ECG DE-NOISING TECHNIQUES FOR DETECTION OF ARRHYTHMIA

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Abstract—Removing motion artifacts from an electrocardiogram (ECG) is one of the important issues to be considered during real-time heart rate measurements in telemetric health care. However, motion artifacts are part of the transient baseline change caused by the electrode motions that are the results of a subject's movement. Baseline correction and noise suppression are the two important pre-requisites for conditioning of the ECG signal and thereby detecting Arrhythmia. In this paper, morphological filtering technique for removing baseline drift using a non-flat structuring element is used. Later, we compare different methods which will eliminate the remaining noise. To extract the quality ECG signal from the raw noisy ECG signal Descrete Wavelet Transform based denoising were employed by using three wavelet function and four thresholding rules.

Keywords — arrhythmia; sinus rhythm; Savitzky-Golay Filter; Morphological Filter; Wavelet Transformation

1. Introduction

According to the World Health Organization, cardiovascular diseases are among the top three leading causes of death worldwide regardless of country income levels. In 2005, 17 million people died from cardiovascular diseases globally and the World Health Organization expects this number to reach 20 million by 2017.

Therefore, it is necessary to have proper methods to determine the cardiac condition of the patient. Electrocardiography (ECG) is a tool that is widely used to understand the condition of the heart. The electrocardiograph signal is the electrical representation of the heart's activity. Computerized ECG analysis is widely used as a reliable technique for the diagnosis of cardiovascular diseases. However, ambulatory ECG recordings obtained by placing electrodes on the patient's chest are inevitably contaminated by several different types of artifacts. Commonly encountered artifacts include : Power line interference, Electrode contact noise, Motion artifacts, Baseline drift, Instrumentation noise generated by electronic devices and electro-surgical devices.

2. ELECTRICAL CONDUCTION SYSTEM OF THE HEART

Each heart beat originates as an electrical impulse from a small area of tissue in the right atrium of the heart called the sinus node or sino-atrial node or SA node. The impulse initially causes both atria to contract, then activates the atrio-ventricular node which is normally the only electrical connection between the atria and the ventricles. The impulse then spreads through both ventricles via the Bundle of His and the Purkinje fibres causing a synchronized contraction of the heart muscle and, thus, the pulse. In adults the normal resting heart rate ranges from 60 to 80 beats per minute. The resting heart rate in children is much faster. In athletes though, the resting heart rate can be as slow as 40 beats per minute, and be considered as normal.

3. CARDIAC RHYTHM DIAGNOSIS

Study of a patient's **cardiac rhythms** using an ECG may indicate normal or abnormal conditions. Abnormal rhythms are called arrhythmia or sometimes, dysrhythmia. Arrhythmia is an abnormally slow or fast heart rate or an irregular cardiac rhythm. During a single heart beat, several electrical events occur. These events are part of an ECG tracing and are called P, Q, R, S, T and U.

3.1 DIFFERENTIATING P, QRS and T WAVES

Because of the anatomical differences between the atria and the ventricles, their sequential activation, depolarization, and re-polarization produce clearly differentiable deflections. Identification of the normal QRS-complex from the P- and T-waves does not create difficulties because it has a characteristic waveform and dominating amplitude. This amplitude is about 1 mV in a normal heart. The normal duration of the QRS is 0.08-0.09s.

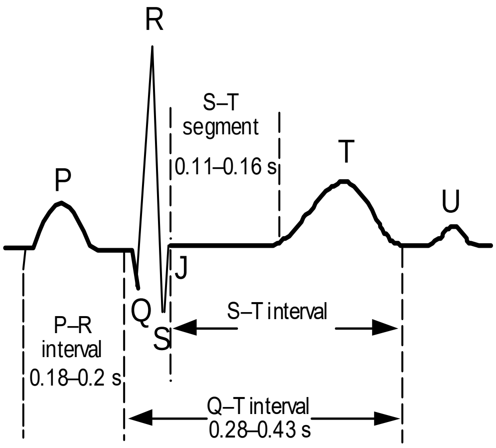

Fig.1. Typical ECG waveform

Normally, the P-wave has an amplitude of about 0.1mV and duration of 0.1s. For the T-wave, it is about 0.2mV and 0.2s. The T-wave can be differentiated from the P-wave by observing that the T-wave follows the QRS-complex after about 0.2s.

