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ECG Baseline Wandering Reduction Using Discrete Wavelet Transform

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Abstract: The aim of this study is to use discrete wavelet transform (DWT) for ECG signal processing, specifically for reduction of ECG baseline wandering. The main reasons for using discrete wavelet transform are the properties of good representation nonstationary signals such as ECG signal and the possibility of dividing the signal into different bands of frequency. This makes possible the detection and the reduction of ECG baseline wandering in low frequency subsignals. For testing presented method, were used two original ECG signal types; ECG signals recorded in our university and ECG signals taken from MIT-BIH arrhythmia database. The method has been compared with traditional methods such FIR and on-line averaging method and more advanced method such as wavelet adaptive filter (WAF)[1]. It was noticed that presented method is superior to WAF in terms of signal quality and ST-segment distortion, because it cuts the drift from each beat basing on the PQ-segment level.

Key words: Discrete wavelet transform, ECG signal, baseline wandering, filtering, noise

INTRODUCTION

When an Electrocardiog gam (ECG) is recorded, many kinds of noise are recorded[1], such as:

- Baseline wandering, which is caused by low pass noise.
- 50 or 60 Hz power line interference.
- ElectromyoGram (EMG), which is an electric signal caused by the muscle motion during effort test.
- Motion artifact, which comes from the variation of electrode-skin contact impedance produced by electrode movement during effort test.

These noises can make clinical diagnosis very difficult and thus, several algorithms have been created. DWT has been described as a good tool for the reduction of ECG signal baseline wandering. The wavelet functions (mother and its scaled version) are used as orthonormal bases for representing other functions (signals) in DWT in time and frequency domains. The DWT is a linear operation, which decomposes a signal into different components[2], which appear at different scales or resolutions. In this study the authors show how DWT coefficients, by using the modified on-line averaging method[1], can reduce the baseline wandering in ECG signal without signal distortion, even when the signal is very noisy.

Reduction of ECG baseline wandering is very important for measurement of the S-T segment with high accuracy (Fig. 1), which is used for diagnosing ischemia, myocardial infarction and indicating an imbalance of myocardial oxygen supply. The American Heart Association (AHA) recommended that to preserve linear phase, the cut-off frequency of high pass filters, may be chosen equal to the fundamental frequency of the heart rate or lower (< 0.8 Hz)[3,4]. Several filters have been designed for the reduction of baseline wandering such as:

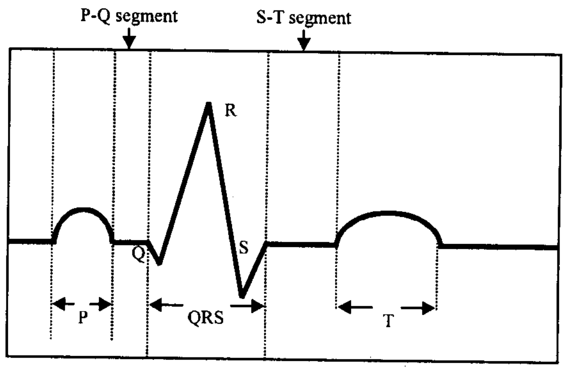

Fig. 1: A typical electrocardiogram

- FIR and IIR filters, by fixing cut-off frequency. These filters have the disadvantage that the signal is deformed as the cut-off frequency increases[3].
- Cubic spline filters, without effect of deformation[3,5]. These filters make several errors when the sampling rate is low or when the baseline suddenly changes.
- Adaptive filters, which determine the signal and adaptively remove the noise uncorrelated with the deterministic signal[3,6]. The disadvantage of these filters is the distortion of S-T segment.

DISCRETE WAVELET TRANSFORM (DWT) AND CONTINUOUS WAVELET TRANSFORM (CWT)

The orthonormal wavelet functions (bases) are analogous to trigonometric sine and cosine. These functions are fundamental functions for building the signals. As with sine and cosine, are oscillated about zero. However the oscillation for wavelets damp down fast to zero.

