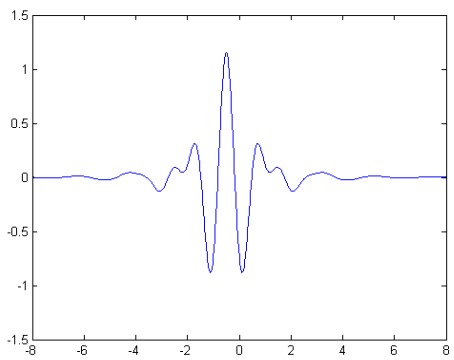

Fig.1 Meyer mother wavelet functions

The signal $f(t)$ can be analyzed and expressed products of the coefficient and function (linear decomposition of the sums). In the wavelet expansion, the two-parameter system is constructed such that one has a double sum and the coefficients with two indices. The wavelet series expansion maps a function of a continuous variable into a sequence of coefficients called Discrete Wavelet Transform (DWT) of $f(t)$ with the main useful four properties:

- The representation of local basis functions to make the algorithms adaptive in-homogeneities of the functions;
- They have the unconditional basis property for a variety of function classes to provide a wide range of information about the signal;
- They can represent smooth functions.

$$f = \sum_{m,n} (f, \psi_{m,n}) \tilde{\psi}_{m,n} \quad (2)$$

2 Filtration of ECG signal

DWT of a signal is a two variables (indices) function, the time translation k and the scaling index j , which makes it difficult to illustrate.

To understand how wavelet transforms works, several articles are published. Recent works by Donoho and John stone gives a better understanding of how wavelet transforms work. This new understanding combined with nonlinear processing solves currently problems and gives the potential of formulating and solving completely new problems [6].

The basic steps of the method are shown in fig.2. First, we perform the DWT of the signal. Second we pass the transform through a threshold to remove the coefficients below a certain value. Third, we take the Inverse DWT (IDWT).

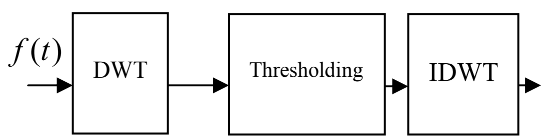

Fig. 2 Basic steps of filtration method

This able to remove noise and achieve high Signal-to-Noise ratios (SNR) because of the concentrating ability of the wavelet transform. The signal has coefficients relatively large compared to any other signal or noise that has its energy spread over a large number of coefficient. Thresholding or shrinking the wavelet transform will remove the low amplitude noise or undesired signals and any noise overlap as little as possible in the frequency domain and linear time-invariant filtering will approximately spare them. It is the localizing or concentrating properties of the wavelet transform that make it particularly effective when used with this nonlinear method.

3 Mathematical Model

In the wavelet transform, the original signal (1-D, 2-D , 3-D) is transformed using predefined wavelets. The wavelets are orthogonal, orthonormal, or biorthogonal, scalar or multi-wavelets. We can write the continuous wavelet transform as follow:

$$(T^{wav} f)(a,b) = |a|^{-1/2} \int f(t)\psi\left(\frac{t-b}{a}\right)dt \qquad (3)$$

with ψ a function of our basis series. The continuous inverse wavelet transforms:

$$f = C_{\psi}^{-1} \iint \frac{1}{a^2}(T^{wav} f)(a,b)\psi^{a,b} dadb \qquad (4)$$

In discrete case, the wavelet transform is modified to a filter bank tree using the decomposition/reconstruction as shown in Fig. 3. The results in the preceding section give us the theoretical basis for the discrete wavelet transform.

We can show that given any multi-resolution V_j, we have two functions: ϕ (known as the scaling function), and ψ (the wavelet) that are contained in V_0 translated and dilated versions of which form an orthonormal basis of V_j. We have:

$$\phi(x/2) = 2^{1/2}\sum_n h(n)\phi(x-n) \qquad (5)$$

$$\phi(x/2) = 2^{1/2}\sum_n g(n)\phi(x-n) \qquad (6)$$

where $g(n) = (-1)^{1-n} h^*(1-n)$.

This means that given a signal at a resolution 2^{-j}, we can form the approximation at a lower resolution $2^{-(j-1)}$ by correlating the signal with $h(n)$ and down-sampling the result. The details (the error in the approximation) may be obtained by correlating the signal with $g(n)$ and down-sampling the result. Because $\phi_{j+1,n}$ and $\psi_{j+1,n}$ form a basis of the orthogonal subspaces V_{j+1} and W_{j+1} which in turn resolve back into V_j, no information is lost in this process.