3.2 Normal sinus rhythm

Normal sinus rhythm is the rhythm of a healthy normal heart, where the sinus node triggers the cardiac activation. This is easily diagnosed by noting that the three deflections, P-QRS-T, follow in this order and are differentiable. The sinus rhythm is normal if its frequency is between 60 and 100/min.

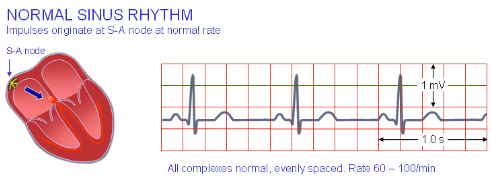

Fig.2. Normal sinus rhythm

4 Arrhythmia

An irregular heartbeat is an arrhythmia (also called dysrhythmia). Heart rates can also be irregular. A normal heart rate is 60 to 100 beats per minute. Arrhythmias and abnormal heart rates will not necessarily occur together. Arrhythmias can occur with a normal heart rate, or with heart rates that are slow (called bradyarrhythmias -- less than 60 beats per minute). Arrhythmias can also occur with rapid heart rates (called tachyarrhythmias -- faster than 100 beats per minute). Different types of arrhythmia are as follows:

(i) Atrial Fibrillation

(ii) Atrial Tachycardia

(iii) Ventricular Tachycardia (iv) Ventricular Fibrillation

4.1 Atrial fibrillation

The activation in the atria may also be fully irregular and chaotic, producing irregular fluctuations in the baseline. A consequence is that the ventricular rate is rapid and irregular, though the QRS contour is usually normal. Atrial fibrillation occurs as a consequence of rheumatic disease, atherosclerotic disease, hyperthyroidism, and pericarditis.

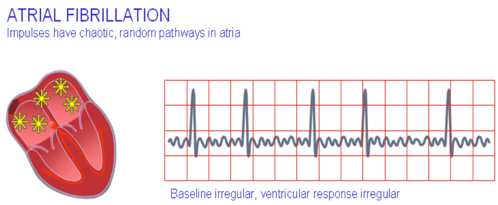

Fig.3: Atrial Fibrillation

4.2 Atrial Tachycardia

A sinus rhythm of higher than 100/min is called sinus tachycardia. It occurs most often as a physiological response to physical exercise or psychical stress, but may also result from congestive heart failure.

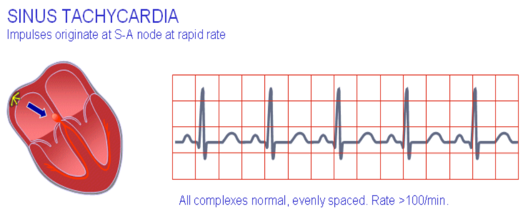

Fig.4: Atrial Tachycardia

4.3 Ventricular Tachycardia

A rhythm of ventricular origin may also be a consequence of a slower conduction in ischemic ventricular muscle that leads to circular activation (re-entry). The result is activation of the ventricular muscle at a high rate (over 120/min), causing rapid, bizarre, and wide QRS-complexes; the arrythmia is called ventricular tachycardia. As noted, ventricular tachycardia is often a consequence of ischemia and myocardial infarction.

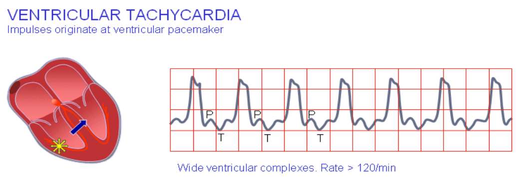

Fig.5 : Ventricular Tachycardia

4.4 Ventricular fibrillation

When ventricular depolarization occurs chaotically, the situation is called ventricular fibrillation. This is reflected in the ECG, which demonstrates coarse irregular undulations without QRS-complexes. The cause of fibrillation is the establishment of multiple re-entry loops usually involving diseased heart muscle. The lack of blood circulation leads to almost immediate loss of consciousness and death within minutes. The ventricular fibrillation may be stopped with an external defibrillator pulse and appropriate medication.