The f(t) continuous approximation by wavelet orthonormal basis can be defined as

$$f(t)=\sum_k S_{J,k}\,\phi_{J,k}(t)+\sum_k d_{J-1,k}\,\psi_{J-1,k}(t)+....+\sum d_{l,k}\,\psi_{l,k}(t)+.....+\sum_k d_{1,k}\,\psi_{1,k}(t) \quad (1)$$

Where, J is the scale, k the translation parameter, sJ, k, dJ, k are the wavelet approximation coefficients, $\psi_{J,k}(t)$ and $\phi_{J,k}(t)$ are wavelet approximation functions. Wavelet functions have two forms: ψ, mother wavelets (wavelet function) and ϕ, father wavelets (scale function)[7] (Fig. 2). Roughly speaking, ψ (t) represents high frequency parts of signal and ϕ (t) represents smooth and low frequency parts of signal. The generally used wavelet types are Haar, Daubechies, Symmlets and Coiflets. Functions $\psi_{j,k}(t)$ and $\phi_{j,k}(t)$ are the scaled and translated version of ψ and ϕ:

$$\psi_{j,k}(t)=2^{-j/2}\psi(2^{-j}t-k),\phi_{j,k}(t)=2^{-j/2}\phi(2^{-j}t-k) \quad (2)$$

Discrete wavelet transform is used to calculate the wavelet approximation coefficients. For example, for discrete and finite signal $f=(f_1, f_2, ..., f_N)$, DWT calculates m coefficients vector $w=(w_1, w_2, ...,w_m)$, which consists of wavelet approximation coefficients $s_{j,k}$ and $d_{j,k}$, $j = 1, 2, ..., J$. In mathematical terms DWT is derived by:

$$w = Wf \quad (3)$$

Where, W is DWT matrix.

To calculate the wavelet approximation coefficients we apply the known Mallat's Algorithm (MA)[8]. This algorithm applies decimation operation and after that, convolutes the signal with wavelet function and its scaled version as low pass and high pass filters (H, L)[8,9]. By Mallat's algorithm we decompose the original signal into subsignals ($d_1, d_2, d_3 ..., d_J, s_J$, where $d_J=(d_{j,1}, d_{j,2}, ..., d_{j,N/2^j})$ and $s_J=(s_{J,1}, s_{J,2}, ..., s_{J,N/2^j})$) with different bands of signal frequency (Fig. 3a and b).

The second Mallat's algorithm is inverse discrete wavelet transform (IDWT)[7,8]. This algorithm applies zero-padding operation (Fig. 4), which gives zero between samples to double sampling frequency f_s. Afterwards, convolutes the signal with wavelet conjugate function and its scaled conjugate version (H^*, L^*)[10].

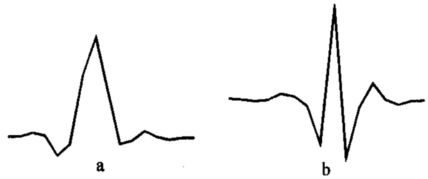

Fig. 2: The wavelet functions a: The scaled version (father) of symmlets and b: Mother of symmlets

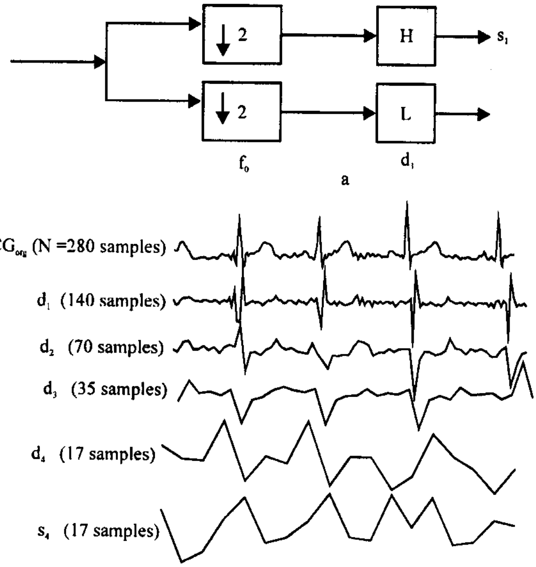

Fig. 3a: Mallat's Algorithm, f_0- original signal. b: Wavelet approximation subsignals of ECG signal