This process can be expressed completely in terms of the digital filters $g(n)$ and $h(n)$ as follows:

$$d_{j+1}(p) = \sum_n g(n-2p)a_j(n) \qquad (7)$$

$$a_{j+1}(p) = \sum_n h(n-2p)a_j(n) \qquad (8)$$

where the set of numbers $a_j(n)$ represents the approximation of the signal at the resolution 2^{-j} and the set of numbers $d_j(n)$ represents the details lost in approximating the signal at resolution $2^{-(j-1)}$ at the resolution 2^{-j}.

Thus, given a digital signal, we can assume that it is at the resolution 2^0 (and is therefore equal to $a_0(n)$ and decompose it into two sets of numbers $a_1(n)$ and. $d_1(n)$. The set of numbers $a_1(n)$ can be decomposed into $a_2(n)$ and $d_2(n)$ and so on.

Most applications of this result hinge on constructing wavelets such that a few non-zero coefficients approximate the signal, i.e. the detail sequence at higher resolutions is close enough to zero so as to be ignored.

4 Methodology

All following experiments, it is used (ECG) signal *x*, which was recorded by (ECG) apparatus, with sampling frequency f_s equals to 400 *Hz*, spectral band of frequency equals to 0.5-70 *Hz* and standard deviation (σ) equals to 0.9. The (ECG) signal *x* is summed with noise signal *s*, which is received from another registration, by old generation (ECG) apparatus, where are recorded strong interference. The parameters of this noise signal are: spectral band of frequency equals to 0.5-250 *Hz*, and (σ)

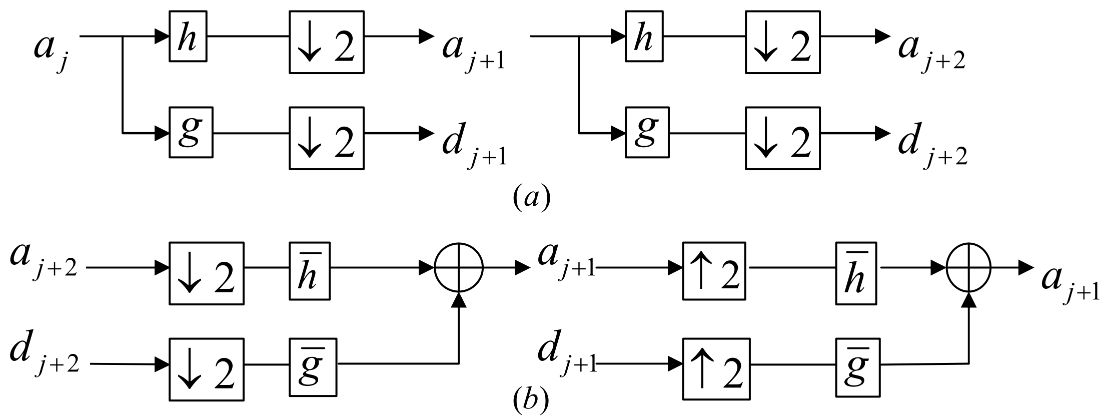

Fig. 3 Filter bank trees of a) Decomposition (DWT) and b) Reconstruction (IDWT)