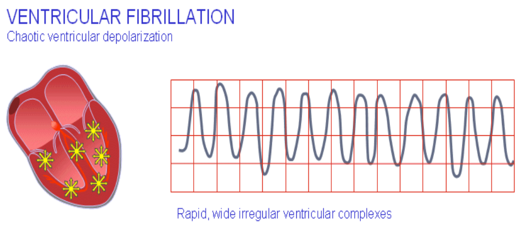

Fig.6 : Ventricular fibrillation

5 DE-NOISING OF ECG SIGNAL

Block diagram for denoising the ECG signal is shown below. The step by step procedure for denoising is explained as follows.

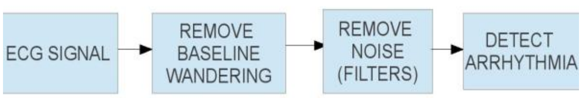

Fig.7: Block diagram representation

5.1 Simulation Of ECG Signal

For simulation purposes in the present work, ECG signals are adapted from internationally accepted **Massachusetts Institute of Technology – Beth Israel Hospital** (MIT-BIH) database that consists of recordings which are observed in clinical practice.

5.2 Creating a Noisy ECG Signal

The ECG recordings were created using two clean recordings from the MIT-BIH Arrhythmia Database to which calibrated amounts of noise from record 'em' and from record 'bw' were added which are termed as Noise Stress Databases.

5.3 Removal Of Noise Using Filters

(i) Savitzky-Golay Filter

The Savitzky–Golay smoothing filter is a filter that essentially performs a local polynomial regression (of degree k) on a series of values (of at least k+1 points which are treated as being equally spaced in the series) to determine the smoothed value for each point. The main advantage of this approach is that it tends to preserve features of the distribution such as relative maxima, minima and width, which are usually 'flattened' by other adjacent averaging techniques.

(ii) Moving Average Filter

A moving average filter is a type of finite impulse response filter used to analyze a set of data points by creating a series of averages of different subsets of the full data set. Given a series of numbers and a fixed subset size, the first element of the moving average is obtained by taking the average of the initial fixed subset of the number series. Then the subset is modified by "shifting forward", that is excluding the first number of the series and including the next number following the original subset in the series. This creates a new subset of numbers, which is averaged. This process is repeated over the entire data series. The plot line connecting all the (fixed) averages is the moving average. A moving average is a set of numbers, each of which is the average of the corresponding subset of a larger set of datum points. A moving average may also use unequal weights for each datum value in the subset to emphasize particular values in the subset.

(iii) FIR Filter

A finite impulse response (FIR) filter is a filter whose impulse response (or response to any finite length input) is of finite duration, because it settles to zero in finite time. This is in contrast to infinite impulse response (IIR) filters, which may have internal feedback and may continue to respond indefinitely (usually decaying). The impulse response of an Nth-order discrete-time FIR filter lasts for N + 1 samples, and then settles to zero.

(iv) Butterworth Filter

The Butterworth filter is a type of signal processing filter designed to have as flat a frequency response as possible in the pass band and monotonic overall. Butterworth filters sacrifice rolloff steepness for monotonicity in the pass- and stop bands. The smoothness of the Butterworth filter output is maximum when compared with other digital filters. It is also referred to as a maximally flat magnitude filter.

(v) Morphological Filter

Morphological filtering is a non-linear transformation technique in which shape information (of features) is extracted by using a structuring element (of appropriate dimensions) to operate on the input signal. Erosion, dilation, opening and closing are the common morphological operators used. Erosion of a signal by structuring element is defined as moving local minima of the signal inside the structuring element or mask. Similarly dilation is defined as moving local maxima of the signal inside the structuring element. Therefore dilation enlarges the maxima of the signal while erosion enlarges the minima of the signal. Opening (erosion followed by dilation) by structuring element smoothes the signal from below by cutting down its peaks. Similarly, closing (dilation followed by erosion) by structuring element smoothes the signal from above by filling up its valleys. Hence, opening and closing operations can be used for detection of peaks and valleys in the signal. Improper selection of size of structuring element may distort the adjacent wave in the ECG signal. Hence, the size of structuring element should be greater than the width of the characteristic wave. Flat structuring elements often lead to distortion due to overlap of low frequency ST segment with the baseline wandering, thereby causing loss of relevant information. Hence, a non-flat (ball-shaped) structuring element is proposed as it improves the performance of morphological filtering in terms of smooth opening and closing of ECG signal. After removing the baseline wandering, any noise left is also suppressed using the morphological operation.

