Pre-processing of ECG signals for ambulatory use

Raghu Vishnubhotla

***Abstract*—This project aims to use signal processing techniques for conditioning of ambulatory electrocardiogram (ECG) signals and make them fit for diagnostic use. ECG signal from a healthy subject was recorded under ambulatory conditions artifact removal and detection of QRS complexes has been performed.**

***Index Terms*—ECG signal processing, wavelets, ambulatory, cubic spline filtering.**

I. Introduction

The ECG records the electrical activity of the heart recorded by electrodes placed on the hearts surface. The voltage variations measured by the electrode are caused by the action potentials of the excitable heart cells as they make the cells contract. The resulting heart beat in the ECG is manifested by a series of waves whose morphology and timing convey information which is used for diagnosing diseases that are reflected by disturbances of the heart's electrical activity.

In recent years computer aided ECG signal analysis has gained momentum and tremendous amount of work has been carried out. One of the major outcomes to such research is ambulatory ECG. Ambulatory ECG (AECG) monitoring is used to identify patients with transient symptoms, e.g., palpations, light-headedness, or syncope, which are indicative of arrhythmias. Another group of patients are those at high risk of sudden death after infarction. A general system for robust estimation of transient heartbeat diagnostic and morphological feature-vector time series in long-term ECG's (like the AECG) for the purpose of ST segment analysis always begins with pre-processing.

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II. Preprocessing

In general, the aim of preprocessing steps is to improve the general quality of the ECG for more accurate analysis and measurement. Noises may disturb the ECG to such an extent that measurements from the original signals are unreliable. The main categories of noise are: low frequency base line wander (BW) caused by respiration and body movements, high frequency random noises caused by mains interference (50 or 60Hz) and muscular activity and random shifts of the ECG signal amplitude caused by poor electrode contact and body movements. A number linear and non-linear technique has been developed to eliminate these artifacts.

The preprocessing comprises of three steps: removal of base line wander (elimination of very low frequencies) removal of high frequency noise and QRS detection [1].

III. Base line wander

Baseline wander (BW) is an extragenoeous low-frequency activity in the ECG which may interfere with the signal analysis, rendering clinical interpretation inaccurate and misleading. ST-T changes in the ECG are measured with reference to the isoelectric line. When BW is present the isoelectric line is no longer well defined and hence ST analysis becomes inaccurate.BW may result from various noise sources including perspiration, respiration, body movements, and poor electrode contact. Its spectral contact is usually well below 1Hz, but may contain higher frequencies during strenuous exercise. Two major techniques are usually employed for BW removal, namely linear filtering and polynomial fitting.

Linear filtering involves the design of an LTI high pass filter with cut off so that the clinical information in the ECG is preserved and as much as possible of the BW is removed. This cut off is based on the lowest heart rate which is around 40beats/min during bradycardia, which implies that, the lowest frequency component in the ECG 0.67Hz [2]. Therefore the cut off chosen is around 0.5 Hz. But using a high pass filter for BW removal causes ringing effect (Gibbs phenomenon) in the ECG causing problems for ST analysis. To solve this problem a method called as polynomial fitting (PF) or cubic spline filtering (CSF) is used. The PF method fits polynomials to representative points (knots) in the ECG, with one knot for each beat. Knots selected from a 'silent' segment, often the best choice is the PQ interval. A polynomial is fitted so that it passes through every knot in a smooth fashion. In contrast to linear filtering, BW removal by polynomial fitting requires that QRS complexes first be detected and that the corresponding PQ intervals be accurately determined. By using higher order polynomials, the likelihood of producing an accurate baseline estimate increases, although it is associated with increased computational complexity. Instead of letting the order increase as the number of knots increases, third order polynomial fitting to successive triplets of knots is a popular trade off. [3].