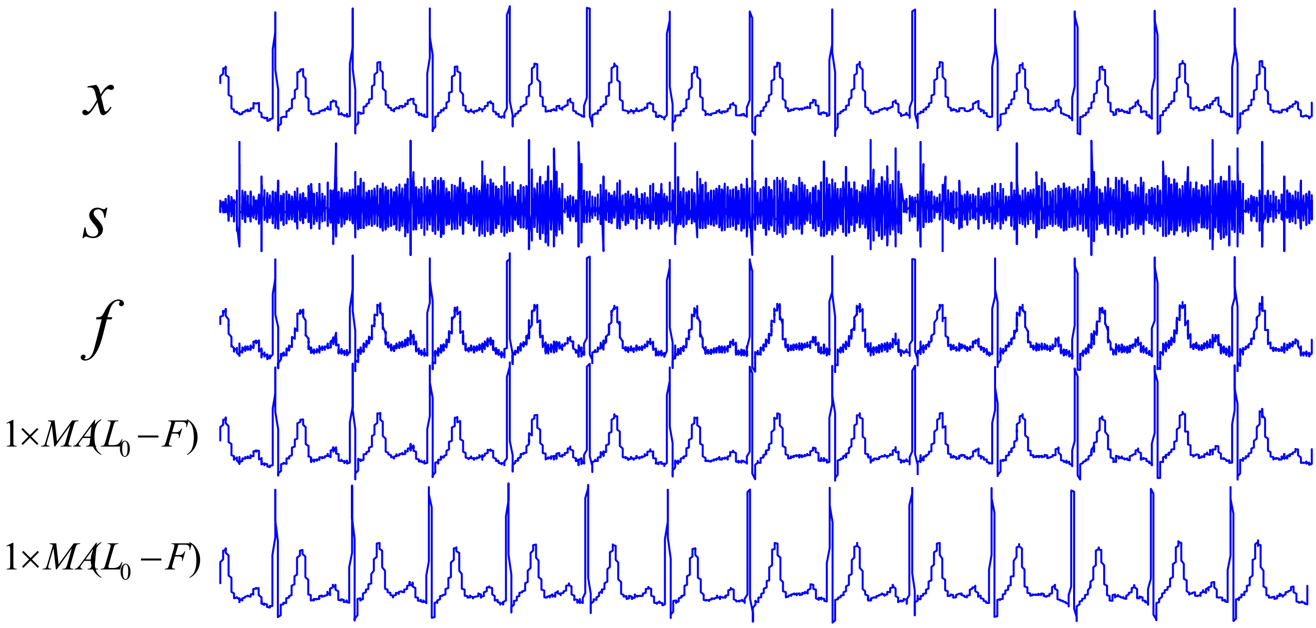

Figure4. Filtration of (ECG) signal by MA (Lo.F) $1\times MA(L_0 - F)$ one time and $3\times MA(L_0 - F)$ three times)

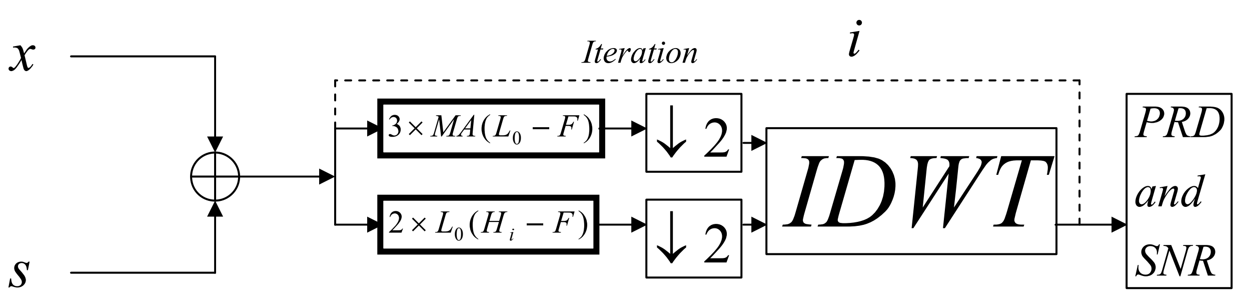

Fig. 5 The filtration system using MA (Lo-F) and MA (Hi-F) filters, where (i) is the number of the system repeating (iteration)

equals to 0.044, 0.09, 0.44 and 0.9. In this paper, two filters are used:

1. Low pass filter MA(Lo-F), which is a convolution operation of noisy signal $f(t) = [x(t) + s(t)]$ and MA(Lo) illustrated in (Fig.1), which is a modified scaled version of db1:

$$MA(Lo)_n = 1/(21/2)\int \phi(t)\phi(2t-n)dt \qquad (9)$$

noise signal *s(t)*. This operation can be repeated many times to get only the (ECG) signal frequency band that can be noticed at last signal shown in Fig. 4.

