Computer Technology and Application 5 (2014) 98-104

Electrocardiogram Signal Denoising Using Discrete Wavelet Transform

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Abstract: The most common noises in ECG (electrocardiogram) signal processing are BW (baseline wandering) and the 50 or 60 Hz PLI (power line interferences). In order to remove these two major source of noises, we have used the recent powerful DWT (discrete wavelet transform) signal processing in ECG signals which are obtained from MIT-BIH Arrhythmia Database. The results indicate that DWT is a good method for filtering noises without changing the morphology of ECG, and can be applied to all types of ECG signals, whether normal or presenting arrhythmias.

Key words: ECG, Signal processing, 60 Hz PLI, baseline wander, DWT.

1. Introduction

Muscular contraction is associated with electrical changes known as depolarization. The ECG is a measure of this electrical activity associated with the heart. The ECG is measured at the body surface and results from electrical changes associated with activation first of the two small heart chambers, the atria, and then of the two larger heart chambers, the ventricles. Analysis of the local morphology of the ECG signal and its time varying properties has produced a variety of clinical diagnostic tools. It is also an essential tool to allow monitoring patients at home, thereby advancing telemedicine applications.

Producing an algorithm for the detection of the P wave, QRS complex and T wave in an ECG is a difficult problem due to the time varying morphology of the signal subject to physiological conditions and the presence of noise. There are several types of noises that affect the ECG. The BW (baseline wander) and 50 or 60 Hz interferences are some of these types. The goal of ECG enhancement is to separate the valid ECG from the undesired artifacts so as to present a signal that allows easy visual interpretation [1].

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2. ECG Wave Pattern

2.1 ECG Signal

ECG is a recording of biopotential signal that is generated by electrical cardiac activity and it is used by clinicians to identify various heart diseases such as myocardial infarction, conduction defects and arrhythmia. ECG signal consists of a well defined successive set of: P wave, PQ interval (or PR), QRS complex, ST segment and T wave.

The P wave represents the depolarization of left and right atria that generates the contraction of the atria and the ejection of blood to the ventricles. The QRS segment represents the depolarization of the left and right ventricles that generates the contraction of the ventricles and the ejection of blood to the aorta and pulmonary artery. The T wave represents the period of time when the ventricles repolarize. Fig. 1 shows a typical ECG signal.

2.2 Power Spectrum of the ECG

The ECG waveform contains, in addition to the QRS complex, P and T waves, 60 Hz noise from power line interferences, EMG from muscles, motion

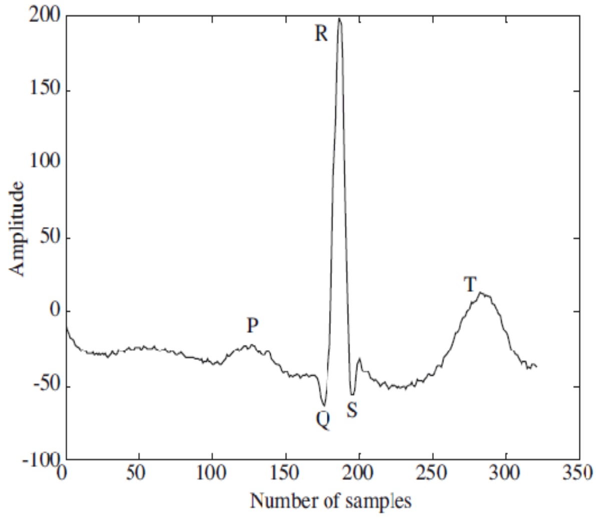

Fig. 1 Typical ECG signal with P-wave, QRS complex, and T-wave (sampling frequency is 360 Hz).