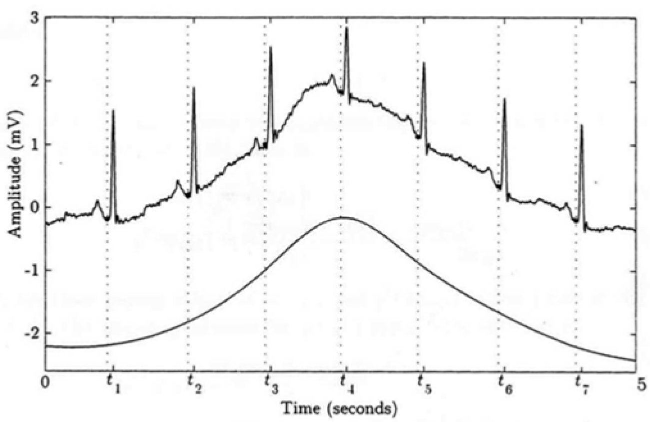

Figure 1 Polynomial fitting for baseline wander removal based on a series of knots positioned within PQ intervals. Note that the base line estimate is plotted with an offset from the signal.

IV. HIGH FREQUENCY NOISE REMOVAL USING WAVELETS

Denoising is the primary processing to remove all the high frequency as well as power supply interference from the ECG signal. Several researches have been attempting wavelets for denoising of biomedical signals [4]. To estimate the performance of wavelet in denoising, biomedical researchers have made several attempts employing various wavelet basis functions like Coiflets, Haar, etc [5] The outcome of this study revealed that the performance of the Daubechies (DB4) wavelet basis function in denoising is extremely well and has the basis function graphically shown in Fig 2. Also, the Daubechies wavelet was chosen for this work on the basis of the resemblance and similar frequency response characteristics of the db4 basis function with the ECG waveform.

Using wavelets to remove noise from a signal requires identifying which component or components contain the noise, using optimal methods to threshold them, and then reconstructing the signal using the thresholded coefficients. there is another thresholding technique allows to define, level by level, time-dependent (x-axis-dependent) thresholds, and then increase the capability of the de-noising strategies handling non-stationary variance noise. More precisely, the model assumes that the observation is equal to the interesting signal superimposed on noise. This technique is called adaptive variance thresholding. In this work, adaptive variance threshold technique has also been used in a few cases for effective denoising.

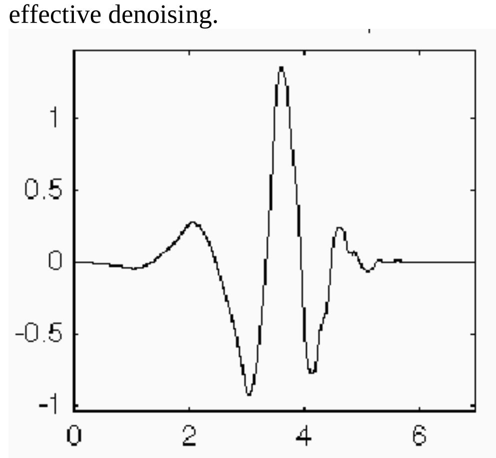

Figure 2 Daubechies 4 wavelet

V. QRS DETECTION

The main tasks of a QRS complex detector include detecting QRS complexes of heartbeats and generating a stable fiducial point for each individual heartbeat. The fiducial point and its placement should be robust and insensitive to subtle morphological variability in the QRS complex. In the literature, there are some excellent QRS complex detectors present [6,7] In this project however the real time QRS detector proposed by Pan and Tomkins has been used for its intrinsic simplicity and low computational complexity. It algorithm includes differentiation followed by squaring and then moving window integration. The information about the slope is obtained in the derivative stage. The squaring process intensifies the slope of the frequency response curve of the derivative and helps restrict the false positive waves caused by the T waves with higher than usual spectral energies. The moving window integrator produces a signal that includes information about both the width and slope of the QRS complex. Then a simple threshold is applied to detect the peaks.

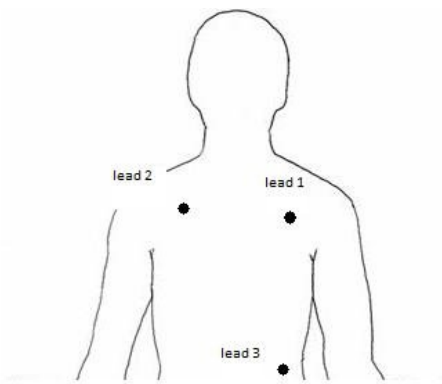

Figure 3 ECG lead Placement

VI. Experimental Setup

The ECG signals for this project were taken using the 'ECG lab medical kit' developed by Clevemed Inc. The medical kit has a base unit which is connected to a PC and a wireless radio to which the ECG leads are connected. Since it is a wireless device, data acquisition can be done while the subject is doing his daily activities. The signal is sampled at 600Hz at 24bit resolution. The device also comes with its own software for easy viewing and storage of the ECG data. A 3 lead ECG setup was used as shown in Fig3. The subject was a healthy man of age 22. He was asked a wear the device and carry on with his activities for a period of 3 hours with in the vicinity of the lab. His activities included sitting, walking, using the computer etc. The goal was, for the setup to be as close as possible to the actual ambulatory ECG.