After repeating convolution operation of ECG signal with MA(Lo), as a low pass filtration, the noisy signal f loses the part of the noise of high frequency, where original signal part of high

frequency is eliminated by the way, which is very important in biomedical signals case, particularly in ECG signal. The ECG signal is used for clinical diagnosis, so each change in amplitudes or time intervals leads to bad medical analysis. To preserve the original signal, Author gets back the lost information by high pass filtrating f signal using

2. High pass filter MA(Hi-F) as:

A convolution operation of noisy signal f and MA(Hi), which is modified scaled version of mother function (type db1):

$$MA(Hi)_n = 1/(21/2)\int \psi(t)\phi(2t-n)dt \qquad (10)$$

$MA(Hi)_n$ is filtered by $MA(Lo)_n$ to discard the high pass noise, This is denoted by $2 \times L_0(H_i - F)$ (see Fig.5).

Now the result of high pass and low pass filters are summed. But the addition operation can deform the output signal; therefore, the best way for adding is using IDWT as illustrated in Fig. 5. Direct reconstruction of these two parts of the original signal causes the aliasing phenomena (putting on spectra's) Fig. 6. The reason of aliasing phenomena is the fact that the two signals have the same number of samples as like as the original signal, so the reconstruction for the same number of samples leads to putting on spectra's of the two signals. To avoid this problem, decimation operation of the two signals before reconstruction is used.

5 Results and Conclusion

As explained in the methodology, that original ECG signal is filtered by low pass filter and the process was repeated many times, the residual of high pass filter is filtered out by low pass filter before the reconstruction of the original signal by IDWT. The number of repeating process of the *MA(Lo-F)* to the original signal and the number of repeating process of the *MA (Lo-F)* to the residual of high pass filter *(Lo(Hi.F))* is determined empirically as in 3 and 2, respectively, where the result of filtration has the least signal distorting. For getting best quality of filtration, the filtration system is repeated many times (i), particularly for noise signal with big (σ). It means that, the system presented in this paper thresholds the noise, which has high frequency above 70 Hz, but its immunity of interference depends on how much (σ) is big.

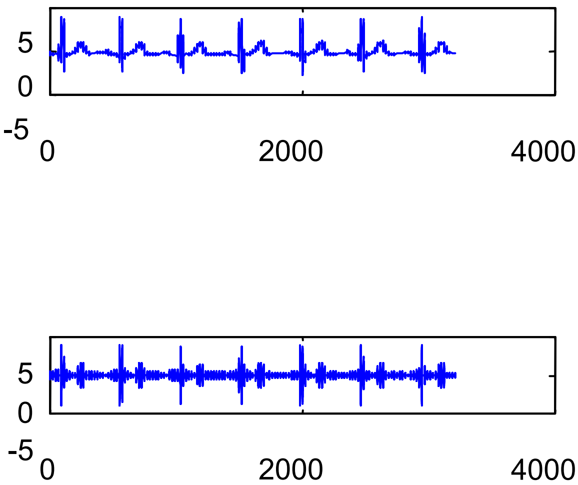

Fig. 6. Two examples Aliasing phenomena

Fast Fourier Transform FFT(F^1) and FFT(F^8); show the difference between the filtered signal by 8 times of repeating the system and 1 time of repeating the system. The curve FFT(F^8) is smooth as good as FFT(x), but is it really the best quality? It is difficult to evaluate the quality of filtration using only FFT.

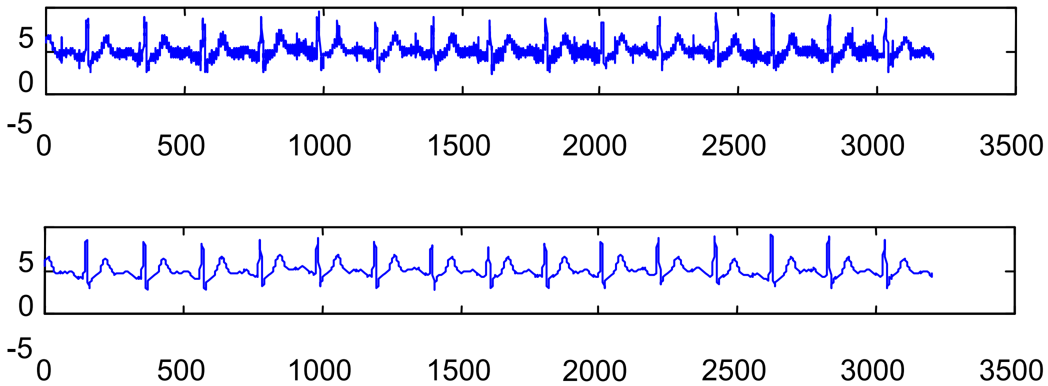

Figure.7 The filtration result for noise of σ =0.44, where the system was repeated 3 (i) times F^3