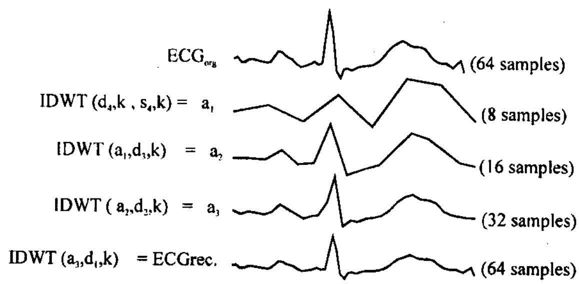

Fig. 4: Reconstruction of one beat ECG signal from its wavelet approximation subsignals by IDWT

$$H^* = H(-n), \qquad L^* = L(-n) \quad (4)$$

The Continuous Wavelet Transforms:is defined as:

$$F_{CWT(f(t),j,k)}=\int_{-\infty}^{\infty} f(t)\,\psi^*_{j,k}(t)dt \quad (5)$$

Where, $j\in R^+$, $k\in R\pm$ and ψ^* is algebraic dual of mother wavelet ψ, which must satisfy an admissibility condition:

$$\varsigma=\int_{-\infty}^{\infty}\left|\psi(\omega)\right|^{2}/\omega\, d\omega \qquad (6)$$

This condition guarantees the existence of the inverse wavelet transform.

MATERIALS AND METHODS

The wavelet reduction baseline wandering system has three steps (Fig. 6): the first step is DWT signal decomposing, the second is Wavelet Averaging Filtering (WAF) and the last step is reconstruction the original signal by IDWT (Fig. 7). The ECG signals used in this point has standard deviation ' = 0.88:0.91 mV and sampling frequency f_s = 400Hz, or ' = 200:330 mV and f_s = 100Hz.

DWT decomposing: The first step of the system is decomposing the ECG signal using DWT into two components d_1, s_1. To get two subsignals (Fig. 4 and Fig. 5), the first subsignal d_1 is responsible of high frequency and the second s_1 is responsible of low frequency (Fig. 3 can be noticed, that s_1 is reconstructed from d_2, d_3, d_4 and s_4). s_1 has the low frequency noise, which should be filtered. The decomposing of ECG signal into two components d_1, s_1 assists greatly in the detection of the main ECG parameters, when the signal is contaminated by high frequency noise. This is particularly observed in s_1.

Wavelet averaging filtering: The first step of wavelet averaging filtering is to divide s_1 into windows of one beat ($T_{i\,offset}$-$T_{i+1offset}$ interval, where i is the consecutive index of the window in s_1) or into R-R windows and to detect in each window the isoelectric line level. In this study the authors propose the average of P-Q segment as a value (A), which represents isoelectric line level, because P-Q segment has always been used to detect the isoelectric line. After averaging of P-Q segment, the reduction of the drift in each window in s_1 is accomplished by:

$$F_i(n)=f_i(n)-A_i; \quad n=1, 2, ..., N \qquad (7)$$

and A_i can be found by:

$$A_i = 1/M\left(\sum_{m=1}^{M} f_{P-Q}(m)\right) \qquad (8)$$

Where:

$F_i(n)$ the filtered sample in i window,
$f_i(n)$ the sample with the drift in the window,
$f_{P-Q}(m)$ P-Q segment m-sample.
m the index of samples in P-Q segment in the window,
N the number of samples in the window.
(when it is not possible to detect P-Q, the T-P interval can be used).

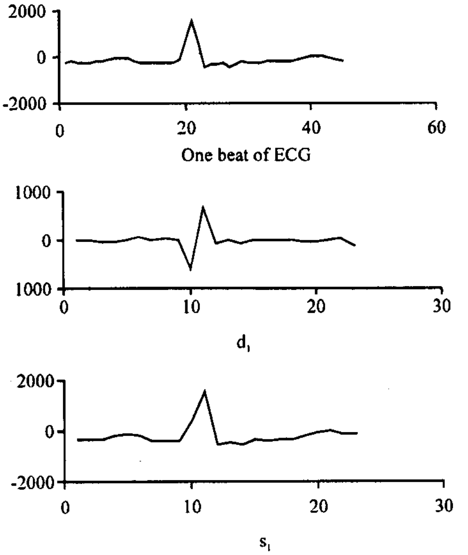

Fig. 5: Two DWT components of one beat signal window (d_1, s_1)