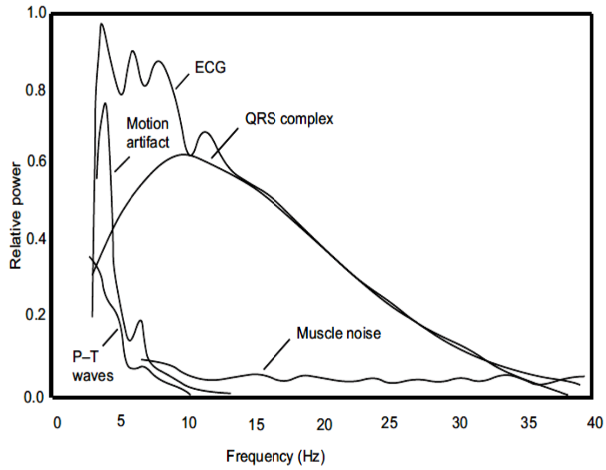

Fig. 2 Relative power spectra of QRS complex, P and T waves, muscle noise and motion artifacts based on an average of 150 beats.

artifact from the electrodes and skin interfaces, and possibly other interferences.

Fig. 2 summarizes the relative power spectrum of the ECG, QRS complexes, P and T waves, motion artifact, and muscle noise [2].

The recorded ECG signal is often contaminated by different types of noises and artifacts that can be within the frequency band of ECG signal, which may change the characteristics of ECG signal. Hence it is difficult to extract useful information of the signal. The corruption of ECG signal is due to following major noises [3-5].

2.3 Baseline Wander

BW of ECG signals is usually caused by respiration or movement of the subject and appears as a low frequency artifact. The removal of this disturbance is an important step in ECG signal analysis, not only to produce a stable signal for subsequent automatic processing, but also for reliable visual interpretation. As the frequency of ECG signals varies with time, using an ordinary high-pass filter can distort the waveform. As an alternative, an improved method involving DWT is proposed.

2.4 Power Line Interferences

Power line interferences contains 60 Hz pickup (in USA) or 50 Hz pickup (in Morocco) because of improper grounding. It is indicated as an impulse or spike at 60 Hz/50 Hz harmonics, and will appear as additional spikes at integral multiples of the fundamental frequency. Its frequency content is 60 Hz/50 Hz and its harmonics, amplitude is up to 50 percent of peak-to-peak ECG signal amplitude. A 60 Hz notch filter can be used to remove the power line interferences, but in this work the proposed method using DWT yields good results.

3. Wavelet Transform

The wavelet transform has emerged over recent years as a key time-frequency analysis and coding tool for the ECG. Its ability to separate out pertinent signal components has led to a number of wavelet-based techniques which supersede those based on traditional Fourier methods. In its continuous form, the CWT allows a powerful analysis of non-stationary signals, making it ideally suited for the high-resolution interrogation of the ECG over a wide range of applications. In its discrete form, the DWT provides the basis of powerful methodologies for partitioning pertinent signal components which serve as a basis for potent compression strategies.

3.1 Continuous Wavelet Transform

The CWT transforms a continuous signal into highly redundant signal of two continuous variables: translation and scale. The resulting transformed signal is easy to interpret and is valuable for time-frequency analysis. The continuous wavelet transform of continuous function, x(t) relative to real-valued wavelet, ψ(t) is described by:

$$W_{\Psi}(s,\tau)=\int_{-\infty}^{+\infty} x(t)\psi^{*}_{s,\tau}(t)dt \tag{1}$$

where,

$$\psi_{s,\tau}(t)=\frac{1}{\sqrt{s}}\psi(\frac{t-\tau}{s}) \tag{2}$$

s and τ are called scale and translation parameters, respectively. $W_{\psi}(s,\tau)$ denotes the wavelet transform coefficients and ψ is the fundamental mother wavelet.

3.2 Discrete Wavelet Transform

The DWT has become a powerful technique in biomedical signal processing. It can be written on the same form as Eq. (1), which emphasizes the close relationship between CWT and DWT. The most obvious difference is that the DWT uses scale and position values based on powers of two.The values of s and τ are: $s = 2^j$, $\tau = k*2^j$ and $(j, k) \in Z^2$ as shown in Eq. (3).