Tab.1 PRD and SNR where (i) equals to 1:8, for noise signal s of (σ) equals to 0.044 mV, 0.09 mV, 0.44 mV and 0.9 mV

Filtration σ_s=0.044	*f*	F^1	F^2	F^3	F^4	F^5	F^6	F^7	F^8
PRD[%]	0.136	0.017	0.054	0.120	0.2115	0.2115	0.3259	0.3259	0.4631
SNR	2.56	3.45	2.95	2.617	2.3738	2.3738	2.1859	2.1859	2.0333
Filtration σ_s=0.09	*f*	F^1	F^2	F^3	F^4	F^5	F^6	F^7	F^8
PRD[%]	0.56	0.0305	0.05	0.1202	0.2107	0.2107	0.3251	0.3251	0.4625
SNR	1.96	3.2147	2.94	2.6189	2.3754	2.3754	2.1869	2.1869	2.0339
Filtration σ_s=0.44	*f*	F^1	F^2	F^3	F^4	F^5	F^6	F^7	F^8
PRD[%]	13.6	0.4695	0.149	0.1405	0.2128	0.2128	0.3227	0.3227	0.4590
SNR	0.56	2.0273	2.52	2.5514	2.3709	2.3709	2.1902	2.1902	2.0371
Filtration σ_s=0. 9	*f*	F^1	F^2	F^3	F^4	F^5	F^6	F^7	F^8
PRD[%]	54.4	1.8139	0.46	0.2245	0.2367	0.2367	0.3287	0.3287	0.4595
SNR	–0.03	1.4404	2.03	2.3477	2.3248	2.3248	2.1821	2.1821	2.0367

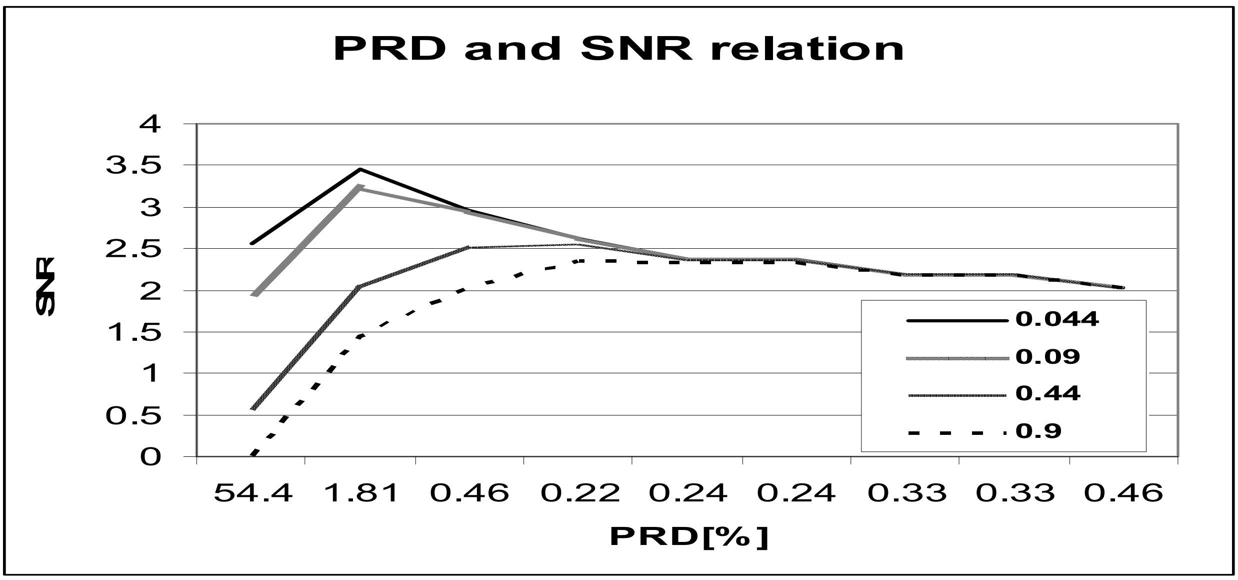

Fig.8 PRD and SNR relation

For evaluation of the quality of filtration, we use percent rms difference method (PRD), which is defined as:

$$PRD = \left[\left(\sqrt{\sum_{i=1}^{N} (X_i - F_i)^2 / \sum_{i=1}^{N} X_i^2} \right) \times 100 \right] \quad (11)$$

where X_i is original signal sample, F_i is filtered signal sample, N is the length of filtered signal. To evaluate the quality of filtration, we propose the following experiment using the scheme illustrated in Fig. 3 and presented by PRD as a percent of distortion of the filtered signal and the SNR, which is defined as:

$$SNR = 10\log\left[\sum (F_{ii})^2 / \sum (X_i - F_{ii})^2\right] \quad (12)$$

The results of the experiment are presented in Table 1. The results show the influence of (σ) of noise values at PRD and SNR. We can notice that, when (σ) values of noise were small (0.044 mV, 0.09 mV), the best filtration(biggest SNR and smallest PRD) is F1, but when (σ) values of noise were big (0.44 mV and 0.9 mV), the best filtration (biggest SNR and smallest PRD) is $\mathbf{F^3}$ (Fig. 6), it means that (*i*) depends on (σ) of the noise. SNR value is biggest when PRD is smallest as a percent of distortion (Figure 8).

6 Comparisons with Other Methods

Several methods to enhance (ECG) signal have been presented in literature by many authors. The most widely used is the least mean square adaptive algorithm (LMS). But this algorithm is not able to track the rapidly varying non-stationary signal such as (ECG) signal within each heart beat, this causes excessive low pass filter of mean parameters such QRS complex. In [3, 4, & 5] a presentation of some of these algorithms that use (LMS) such as the adaptive impulse correlated filter (AICF), the time sequence adaptive filter (TSAF) and the signal-input adaptive filter (SIF). The disadvantages of AICF are being not very robust to noise, and its repetitive, it means that for example amplitude R or P is the same in each beat. The TSAF is not robust to noise, and has null output if the beat period increases (it means make it have no effect). The SIF is the best, it's no repetitive and it's robust to noise, but it slightly smoothes the mean parameters like R or P amplitudes. Using presented system in this point, these all problems can be avoided, because WT is suitable for non-stationary signals such as (ECG) signal. We can see in Fig. 4. that the system is not repetitive, very robust to noise and after comparing the results of QRS detector [11] between the input signal f and the output signal F3, we can notice that the system doesn't smooth QRS complex or R-R interval as shown in table 2:

Table 2 QRS complex detector results.

f (16 indexes of R peaks) **HR** = 102.3309 **HRD** =Tachycardia							
161	388	616	846	1080	1317	1556	1795
2034	2273	2509	2743	2976	2273	2509	2743
F^3 (16 indexes of R peaks) **HR** = 102.3309 **HRD** =Tachycardia							
161	388	616	846	1080	1316	1556	1795
2034	2273	2509	2743	2976	2273	2509	2743

In [11] author compares PRD results of ECG using average moving filter and median filter for noise with spectral band of frequency equal to 0.5-45 Hz and (σ) equals to 0.070 mV. The results show that PRD of optimal filtration by average moving filter equals to 0.9 % and PRD of optimal filtration by median filter equals to 1.65 %. It is easy to notice that the PRD in the system of filtration presented in this paper is less than 0.04% for (σ) equals to 0.090 *mV*.

Table 3 presents another comparison based on PRD using the noise of (σ) equals to 0.044 mV. Two methods are used: wavelet denoising method by D. L. Donoho [12], Daqrouq filter based on denoising wavelet transform coefficients DWTC[2] and filter FIR using the window as [0.707 0.707].

Table 3 Comparison with other methods

Method	PRD [%]
Presented method	0.018
Donoho's	0.187
DWTC	0.027
FIR	0.511

The Donoho's method is based on thresholding the WT subsignals $d_1, d_2, \cdots, d_J$ and s_J. The thresholding procedure in Donoho's is achieved by

$$T = \sigma\sqrt{2\log(n)} \tag{12}$$

So every thresholded subsignal individually depends on its standard deviation. This algorithm is very good filter, particularly, in processes having stochastic nature because these processes contain statistically form in standard deviation function. That based on averaging the coefficient between samples and its mean value. Our algorithm has many trials (iterations) till accomplishing the optimum errors (PRD). Daqrouq's method that based on comparing the results in each subsignal to original subsignal suffers from the same problem.
The FIR filter smoothes the clinical information contained in ECG signal as its window is changed.