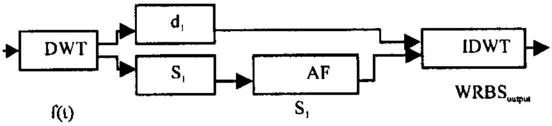

Fig. 6: The scheme of WRBS

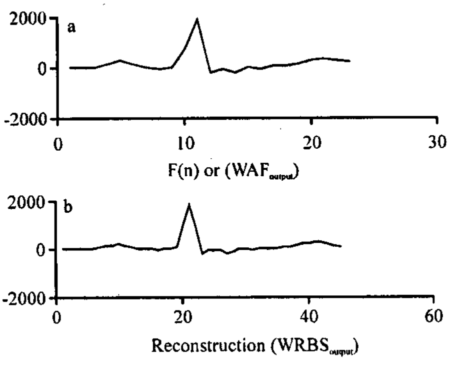

Fig. 7a: The (WAF_{output}) result of s_1 in Fig. 4 b: ($WRBS_{output}$) of one beat window signal of the signal in Fig. 4

The second step is to link the windows $F_i(n)$ to get the entire filtered S_1 signal

$$S_1 = [F_1(n), F_2(n), ..., F_k(n)] \qquad (9)$$

Where F_k (n) is the nth filtered sample in the last linked window in s_1 and S_1 is s_1 without baseline wandering or drift.

Reconstruction: The last step of this system is to reconstruct the original signal from S_1 and d_1 by the inverse discrete wavelet transform as the output of WRBS (Fig. 7).

ECG SIGNAL FIDUCIAL POINTS DETECTION

It was shown by Mallat[1], that the zero crossing of CWT using the mother wavelet as the second derivative of a smoothing (scaled) function, detects the peak of the signal such as R peak. Authors create ECG signal parameters detection method using CWT for testing and showing CWT possibility of detecting (Fig. 8) the fiducial points of ECG signal. For this aim, CWT with wavelet function db1 (Haar) (Table 1) at suitable scale (2^j) is used, which detects the peak of the signal as the first sample after zero crossing point. It is one of Daubechies wavelets, generally, have the following properties:

- Compactly supported.
- Wavelet with extreme phase and highest.
- Associated scaling filters are minimum-phase filters.
- Far from symmetry.
- Orthonormal and bioorthonormal.

The detection of fiducial points is based on maxima; minima and zero crossing CWT curve[5,6,11,12]. For symmetric waveforms like P, R or T waves, the first positive point after zero crossing point between its CWT minima and maxima (two double waves) (Fig. 8) using wavelet function db1 (Haar) at scale 2^1 (for f_s=100Hz and 2^5 for f_s=400Hz), will correspond to the peak of P wave. The onset of the negative waves (the first sample of the negative slope), will correspond to the onset of the P wave and the offset of the positive wave (the last sample of the positive wave), will correspond to the offset of the original wave.

Detection of isoelectric level: Detecting the PQ interval always has signified the isoelectric level. It can be detecting by CWT at scale 2^1 (Fig. 9) as the flat portion between the offset of P and the onset of Q. The onset of Q is detected as the onset of the first wave after P offset at CWT curve.

SIMULATION AND GRAPHICAL VERIFICATION OF WRBS

The filter presented in this study, based on DWT and the concept of an on-line averaging method, but with some modification of the choice of the interval window to