$$\psi_{s,\tau}(t)=\frac{1}{\sqrt{2^{j}}}\psi(\frac{t-k*2^{j}}{2^{j}}) \tag{3}$$

The key issues in DWT and inverse DWT are signals decomposition and reconstruction, respectively. The basic idea behind decomposition and reconstruction is low-pass and high-pass filtering with the use of down sampling and up sampling ,respectively. The result of wavelet decomposition is hierarchically organized decompositions. One can choose the level of decomposition j based on a desired cutoff frequency. Fig. 3a shows an implementation of a three-level forward DWT based on a two-channel recursive filter bank, where $h_0(n)$ and $h_1(n)$ are low-pass and high-pass analysis filters, respectively, and the block ↓2 represents the down sampling operator by a factor of 2. The input signal x(n) is recursively decomposed into a total of four subband signals: a coarse signal $C_3(n)$, and three detail signals, $d_3(n)$, $d_2(n)$, and $d_1(n)$, of three resolutions. Fig. 3b shows an implementation of a three-level inverse DWT based on a two-channel recursive filter bank, where $\tilde{h}_0(n)$ and $\tilde{h}_1(n)$ are low-pass and high-pass synthesis filters, respectively, and the block ↑2 represents the up sampling operator by a factor of 2. The four subband signals $C_3(n)$, $d_3(n)$, $d_2(n)$ and $d_1(n)$ are recursively combined to reconstruct the output signal $\tilde{x}(n)$. The four finite impulse response filters satisfy the following relationships:

$$h_1(n)=(-1)^n h_0(L+1-n) \tag{4}$$

$$\tilde{h}_0(n)=h_0(L+1-n) \tag{5}$$

$$\tilde{h}_1(n)=(-1)^{n-1} h_0(L+1-n) \tag{6}$$

where, L is the length of filters, and n = 1,2,…,L.

So that the output of the inverse DWT is identical to the input of the forward DWT [6, 7].

4. Methodology

In the simulation studies, test ECG signals came from MIT-BIH Arrhythmia Database. They concern leads V1 and D2, and they were digitized at 360 samples per second with 11 bit resolution over ±5 mV range. Sample values thus ranged from 0 to 2,047

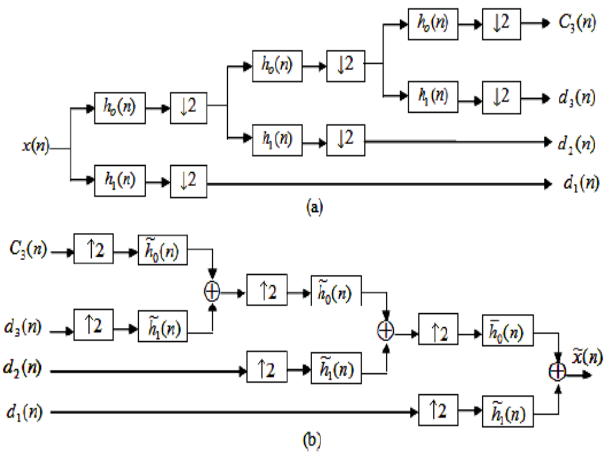

Fig. 3 A three-level two-channel iterative filter bank: (a) forward DWT; (b) inverse DWT.

inclusive, with a value of 1,024 corresponding to 0 mV[8].

4.1 Baseline Wander

Baseline drift having a frequency range of (0Hz,...,0.5Hz). In accordance with Nyquist's rule, if the original signal has a highest frequency $f_{\max}$, it requires a sampling frequency $f_s \geq 2f_{\max}$. Hence, at each decomposition level j, the frequency axis is recursively divided into halves at the ideal cut-off frequencies $f_j = f_{\max}/2^j$ [9].

The ECG records taken from the MIT-BIH arrhythmia database are sampled at 360 Hz (f_s = 360Hz). The maximum frequency is on the order of 130Hz ($f_{\max}$ = 130Hz) [9, 10]. Therefore, the range of real frequency components of the signals is between 0 Hz and 130 Hz. The correspondence between DWT coefficients and range of frequencies is given inTable1.

The proposed method for cancelling the BW is based on wavelet decomposition up to level 8, which generates a set of approximation coefficients(C8), and eight sets of detail coefficients(*d1*,…,*d8*). By cancellation of approximations, the filtered signal is recovered from the details only. This is equivalent to a high-pass filter cutoff frequency $f_c = f_{\max}/256$.

Fig.4 shows an example of the BW removal. The original ECG signal has low-frequency fluctuations; after removing it, the filtered ECG signal appears centered around a horizontal line.