7 Statistical Quality Evaluation Method

In this part, statistical evaluation method is presented. This method based on two main stages. First stage is an ECG signal windowing. This is very important in nonstationary nature signals due to the small windows the nonstationary signal becomes stationary. This stage is done for free of noise signal (fig.9a) and for filtered signal (fig.9b). In second stage, the standard deviation is calculated for every window for free and filtered signals. Standard deviation can be calculated using the formula

$$\sigma_x = \sqrt{\sum_{n=1}^{N} \frac{(x_n - \bar{x})^2}{N}} \tag{13}$$

where is x_n the ECG signal sample and $\bar{x}$ is the mean value of all samples in the signal.

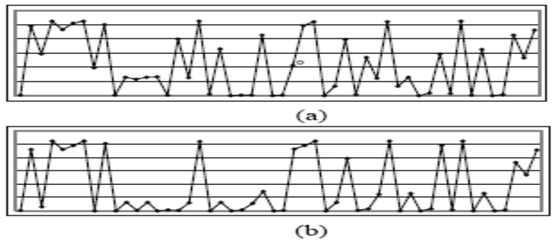

Fig.9 Statistical quality evaluation method results

From fig.9, we can see that x σ is accurate parameter of fluctuation of samples about mean value determination. Using this method, we can help greatly in finding out deformation place occurred in windows. So, it is very easy now to determine the deformation place such in $w_3, w_5, w_6, \cdots$. The simulation results presented in table 1 and Fig. 10 are extracted using the MatLab program (see Appendix)

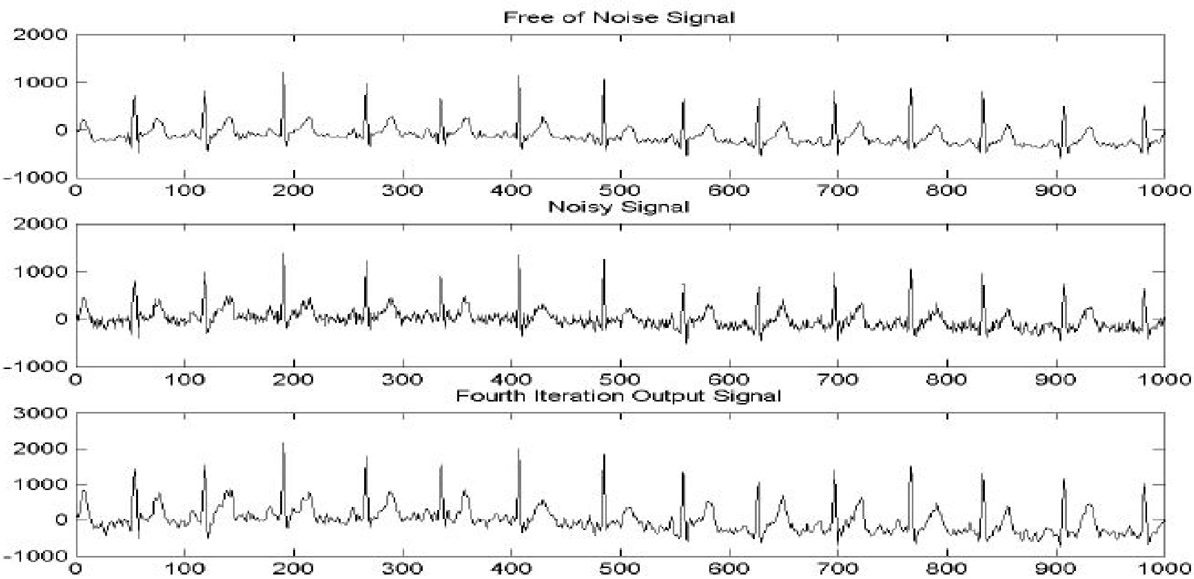

Fig.10 ECG free, noisy and filtered signals

References

[1] S. Jalaleddini, R. Strattan, W. Ceberly, ECG data compression techniques, IEEE Transactions on Biomedical Engineering, Vol. 37, No. 4, pp. 329-342.

[2] Mikhled Alfaouri and Khaled Daqrouq, 2008. *ECG Signal Denoising By Wavelet Transform Thersholding*, American Journal of Applied Sciences 5 (3): pp: 276 – 281.

