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Removal of baseline wanders from Physiological signals

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Abstract—Signal spectra of most of the biomedical signals overlap with the noise associated with them. Hence it becomes necessary to eliminate these noise signals to enable correct estimation of the parameters for diagnosis. Often these noises have frequencies and amplitudes comparable to that of the signal of interest. When using filtering methods for removal of noise, the time instances of signal are disturbed. These time instances being crucial parameters in the diagnosis of a particular disease must not be disturbed. Hence utmost care should be taken while removal of noise. This paper aims at proposing a system for removal of baseline wander from the Electrocardiography and Impedance cardiography signals using a signal processing technique based on wavelet transform which would adapt to the signal characteristics.

Keywords-ECG Electrocardiography, ICG Impedance cardiography, Wavelet transform.

I. INTRODUCTION

Electronic advancements have produced instrumentation with the potential of providing accurate acquisition of various physiological signals. Computerized monitors enhance patient assessment by allowing uninterrupted electronic observation of heart ECG and ICG signals with comprehensive automatic reporting mechanisms. Despite these improvements in instrumentation, monitoring systems continue to be plagued by problems related to poor signals. Wandering baselines, power line hum and frequent electrode replacement make patient assessment difficult and induce false heart rate alarms.

Hence, removal of such noises that is artifacts is necessary. Different filters can be used for the same purpose. Unfortunately, the artifactual signals have comparable frequency range and often larger amplitude reach the skin surface and mix with the ECG signals. Thus noise and signal spectra have a fair amount of overlap. So during filtering many a times along with noise, the signal of interest is also filtered out. Also in case of ECG signals RR interval and ECG signal energy vary for different person and age group. Thus the algorithm should adopt to signal characteristics to estimate the baseline drift present in the ECG signal. The algorithm proposed in this paper is based on wavelet decomposition and uses peak amplitude at successive levels if decomposition to determine number of iterations required estimating the baseline wander.

II. TARGETED SIGNALS AND ARTIFACTS

2.1 ECG signal

An ECG is used to measure the heart's electrical conduction system [1]. It picks up electrical impulses generated by the polarization and depolarization of cardiac tissue and translates into a waveform. The waveform is then used to measure the rate and regularity of heartbeats, as well as the size and position of the chambers, the presence of any damage to the heart, and the effects of drugs or devices used to regulate the heart, such as a pacemaker. The heart rate of normal beating heart is between 60 and 100 bpm. [2], these values changes with person, gender and age group.

2.2 ICG signal

Impedance cardiography (ICG) is technique of using sensors to detect the properties of the blood flow in the thorax. Bio-impedance is the response of a living organism to an externally applied electric current. It is a measure of the opposition to the flow of that electric current through the tissues, the opposite of electrical conductivity. A 100 kHz, 4 mA sinusoidal current is passed through body. This signal is amplitude modulated with bio-impedance signal, which is change in envelope due to change in impedance offered by blood flow and can be demodulated to obtain bio impedance signal. The electrical impedance change caused by blood volume change in aorta typically accounts for 2-4% of the base impedance. Whereas the electrical impedance change caused by the respiratory artifact and motion artifact may be 30% or even more [3]. Therefore it is important to estimate this baseline wander. ICG signal range is 0.8 to 20 Hz. One cycle of ICG and ECG are shown in fig. 1[3].

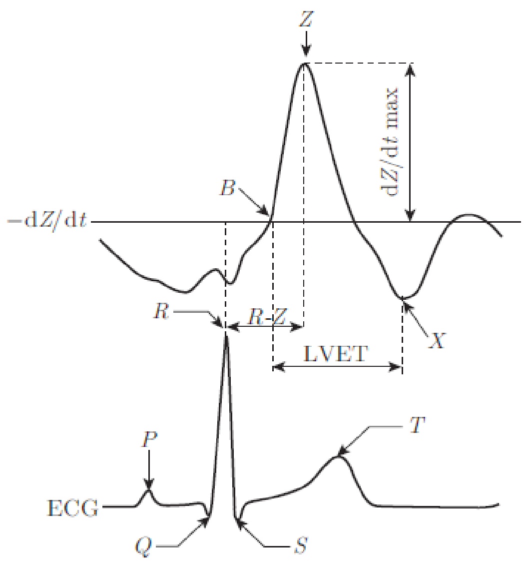

Figure 1. ICG waveform and an Electrocardiogram (ECG) waveform

2.3 Low frequency artifacts in physiological signal

Two types of noise signals whose frequency spectrum overlaps spectrum of physiological signal are motion artifact and respiratory artifact. Respiratory artifact is caused by changes of thoracic volume during breathing. Motion artifact is caused by body movements and contraction of muscle. Baseline wander due to respiration has very low frequency range of 0.04-2 Hz and the frequency of motion artifacts is about 0.1-10 Hz [3].Fig. 2 shows baseline drift in an ECG signal. The following section deals with algorithm for removal of baseline wander from targeted physiological signals.