Table 1: The low and high pass filters of Haar function coefficients

L	0.7071	0.7071
H	- 0.7071	0.7071

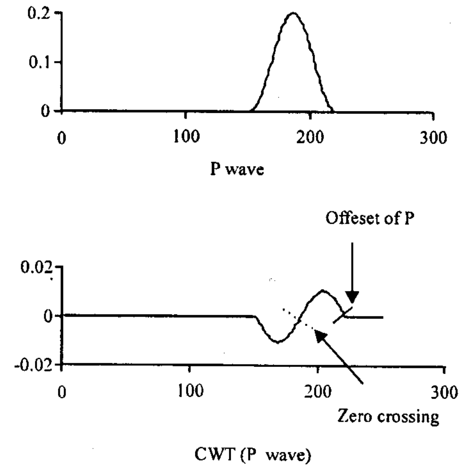

Fig. 8: The detection results of P wave, where i is the index of fidutial point

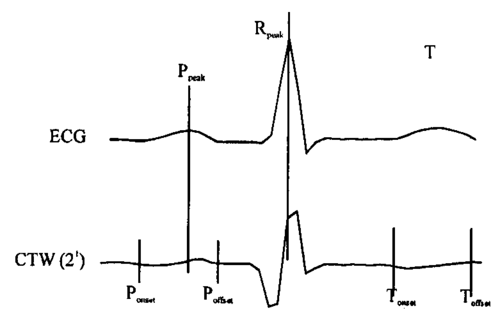

Fig. 9: Detection fiducial points by CWT at scale 2^1

be filtered and the method of detecting the isoelectric level in the unfiltered windows Thakor *et al.*[10] was detected as the average of all samples of ECG signal.

To get exact results, the authors select the one beat window interval to be filtered in this study as $T_{i\ offset}$-$T_{i+1\ offset}$ or R-R interval (Frankie wicz and pietka[1] were filtered the all samples in the signal in the same time) and P-Q segment as the isoelectric level in the unfiltered windows. Because P-Q segment presents the rest phase of heart work, should have zero potential. So using WRBS, the drift is cut and P-Q segment comes back to zero level, where naturally, should be (Fig. 10).

The problem is more difficult in (Fig. 11b), where the drift is not additive in time scale (baseline wandering). In this case, it's difficult to eliminate this wandering without smoothing QRS complex. WRBS reduces the drift in each window without deforming the signal (Fig. 11b, the third beat), by cutting the drift in the window.

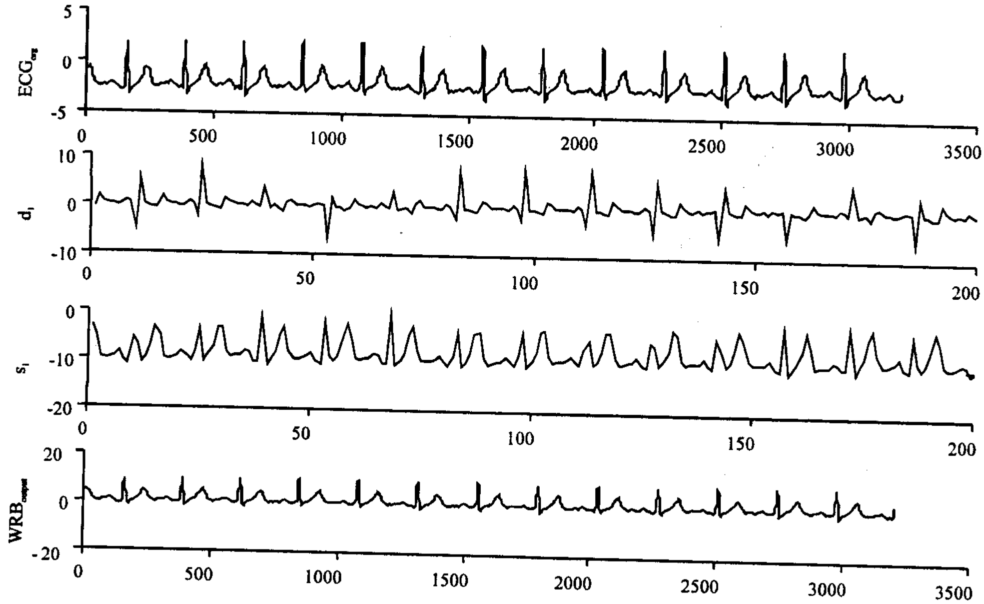

Fig.10: Shows the two DWT components of ECG signal d_1, s_1 and the output of WRBS