4.2 Power Line Interferences

The ECG signals from the database MIT-BIH are affected by 60Hz PLI. This noise was filtered with an analog notch filter, but its influence still appears. We propose, therefore, to add to the test signals, a simulated noise of this form:

$$n(t) = A * \sin(2\pi f_0 t) \tag{7}$$

where, A is the amplitude, and f_0 is the 60Hz frequency of the simulated noise.

The noisy signal may then be expressed by:

Table 1 Range frequencies of DWT coefficients.

DWT coefficients	Range frequencies
d1	65Hz,…,130Hz
d2	*32.5Hz,...,65Hz*
d3	*16.25Hz,...,32.5Hz*
d4	*8.125Hz,...,16.25Hz*
d5	*4.062Hz,...,8.125Hz*
d6	*2.031Hz,...,4.062Hz*
d7	*1.015Hz,...,2.031Hz*
d8	*0.507Hz,...,1.015Hz*
C8	*0Hz,...,0.507 Hz*

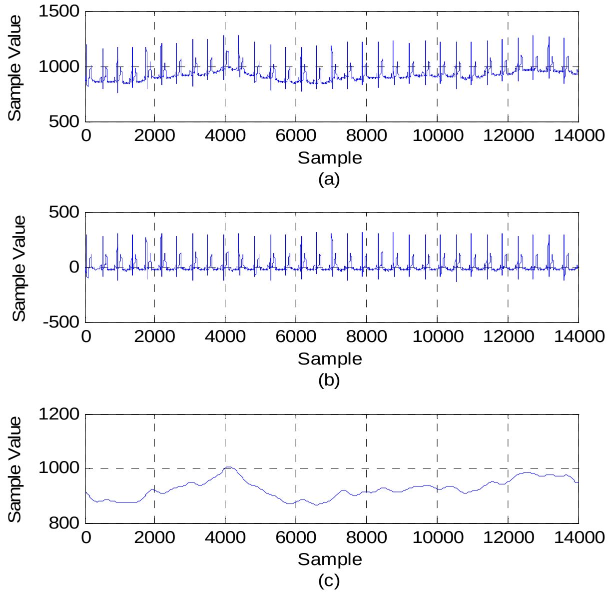

Fig. 4 ECG 117.dat [10000…24000]: (a) noised ECG with BW; (b) filtrered ECG; (c) removed baseline wander.

$$x(t) = ecg(t) + n(t) \tag{8}$$

where, ecg(t) is the signal from the MIT-BIH database.

The filtering process is done in four steps:

Step 1: At level 1, the signal is decomposed into a set of approximation coefficients (*C1*), and a set of detail coefficients (*d1*).

Step 2: Each set of coefficients of level 1 is decomposed into two other sets (Level 2).

Step 3: The coefficients of level 2 are decomposed into two new sets (Level 3).

Step 4: The filtered signal is reconstructed by removing coefficients containing the 60Hz power line noise in their range frequency.

The correspondence between decomposition levels and DWT coefficients is given in Table2.

In Table 3, we can see the correspondence between DWT coefficients and range frequencies.

In our case, the denoised signal is recovered from all coefficients except details *d*33 (48.75 Hz,…, 65 Hz).

Fig. 5 shows an example of the 60 *Hz* power line noise removal.

Figs. 6-8 show the power spectrum density at 60 Hz of noised ECG (117.dat), filtered ECG and 60 Hz power line noise. The amplitude *A* was fixed at 50 (*A* = 50) respectively.

4.3 Denoising Evaluation Criteria

To analyze and evaluate the filtering performance, we used PSD (power spectrum density) [11], percent of COR （cross-corelation coefficient) [12, 13] and PRD (percent of root squared mean difference） [14] as a quantitative criteria.

$$COR = 100 \cdot \frac{\sum_{n=1}^{N} x(n)\cdot y(n)}{\sqrt{\sum_{n=1}^{N} x^2(n)\cdot \sum_{n=1}^{N} y^2(n)}} \tag{9}$$

$$PRD = 100 \cdot \sqrt{\frac{\sum_{n=1}^{N} (x(n)-y(n))^2}{\sum_{n=1}^{N} x^2(n)}} \tag{10}$$

Table 2 DWT coefficients of different levels.