(vi)Wavelet Transformation

In Short Time Fourier Transform (STFT), the window should always have a constant size, and thereby it does not give multi resolution information on the signal. However, the wavelet transform holds the property of multi resolution to give both time and frequency domain information in a simultaneous manner through variable window size. The wavelet transform is scaled and shifted version of the time mother wavelet (a signal with tiny oscillations).The mother wavelet DWT is expressed by:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-a}{a}\right) a\,, b \in R,\, a \rangle\, 0$$

where, 'a' and 'b' are the scaling and the shifting factor, respectively and R is the wavelet space. The mother wavelet must satisfy the condition (admissibility) in Eqn.

$$C_{\psi} = \int_{-\infty}^{+\infty} \frac{|\psi_{\omega}|^2}{\omega} d\omega \,\langle\, \infty$$

where, ψ (ω) is the Fourier transform of the mother wavelet function *(ψa,b (t))*.

5.4 Wavelet Denoising Algorithm

In practice, the raw signal acquired using data acquisition system is expressed by

$$X(n) = s(n) + u(n)$$

In assumption, the raw signals are usually contaminated with noise as shown in the above equation ,

(i) Initially, decompose the input signal using

DWT: Choose a wavelet and determine the decomposition level of a wavelet transform *N*, then implement *N* layers wavelet decomposition of signal *S*.

(ii) Select the thresholding method and thresholding rule for quantization of wavelet coefficients. Apply the thresholding on each level of wavelet decomposition and this thresholding value removes the wavelet coefficients above the threshold value.

(iii) Finally, the denoised signals reconstructed without affecting any features of signal interest. The reconstruction was done by performing the Inverse Discrete Wavelet Transform (IDWT) of various wavelet coefficients for each decomposition level.

Out of the above three steps, the most critical is to select the proper threshold. Because, it directly reflects the quality of the de-noising

6 RESULTS

Firstly, the input ECG signal is corrupted only with the baseline wandering signal. It is observed that morphological filtering is the best solution to remove baseline wandering without losing the characteristic shape of the QRS complex in the signal. In all the other methods (S-Golay, Moving Average, FIR and Butterworth filters), some of the baseline wandering is seen to remain and also the distinctive shape of the QRS complex is lost (that portion of the signal becomes more triangular in shape). Hence morphological filtering is the best solution put forward to remove the baseline wandering.

Another kind of signal examined is the ECG signal corrupted with just noise and no baseline wandering. Here it is observed that morphological filtering technique fails to preserve the distinctive shape of the QRS complex whereas all the other techniques reduces the noise to a great extent without compromising the shape of the QRS peak.

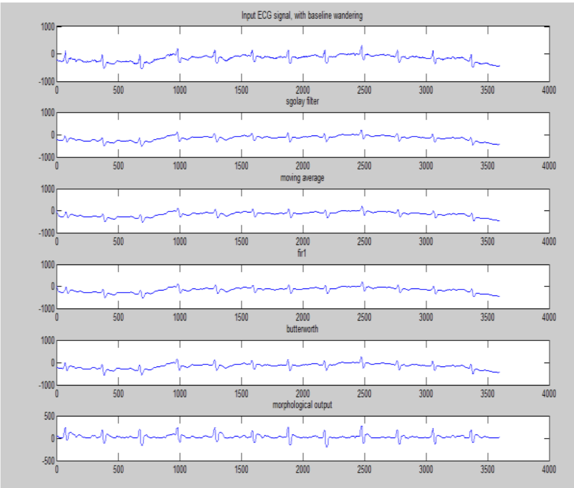

Fig.8 : Denoised output of different filters

Hence, for any kind of noise other than baseline wandering, the other filters are preferred depending on the case considered.