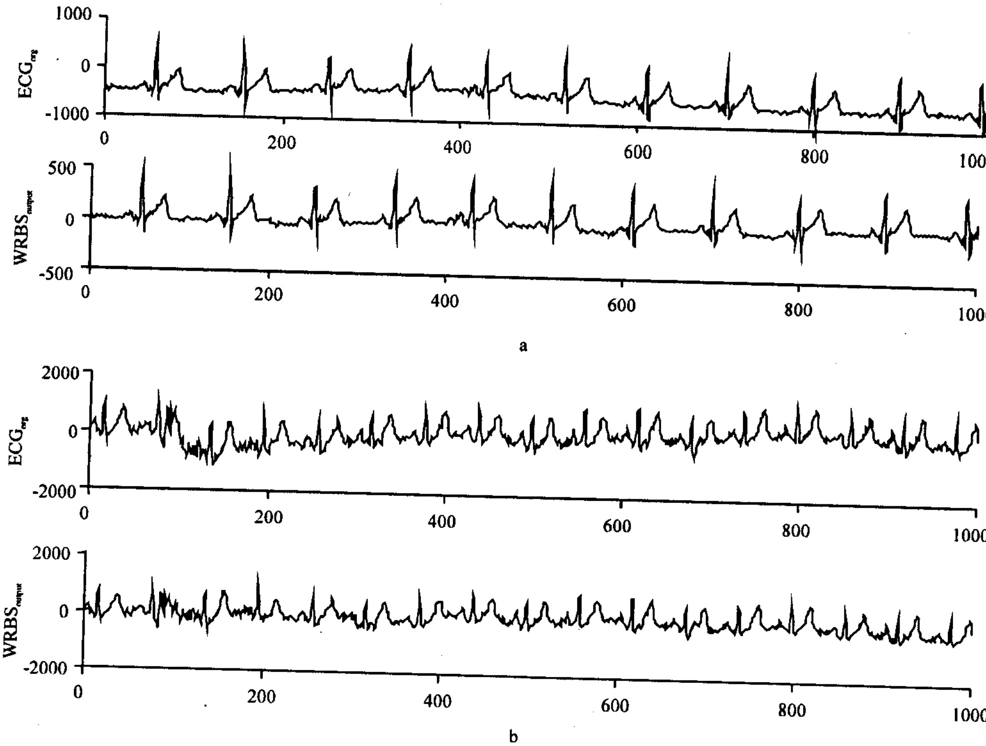

Fig. 11: Two examples (a b) of baseline wandering reduction by WRBS

To show the disadvantage of high pass filter FIR, we use this filter of cut-off frequency equal to 5 Hz for filtering ECG signal taken from Record 124-MIT-BIH arrhythmia database, time 1.6-2.1min (Fig. 12a and b) and the same signal was filtered by WRBS and OLA. The FIR_{output} is very deformed, where S and Q waves are longer