Level	DWT coefficients							
1	C1				d1			
2	C20		d21		d22		d23	
3	C30	d31	d32	d33	d34	d35	d36	d37

Table 3 Range frequencies of DWT coefficients.

DWT coefficients	Range frequencies
C30	0*Hz*,…,16.25*Hz*
d31	16.25*Hz*,…,32.5*Hz*
d32	32.5*Hz*,…,48.75*Hz*
d33	48.75*Hz*,…,65*Hz*
d34	65Hz,…,81.25Hz
d35	81.25*Hz*,…,97.5*Hz*
d36	97.5*Hz*,…,113.75*Hz*
d37	113.75*Hz*,…,130*Hz*

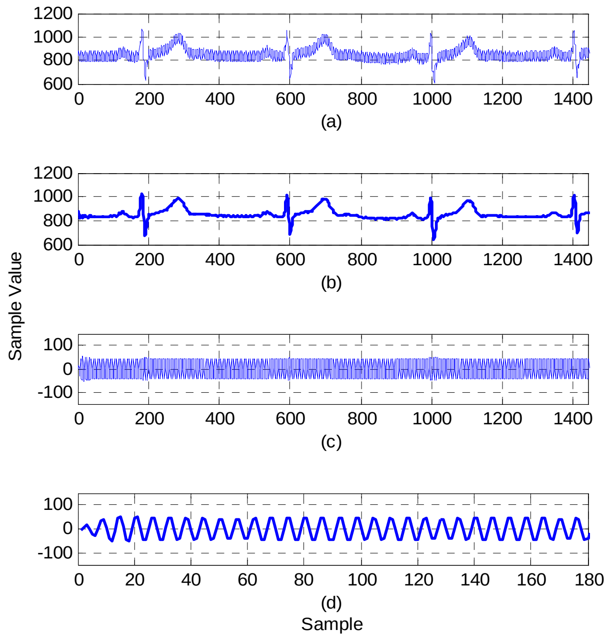

Fig. 5 ECG signal 117.dat [1..1440]: (a) noised ECG; (b) filtred ECG; (c) 60 *Hz* power line noise; (d) 60 *Hz* noise zoomed in 0.5 s.

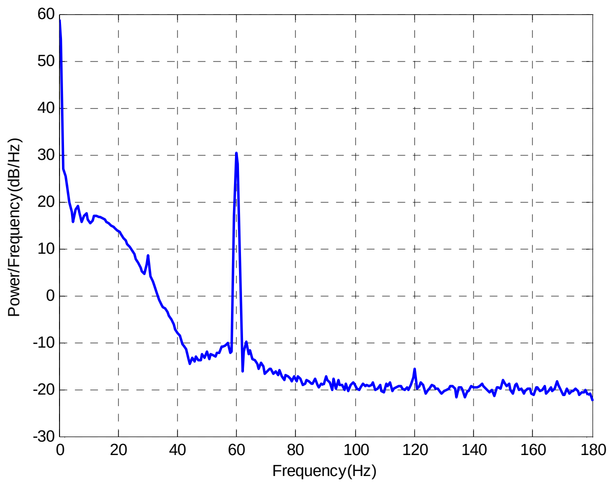

Fig. 6 Power spectrum density of noised ECG 117.dat.

where, x(*n*) is the original signal without noises and y(*n*) is the filtered signal.

x(*n*) is obtained by applying our method in a first step on a ECG records (MIT-BIH) with a natural baseline noise. y(*n*) is obtained by applying the method in a second step on x(*n*) noised by the natural base line drift or artificial 60 Hz interferences.

COR reflects the similitude between the two signals. If the two signals are identical, the value of COR is 100%.