[3] Merri M., Alberto M., Moss A.J.: *Dynamic analysis of ventricular representation Duration from 24-hour recording*, IEEE Transactions on biomedical engineering, Vol. 40, No. 12, December 1993.

[4] C. D. McManus, U. Teppner, D. Neubert: *Estimation and removal of baseline drift in electrocardiogram*, Comput. Biomed. Resear. Vol 18 pp. 1-9, 1985.

[5] N. V. Thakor, Y. Zho: *Application of adaptive filtering to ECG analysis: noise cancellation and arrhythmia detection*, IEEE Transactions on Biomedical Engineering, Vol. 38, No. 8, pp. 785-794, 1991.

[6] J. Mallat: *A theory of multiresolution signal decomposition using the wavelet representation*, IEEE Transactions on pattern analysis and machine intelligence,Vol. 11, No. 7, pp. 674-693, July, 1989.

[7] B. Mrozek ,Z. Mrozek: *MATLAB uniwersalne oerodowisko do oblicze naukowo technicznych*, PLJ, Warszawa, 1996.

[8] Alfaouri Mikhled, (1997). "*Time-Frequency Analysis of Non-Stationary Signal*," AL-Balqa' Journal for Research and Studies, Amman-Jordan, vol. 5, No.1.

[9] V.Almenar, A.Albiol: A new adaptive scheme for ECG enhancement, Signal Processing 75, (1999)253-265

[10] D. L. Donoho: De-noising by soft-thresholding, IEEE Transaction on Information Theory, Vol. 41, Mar., 1991.

[11] Daqrouq, Khaled Abu-Isbeih, Ibrahim N. Al-Qawasmi, Abdel-Rahman, *QRS complex detection based on Symmlets wavelet function*, IEEE explores, ISBN: 978-1-4244-2205-0. Page 1-5

[12] Mukhopadhyay, S.; *Sircar, P. ECG signal synthesis by exponential AM model Volume* , Issue , 15-18 Feb 1995 Page(s):SPC7 - SPC8

[13] P. Laguna1 , R. Jané2, S. Olmos1, N. V. Thakor3, H. Rix4 and P. Caminal2, *Adaptive estimation of QRS complex wave features of ECG signal* ,model Springer Berlin / Heidelberg Volume 34, Number 1 ,1996.

[14] January Gnitecki and Zahra M.K. Moussavi, Separating Heart Sounds from Lung SoundsIEEE Engineering in Medicine and Biology magazine 2006.

[15] Chavdar Levkov, Rositsa Arnaudova, Stephan Dunev, Hovadim Bakardjian, Grigor Neshev ECG Halter Systems - Development and Perspective Electronics, 2006 20 – 22 September, Sozopol, Bulgaria.

[16] Trygve Eftest, Signal Analysis of Out-of-Hospital Cardiac Arrest Electrocardiograms for Decision Support During Cardiopulmonary Resuscitation, Electrical and Computer Engineering Stavanger University College Norway 2000

Appendix

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%filtration of one iteration
[Lo_D,Hi_D] = wfilters('db1','d');
t= conv(x,Lo_D);
t= conv(t,Lo_D);

[Lo_D,Hi_D] = wfilters('db1','d');
t= conv(x,Lo_D);
t= conv(t,Lo_D);
t= conv(t,Lo_D);
t1=conv(x,Hi_D);
t2= conv(t1,Lo_D);
t2= conv(t2,Lo_D);
t3=t2(1:length(t2)-2);
t3= t3(2:length(t3));
t=t(1:length(t)-2);
t=t(2:length(t));
t=t(:);
fs=(t3+t);
t4= conv(t3,Lo_D);
t4= conv(t4,Lo_D);
 t4= conv(t4,Lo_D);
t4= conv(t4,Lo_D);
t5= t4(1:length(t4)-4);
t5= t5(4:length(t5));
t=dyaddown(t);
t3=dyaddown(t3);
fh= idwt(t,t3,'db1',length(x2));
%PRD of filtration
fsn=fs*max(x2)/max(fs);
fsn1= fsn(1:length(fs));
e1=(x2-fsn1);
prds=((sum(e1.^2))/(sum(x2.^2)).^1/2)*100;
%for fh
fhn=fh*max(x2)/max(fh);
fhn1= fhn(1:length(fh));
e3=(x2-fhn1);
prd=((sum(e3.^2))/(sum(x2.^2)).^1/2)*100;
```