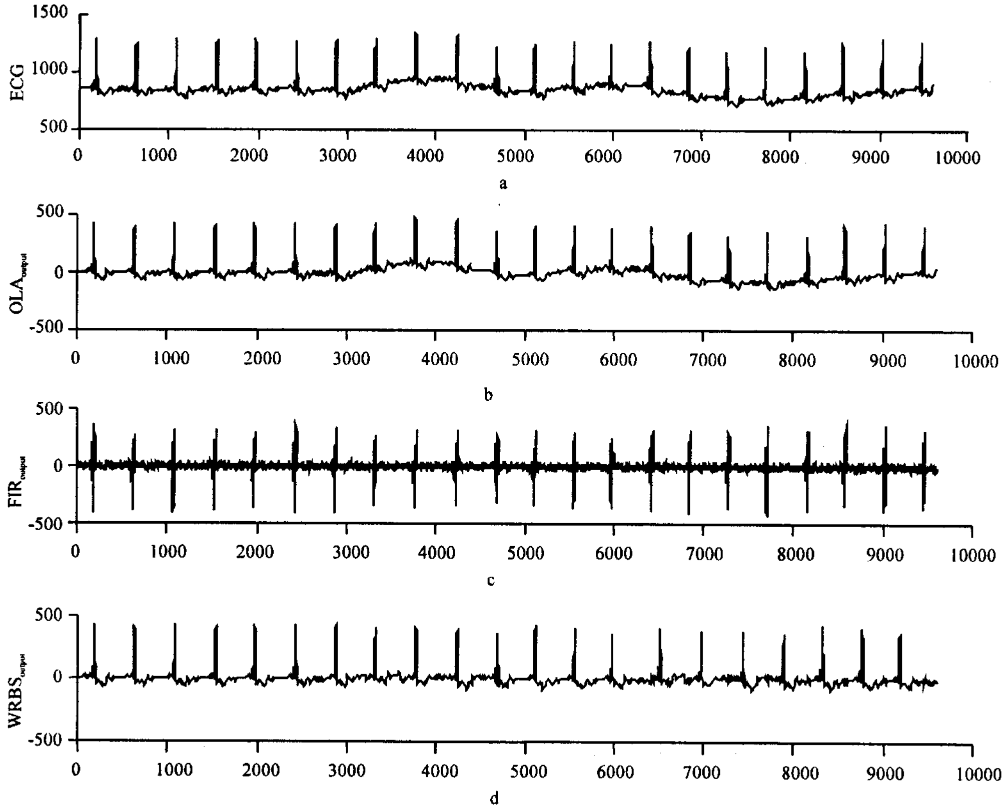

Fig. 12: Baseline wandering elimination of ECG signal from record 124-MIT-BIH arrhythmia database, time 1.6-2.1min a by FIR b OLA c and d WRBS

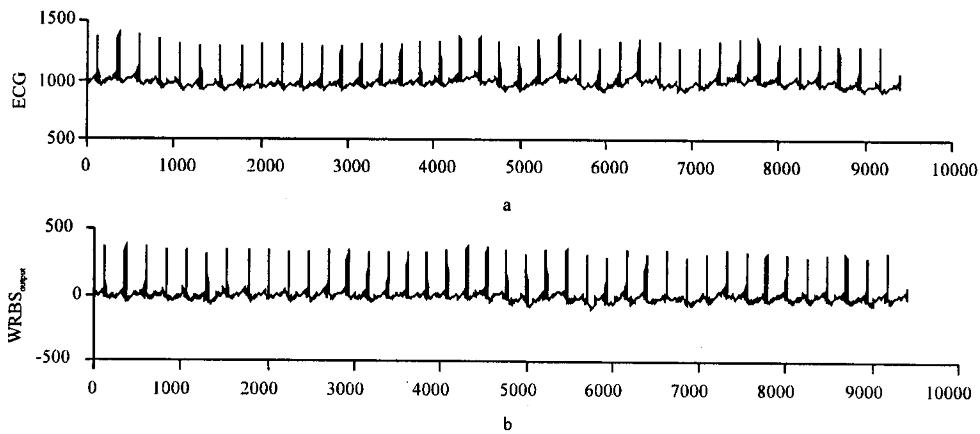

Fig. 13: Baseline wandering elimination of ECG signal from record 234-MIT-BIH arrhythmia database, (a)

than in original ECG and T wave is smallest than in original ECG (Fig. 12c). The performance of FIR could be better by using more special type created for this need, but always many problems in output signal could appear. In OLA filter as explained above, the signal is filtered in the same way; by cutting the mean value of the signal from each sample. So it doesn't eliminate the non additive drift. The designed filter WRBS was superior of these two filters (Fig. 12d).

The designed filter guarantees better results than standard adaptive filters, cubic spline and IIR, FIR, because it doesn't require a cut-off frequency, it doesn't distort the signal. WRBS works even when the signal is very noisy (high band pass noise), because of using the low frequency subsignal s_1, where the high band noise doesn't exist (Fig. 9).

Park *et al.*[3], it has presented a Wavelet Adaptive Filter (WAF) for reduction of baseline wandering in ECG signal. WAF consists of two parts; in the first part the signal is decomposed into DWT subsignals of J=7 and in the second part the seventh lowest band subsignal s_7 is adaptively filtered. It has proven that, adaptive filter was superior to those of WAF and standard filter in terms of low pass noise elimination (baseline wandering reduction). But the WAF was superior to standard filter and adaptive filter in terms of signal quality and signal distortion in ST-segment. We can notice that in WRBS is superior to standard filter, adaptive filter and WAF in terms of signal quality and ST-segment distortion, because WRBS cuts the drift from each beat basing on the PQ-segment level.