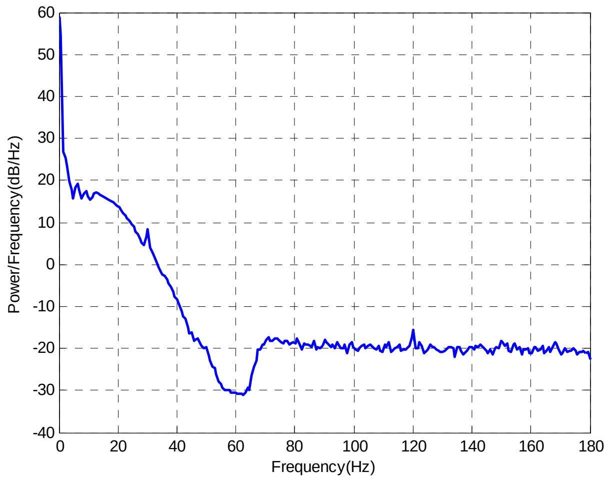

Fig. 7 Power spectrum density of Filtrered ECG 117.dat.

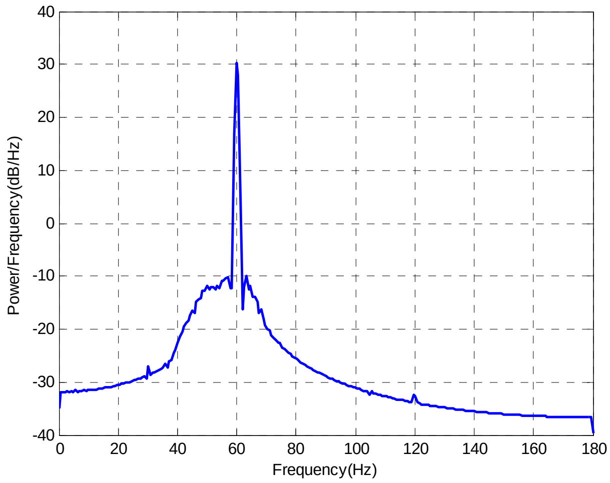

Fig. 8 Power spectrum density of removed 60 Hz PLI.

PRD reflects the relative distance between the two signals. If they are identical, the value of PRD is 0%.

The PSD is evaluated at 0.5 Hz for BW, and at 60 Hz for PLI using Welch method.

5. Results and Discussions

After testing several types of wavelets (Symlet, Coiflet, Daubechies,…), the best results are obtained with the Daubechies wavelet db 45.

Table 4 represents the PSD results obtained for five signals from the MIT-BIH database, with a natural baseline drift; it concerns records: 117, 119, 203, 207 and 210.

Table 5 represents the PSD results for five records, 117, 119, 203, 207, and 210 with an artificial 60 Hz noise for different amplitudes.

Table6 represents the COR and PRD criteria for evaluating both baseline wander and 60 Hz interferences filtering.

The experimental results indicate that this method performs accurate removal (COR = 100%) of ECG BW, while only 92.2% for median filtering method and 99.6% for EMD (empirical mode decomposition) correction method [13].

The results presented in Table4 show a significant attenuation of the PSD after filtering. After baseline suppression, all signals are aligned around the horizontal line.

Table 4 PSD criteria for evaluating the baseline suppression.

ECG	PSD at 0.5 Hz (dB/Hz)		
	Before filtering	After filtering	Attenuation
117	55	27	28
119	54.5	31	23.5
203	55.7	21.6	34.1
207	55.8	26	29.8
210	55.8	17.8	38

Table 5 PSD criteria for evaluating 60 Hz noise suppression.

ECG	Amplitude A	PSD at 60 Hz (dB/Hz)		
		Before filtering	After filtering	Attenuation
117	20	23	-30	53
	100	36	-30	66
119	20	23	-23	46
	100	36	-22	58
203	20	23	-23	46
	100	38	-23	61
207	20	23	-25	48
	100	36	-25	61
210	20	23	-30	53
	100	36	-30	66

Table 6 COR & PRD criteria for evaluating noise suppression.

ECG	Baseline wander		60 Hz interferences	
	COR (%)	PRD (%)	COR (%)	PRD (%)
117	100	0	100	0,152
119	100	0	100	0,290
203	100	$1,44\times10^{-13}$	100	0,691
207	100	$1,93\times10^{-13}$	100	0,221
210	100	$1,57\times.10^{-13}$	100	0,230

For the 60 Hz power line noise, we see that it is completely removed regardless of its magnitude, and we get the sinusoidal shape of the noise. The PSD after filtering has the same value of each signal.