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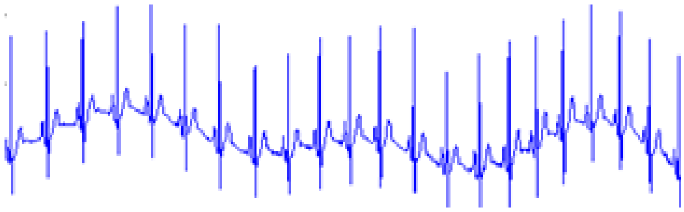

Figure 2. ECG signal with baseline wander

III. IMPLEMENTATION OF NOISE REMOVAL ALGORITHM

In physiological signals ECG and ICG, it is important to preserve all the frequency component of original signal and keep all the time instants intact without phase change. In addition to filtering out noise, it is also important to preserve the temporal relationships between the various characteristic points in physiological signal. Wavelet decomposition is a suitable method to achieve this task as it can give good time resolution at high frequency and good frequency resolution at low frequency.In wavelet decomposition algorithm, the signal is decomposed into approximations and details coefficients [3]. The approximations are the high-scale, low-frequency components of the signal. The details are the low-scale, high-frequency components.

With a given mother wavelet ψ, wavelet transform of a function *f(x)* is defined as,

$$\omega_s f(x) = f * \psi_s(x) = \frac{1}{s}\int_{-\infty}^{\infty} f(t)\, \psi\left(\frac{x-t}{s}\right) dt$$

Where *s* denotes the scale factor of WT. When s = 2j (j ∈*Z*, *Z* is integral set) , and the wavelet transform of *f(x)*is defined as dyadic wavelet transform. The dyadic wavelet transform can be calculated by following two equations:

$$S_{2^j} f(n) = \sum_{k \in Z} h_k S_{2^{j-1}} f\left(n - 2^{j-1}k\right)$$

$$\omega_{2^j} f(n) = \sum_{k \in Z} g_k S_{2^{j-1}} f\left(n - 2^{j-1}k\right)$$

S_2^j represents the smoothing operator and ω_2^jf(n)is the wavelet transform of digital function f(n). gk is the coefficient corresponding HP filter, and hk is the coefficients corresponding LP filter [3].

Physiological signal is decomposed using wavelet transform. The noise is recovered by using approximation coefficients. Number of iterations can be decided using variations in energy content in each level decomposition of ECG signal using wavelet decomposition. Algorithm is based on amplitude of R peaks in original signal and amplitude of peaks in each level wavelet transform. Algorithm for determining number of iterations is as follows.

i. Three to four cycles of signal are taken at a time
ii. Find mean of peaks above 80% of minimum amplitude in original signal and also find average distance between them.
iii. Obtain low frequency signal by wavelet transform and calculate average of peaks at minimum interval of calculated in second step.
iv. Calculate difference of mean value obtained in 2^{nd} step and 3rd step for iterations from 6-10.
v. Now choose iteration for which the value of difference is maximum.

Following figure shows flow chart for baseline wander removal program in MATLAB.