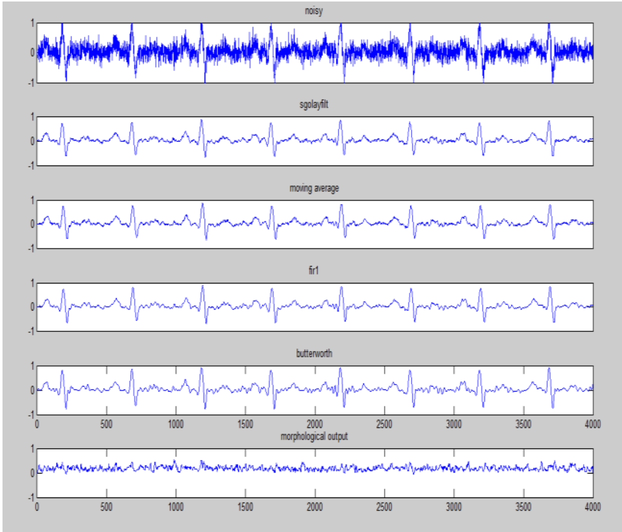

Fig.9:Denoised output with high frequency noise

Next we employed different types of wavelet thresholding methods to remove noises from the ECG signal. Previous researchers have used:*"db4", "coif5"* and *"sym7"* wavelet function for genetic algorithm based denoising in ECG signal. The soft thresholding method investigated with four different thresholding rules (fixed, rigrsure, heursure and minimax) to analyze the denoising performance of ECG signals. Here we used "db4" and the fixed thresholding rules to extract the denoised ecg signal. 16 level decomposition using DWT has been carried out to effectively remove the low frequency noises (baseline wanders). Figure 9 shows the wavelet decomposition on the input ECG signals. On each level of wavelet decomposition, the value of threshold has been calculated by applying the threshold selection rules and the wavelet coefficient above the value of threshold has been removed.

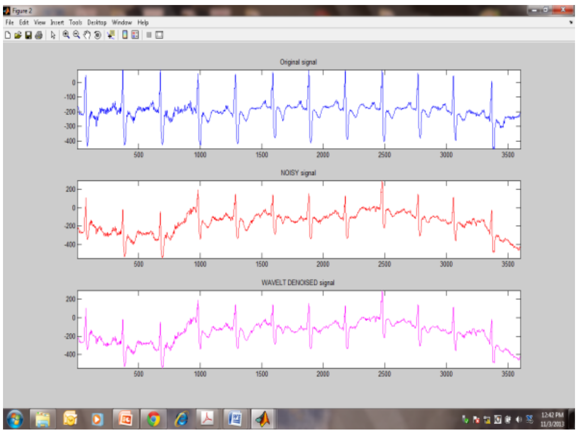

Fig.10 : Denoising using Wavelet Transform

7 DETECTION OF ARRHYTHMIA

7.1 Selection of characteristic scales

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

where s is the scaling factor

According to the power spectra of the ECG signal, that most energies of the QRS complex are at the scales of 2^3 and 2^4, and the energy at scale 2^3 is the largest. Here we select scales from 2^1 to 2^4. The modulus maximum lines corresponding to R waves are determined iteratively at these different scales.

Step 1: Find all of the maxima larger than a threshold at scale 2^4.

Step 2: Find a maximum larger than the threshold at scale 2^3 on the neighbourhood of the scale 2^4. If several maxima exist, then the largest one is selected. But if the largest one is not larger than 1.2 times the others, then the maximum nearest to the maximum of the 2^4 scale is taken.

Step 3: Similarly, the locations of maxima at scales 2^2 and 2^1 are also found. Thus we obtain the location sets of the maximum value points.

8 CONCLUSION

In this paper, various methods to remove the noise from the ECG signal are implemented and compared. The various methods tested are Morphological filter, S-Golay filter, Moving Average filter, FIR1 filter and Butterworth filter. Each technique was found to have its own merits and de-merits and the choice of selection of any one technique depend on the output required.

It was found upon implementation that morphological filtering is the best solution to remove the baseline wandering but it does not perform well in case of other noises like power line interference, instrumentation noise etc. Whereas the other filters tested removed such noises considerably, but failed to preserve the signal shape in case of baseline wandering.

So the best method to undertake would be to use a combination of morphological filtering and filtering technique such as S-Golay, Moving Average, FIR1 and Butterworth filters to eliminate both baseline wandering and other noises. The choice of the latter filter will depend on the specifications of the output desired. Also it must be taken care that the use of both the filters should be in a compromise so as not to degrade the signal, but only enhance it. Such a satisfactorily de-noised ECG signal can be used for diagnostic purposes, including the detection of arrhythmia, as proposed in this paper.

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