VII. Results

For the all data sets, first baseline wander eliminated using cubic spline filtering and other high frequency noise using wavelet denoising.

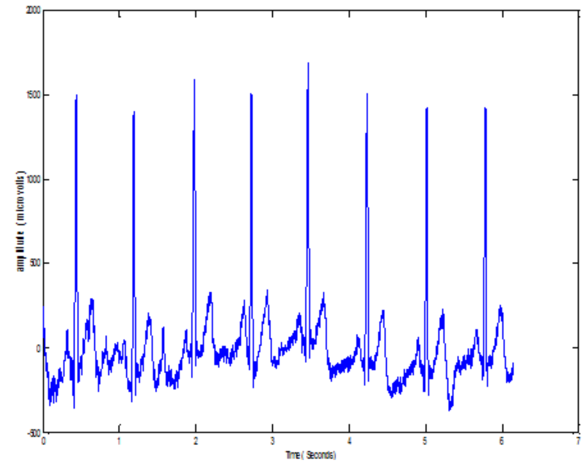

Figure 4 Raw ECG when the subject was sitting. Notice the high frequency noise and baseline wandering.

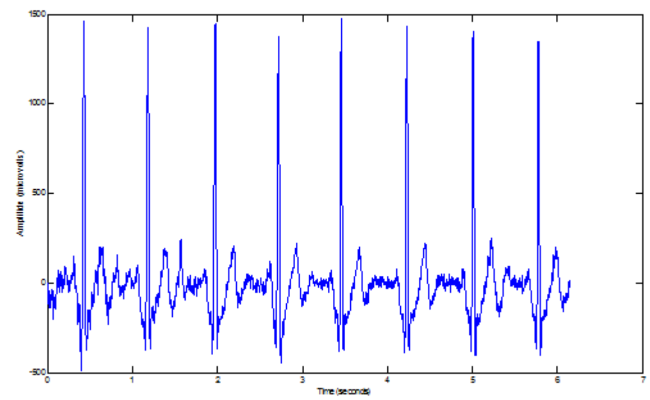

Figure 5 after baseline wandering removal using cubic spline filtering

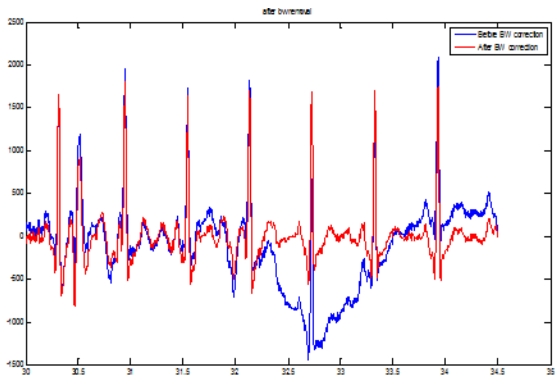

Figure 6 Baseline wander due to sudden body movement and the corrected signal.

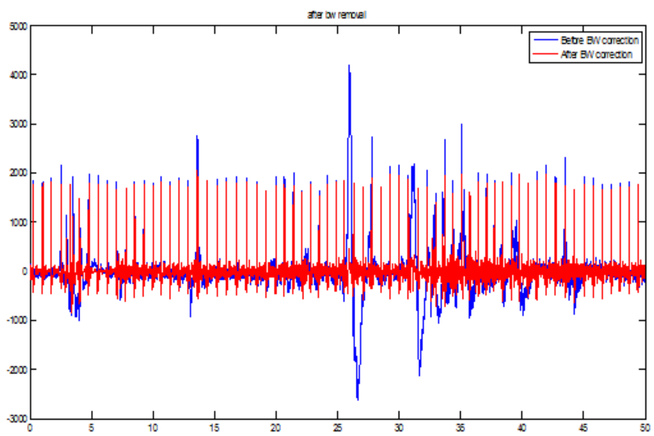

Figure 7 another ECG signal with sudden body movements

The above figures show that the cubic spline filtering is ideally suited for removal of baseline wander. Let us now look at the wavelet denoised signals.