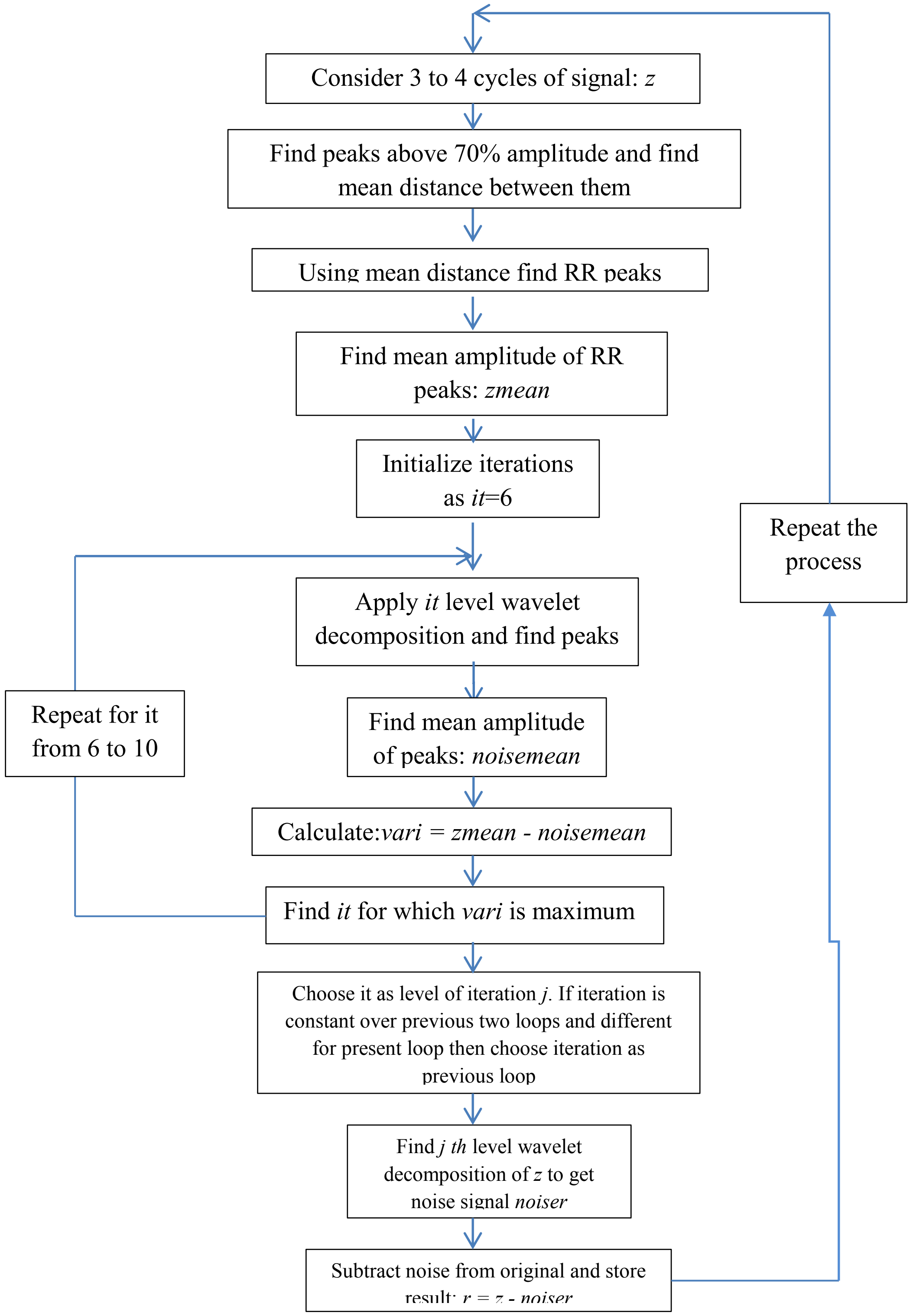

Figure 3. Flow chart for baseline wander removal program in MATLAB.

The accuracy of algorithm depends on the wavelet function and how efficiently the window is chosen such that no characteristic point lies at start and end of window. Comparative study was carried out on number of ECG signals from MITBIH site database [6] and it was found that minimum iterations required to estimate noise are 6. By applying the proposed algorithm it was found that db4 wavelet gives the best result. Thus this wavelet can be used for estimating noise in physiological signals. The db4 wavelet functions closely resembles QRS component of ECG signal and hence it gives better estimate of ECG signal. The average execution time required is less than 1.4 seconds. Result of the simulation of wavelet algorithm for ECG signal using db4 wavelet is as shown in Fig. 4.

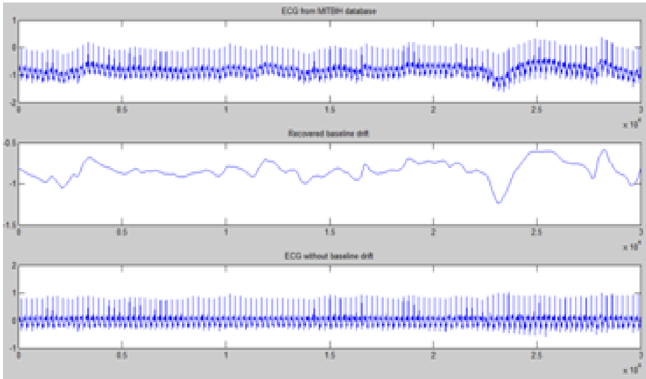

Figure 4.a Result of simulation of wavelet algorithm on 112.dat ECG signal from MITBIH site [6] using db4 wavelet