It is established in Ref. [14] that if the PRD value is between 0% and 9%, the quality of the reconstructed signal is either“very good” or “good”, whereas if the value is greater than 9% its quality group cannot be determined. As we are strictly interested in very good and good reconstructions, it is taken that the PRD value, as measured with Eq. (10), must be less than 9%. Table 6 shows that our method performs a COR equal to 100%, and a PRD equal to 0.691% at most. This reflects that the two signals, before and after denoising, are identical.

6. Conclusion

In this work, we have presented a new approach based on discrete wavelet decomposition for denoising the ECG signals. The results illustrate that the DWT is an efficient technique to filter noises without altering a real morphology ECG signals because the duration, amplitude and shape of the P wave, QRS complex and T wave are not modified. This technique applies to all types of ECG signals, whether they are normal or presenting arrhythmias. Hence, this process allows cardiovascular experts to make a proper analysis. It can be integrated in automatic ECG analysis systems.

References

[1] Addison, S.P. 2005. “Wavelet Transforms and the ECG.” *Physiol. Meas*. 26:R155-99.

[2] Thakor, N.V., Webster, J.G., and Thompkins, W.J. 1984. “Estimation of QRS Complex Power Spectra for Design of a QRS Filter.” *IEEE Trans. Biomed. Eng.* 31: 702–5.

[3] Thakor, N.V.,and Zhu, Y.S. 1991. “Applications of Adaptive Filtering to ECG Analysis: Noise Cancellation and Arrhythmia Detection.” *IEEE Trans. Biomed. Eng.* 38 (8): 785-94.

[4] Weng, B., Blanco-Velasco,M.,and Barner, K.E. 2006. “Baseline Wander Correction in ECG by the Empirical Mode Decomposition.” In*Proceedings of the IEEE 32nd Annual Northeast Bioengineering Conference,* 135–6.

[5] Taouli, S.A.,and Reguig, F.B. 2010. “Noise and Baseline Wandering Suppression of ECG Signals by Morphological Filter.” *Journal of Medical Engineering & Technology*34 (2): 87-96.

[6] Zahhad, M.A., Ahmed, S. M.,and Zakaria, A. 2011. “ECG Signal Compression Technique Based on Discrete Wavelet Transform and QRS-Complex Estimation.” *Signal Processing : An International Journal (SPIJ)* 4 (2): 138-60.

[7] Mallat, S. 1989. “A Theory for Multiresolution Signal Decomposition: The Wavelet Representation.” *IEEE Trans. on Patt. Anal.and Mach. Intell.*11 (7): 674–93.

[8] MIT-BIHd://www.physionet.org/physiobank/database/mitdb/.

[9] Zidelmal, Z., Amirou, A., Adnaneb, M., and Belouchranib, A. 2012. “QRS Detection Based on Wavelet Coefficients.” *Computer Methods and Programs in Biomedicine* 107(2012): 490-6.

[10] Pan, J.,and Tompkins, W. J. 1985. “A Real Time QRS Detection Algorithm.” *IEEE Trans. Biomed. Eng.* 32: 230–6.

[11] Rahul, D.,and Mehrotra, R. K. 2013. “Application of DSP to Remove Noise from ECG Signal.”*International Journal of Engineering Research & Technology (IJERT)* 2 (6): 2421-8.

[12] Pan, N., Mang, V., Un, M.P., and Hang, P.S. 2007. “Accurate Removal of Baseline Wander in ECG Using Empirical Mode Decomposition.” In *Proceedings of NFSI & ICFBI,* 177-80.

[13] Ji, T.Y., Lu, Z., Wu, Q.H., and Ji, Z. 2008. “Baseline Normalisation of ECG Signals Using Empirical Mode Decomposition and Mathematical Morphology.” *ELECTRONICS LETTERS* 44 (2): 82-3.

[14] Zigel, Y., Cohen, A., and Katz, A. 2000. “The Weighted Diagnostic Distortion (WDD) Measure for ECG Signal Compression.” *IEEE Trans. Biomed. Eng.*47: 1422-30.