The system was tested for signals of MIT-BIH database (Fig. 13).

RESULTS

It was noticed after testing WRBS using program, which was written by authors in Matlab environment using wavelet Toolbox that:

- Using DWT assists greatly, because it divides the signal into components of deferent bands of frequency, then the component of low pass frequency (s_1), which alone has the baseline wandering, will be achieved without the high pass frequency noise, which makes the analysis very difficult. Consequently, WRBS works even when signal very noisy.
- Using $T_{i\,offset}$-$T_{i+1\,offset}$ interval as a window to be filtered in s_1 is better than using R-R interval, because it distorts the points of linking (R peak) the windows, as a result of different PQ segment average (A_i) values. What happens, when the baseline wandering in the signal has descending or rising shape?
- WRBS is ideal for signals with additive (in time scale) isoelectric line drift, but it doesn't entirely eliminate strong baseline wandering (Fig. 11a and b). In references, also there are no methods, which can eliminate entirely strong baseline wandering without distorting of the ECG signal[3].
- This algorithm doesn't require a cut-off frequency; the low pass noise is eliminated, by cutting the drift in each window alone, so there is no deformation of the main signal parameters such as QRS complex or the S-T segment, which has very important diagnosing role.
- WRBS has decomposed the signal into just two components (s_1, d_1 where J = 1) to eliminate the baseline wandering, but Park *et al.*[3], where combined DWT with adaptive filter was used J = 7. This means that WRBS has less computational complexity.

REFERENCES

1. Frankiewicz, Z. and E. Piêtka, 1985. Komputerowe eliminacja linii izoelektrycznej z sygna³u EKG, Problemy Techniki Medycznej, XVI: 1.
2. Chen, J. and I. Shuichi, 1993. A wavelet transform-based ECG compression method guaranteeing desert signal quality. IEEE Transactions on Biomedical Engineering, Vol. 45, No. 12.
3. Park, K.L., K.J. Lee and H.R. Yoon, 1998. Aplication of a wavelet adaptation filter to minimise distortion of ST- segment. Medical and Biological Engineering and Computering, 36: 581-586.
4. Van Alste, J.A. and T.S. Schilder, 1985. Removal of baseline wandering and power-line interference from the ECG by an efficient FIR filter with a reduced number of taps. IEEE Transactions on Biomedical Engineering, 32: 1052-1060.
5. McManus, C.D., U. Teppner and D. Neubert, 1985. Estimation and removal of baseline drift in electrocardiogram. Comput. Biomed. Res., 18: 1-9.
6. Thakor, N.V. and Y. Zho, 1991. Application of adaptive filtering to ECG analysis: noise cancellation and arrhythmia detection. IEEE Transactions on Biomedical Engineering, 38: 785-794.
7. Bruce, Andrew, 1996. Applied wavelet analysis with S-plus. New York: Springer-Verlag, XXI, 3385: IL.
8. Mallat, J., 1989. A theory of multiresolution signal decomposition using the wavelet representation. IEEE Transactions on Pattern Analysis and Machine Intelligence, 11: 674-693.
9. Mrozek, B. and Z. Mrozek, 1996. MATLAB uniwersalne œrodowisko do oblicze naukowo technicznych. PLJ, Warszawa.
10. Thakor, V.N., G. Xin-rong, S.Yi-Chun and D. F.hanley, 1993. Multiresolution wavelet analysis of evoked potentials. IEEE, Transactions on Biomedical Engineering, Vol. 40, No. 11.
11. Mallat, S., 1991. Zero-crossing of a wavelet transform. IEEE Transaction on Information Theory, Vol. 37, No. 4.
12. Sahmbi, J.S., S.N. Tandon and R. K. P. Bhatt, 1998. Wavelet based ST-segment analysis. Medical and Biological Engineering and Computering, 36: 568-572.