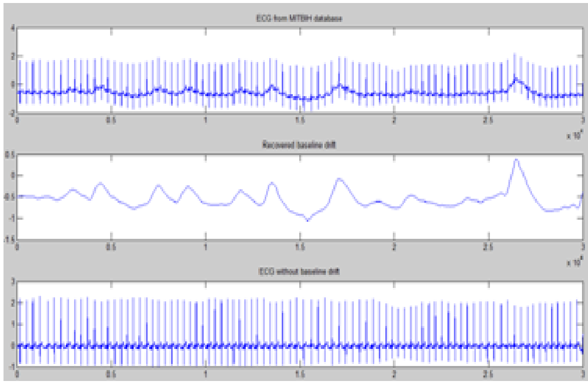

Figure 4.b Result of simulation of wavelet algorithm on 115.dat ECG signal from MITBIH site using db4 wavelet

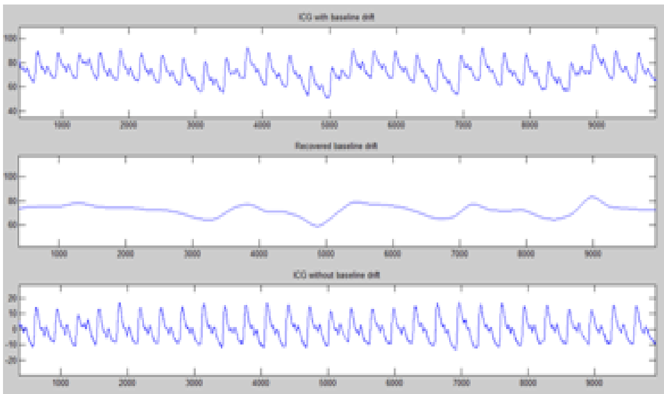

Figure 4.c Result of simulation of wavelet algorithm on ICG signal db4 wavelet

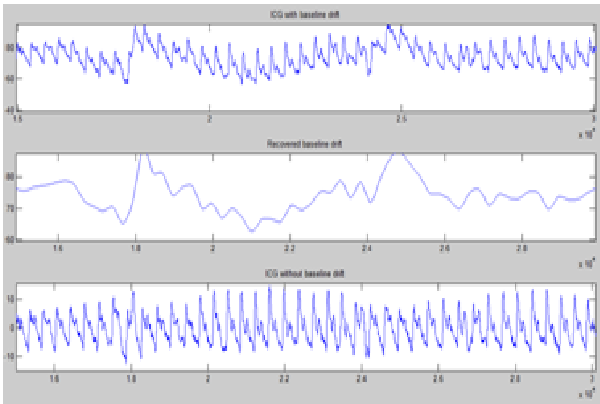

Figure 4.d Result of simulation of wavelet algorithm on ICG signal db4 wavelet

Signal to noise ratio at input and output for some signals, increase in SNR and Change in variance is listed in table 1. Algorithm for calculating signal to noise ratio at input and output:

SNR at input = $10*\log_{10}$(variance of clean signal) $-10*\log_{10}$(variance of noise signal)

SNR at output = 10*$\log_{10}$(variance of signal obtained as clean signal as input) - 10*$\log_{10}$(variance of noise signal obtained as clean signal as input)

Table No 1. SNR at input and output, increase in variance and change in variance

Serial number	Physiological signal	SNR of original signal	SNR of output signal	Increase in SNR	Change in variance
Subject 1	ECG	10.9246	112.9029	90.3%	25.11%
Subject 2	ECG	5.5053	113.1113	95.1%	36.45%
Subject 3	ECG	31.6757	107.5229	70.8%	4.12%
Subject 4	ICG	4.6194	93.4999	95.0%	38.69%
Subject 5	ICG	-0.5873	96.3096	99.3%	51.56%
Subject 6	ICG	-1.3519	122.0598	98.9%	53.37%

IV. CONCLUSION

The wavelet decomposition algorithm was implemented to remove baseline from the ECG and ICG signal. As it is necessary to preserve all the frequency components of original signal and keep all the time instants intact without phase change in biomedical signals, wavelet decomposition gives good results for estimating low frequency baseline wander. Important factor in wavelet decomposition is the level up to which signal has to be decomposed to have correct estimate of baseline. The algorithm proposed in this paper is based on energy content in characteristic points of signal of original signal and energy of maxima at every cycle at successive stages of wavelet decomposition to determine the number of iterations. Wavelet used in algorithm is db4. The wavelet function and scaling function of db4 closely resembles QRS component of ECG signal and hence it gives better estimate of ECG signal.

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