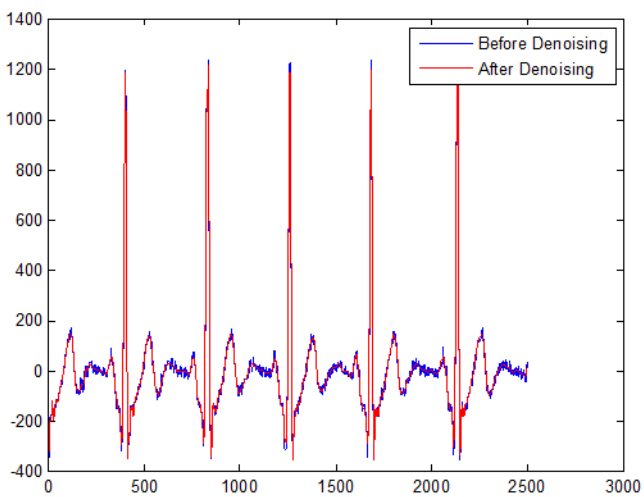

Figure 8 after denoising with db4 wavelet.

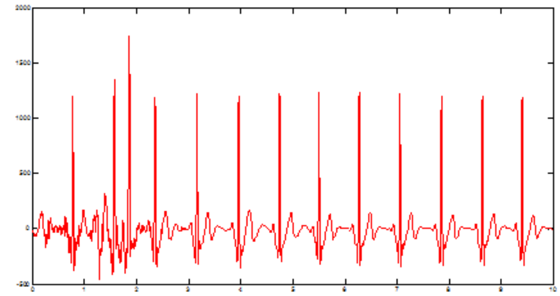

Figure 9 wavelet denoising with global thresholding

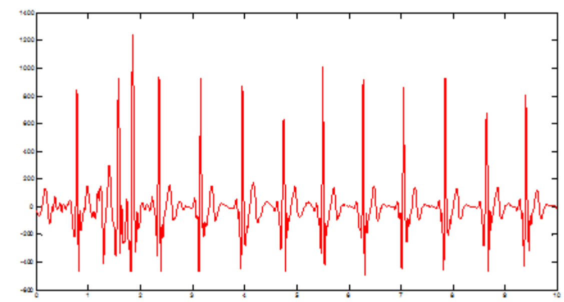

Figure 10 wavelet denoising with adaptive variance thresholding

Fig 7 and 8 show the denoising with global thresholding and adaptive thresholding. It is clear that adaptive thresholding does a better job because the noise is this case is highly non stationary and thresholding based in the variance does a better job.

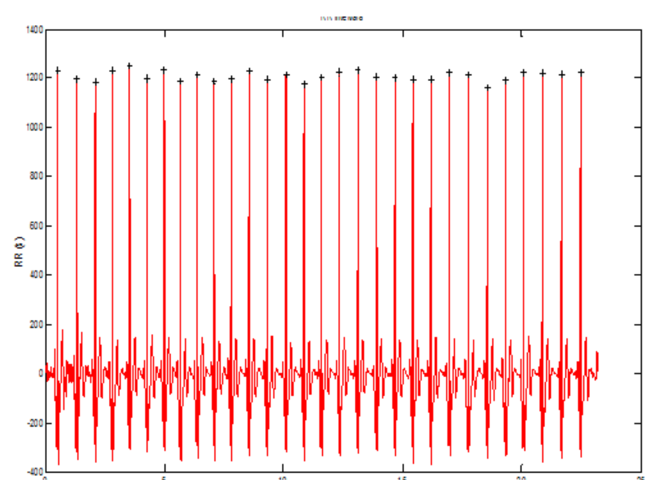

Figure 11 Output of the QRS detector

VIII. Conclusion

Before starting this project, I was under an impression that noise due to any kind of motion is EMG noise. It takes a lot of muscle movement to produce EMG noise, like in a stress test when the patient is on a tread mill. Motion artifact and poor electrode contact are the most important kinds of noise that can affect AECG. If ST detection is the goal, then isoelectric line is extremely important. Hence the filtering techniques used must aid to purpose and must not destroy the subtle morphology of the signal.

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