International Journal of Interdisciplinary Research and Innovations (IJIRI)
Vol. 1, Issue 1, pp: (15-21), Month: October-December 2013, Available at: www.researchpublish.com

New Electrocardiogram Signal Analysis in a Research Laboratory Using LabVIEW

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Abstract: **This paper introduces a powerful tool which provides immediate computation for electrocardiogram (ECG) signal denoising and analysis in a cardiovascular laboratory, based on the Undecimated Wavelet Transform (UWT) which is an effective technique for denoising the ECG signals corrupted by non-stationary noises and has a better capacity on peak detection. The algorithms used have given an accurate and reproducible result on denoising, beats detection, analysis and diagnosis of heart disorders in user-friendly graphical user interface. Also, it has been demonstrated that the developed processing package software is an appropriate analysis tool for electrocardiogram data denoising and analysis.**

Keyword: **ECG, Data processing method, Instrument optimization, LabVIEW**

I. INTRODUCTION

An electrocardiogram (ECG) is a graphic tracing of the electric current generated by the heart muscle during a heartbeat. It provides information on the condition and performance of the heart diseases and the ischemic changes that may occur like the myocardial infarction, conduction defects and arrhythmia and it is one of the life signs monitored in many medical and intensive care procedure. Generally, during the recording process, noise affects the signal heavily and ECG signals collected from different people are heterogeneous. all forms of noise includes baseline wandering, EMG noise, motion artifact, power line interference and electrode pop or contact noise may occur simultaneously and unpredictably. Usually the ECG signal acquisition hardware can remove the power line interference, but the baseline wandering and other wideband noise are not easy to be suppressed by hardware equipment. Instead, we need some software schemes which are powerful, and feasible for offline ECG signal processing.

Several works have been done in the area of ECG denoising and beat detection. Spatial filters have long been used as the traditional means of removing noise from images and signals [1]. These filters usually smooth the data to reduce the noise, but, in the process, also blur the data. In the last decade, several new techniques have been developed that improve on spatial filters by removing the noise more effectively while preserving the edges in the data. An efficient technique for such a non-stationary signal processing is the wavelet transform. The wavelet transform can be used as a decomposition of a signal in the time frequency scale plane. There are many application areas of wavelet transform like as sub-band coding data compression, characteristic points detection and noise reduction [2]. The authors in [3], [4] analyzed the wavelet Transform method for denoising of ECG signal. It also uses a linear operation which makes it suitable to preserve the important phase information of the signal. Authors in [5] propose to use the cubic spline wavelet and interpolation for accurate QRS detection. They conclude that wavelet functions that support symmetry and compactness achieve the highest accuracy on the ECG reading in MIT-BIH arrhythmia database. Though the wavelet transform approach does not discriminate between the noise and signal coefficients of the wavelet decomposition at low SNRs and it is not suitable when high reliability is needed. There are some commercially available tools which are possible to use at home, but their performance is not satisfactory and are based on decimated wavelet transform.

In order to produce more accurate information for the frequency localization and to meet the requirement of providing flexibility in a laboratory style operation’s environment, we develop an ECG-analyzing system based on UWT method and virtual instrument.

II. ECG SIGNAL PROCESSING

A. *Graphical language*

The programming language used in LabVIEW, also referred to as G, is a dataflow programming language. Execution is determined by the structure of a graphical block diagram on which the programmer connects different function-nodes by drawing wires. These wires propagate variables and any node can execute as soon as all its input data become available. Since this might be the case for multiple nodes simultaneously.

With LabVIEW it is very easy to program different tasks that are performed in parallel by means of multithreading. This is, for instance, easily done by drawing two or more parallel while loops. This is a great benefit for test system automation, where it is common practice to run processes like test sequencing, data recording, and hardware interfacing in parallel.

B. *Undecimated Wavelet Transform*

Continuous and discrete are the two main types of wavelet transform. Computer programs use the discrete wavelet transform (DWT) because of its discrete nature. The main drawback of DWT is not translation invariant. Translation of the original signal lead to different wavelet coeffivient.UWT is used to overcome this and to get more comprehensive feature of the analyzed signal. The idea behind UWT is that it does not decimate the signal. Thus, it produces more accurate information for the frequency localization.

The UWT is redundant, linear and shift invariant, more robust and less sensitive to noise, because this method involves finding zero-crossings in the multi-scale UWT coefficients. This method first finds zero-crossings among the coefficients with coarse resolution and then finds zero-crossings among the coefficients with finer resolution. Finding zero-crosses among the coefficients with coarse resolution enables you to remove noise from a signal efficiently. Finding zero-crossings among the coefficients with finer resolution improves the precision with which you can find peak locations. Hence, it gives a better approximation than DWT. These properties provide the UWT to realize using a recursive algorithm. Fig. 1 shows the computation of the UWT where d_n and a_n are called the detail ant the approximation coefficients of the UWT, respectively. The filter H and G are the standard low-pass and hight-pass wavelet filters, respectively.

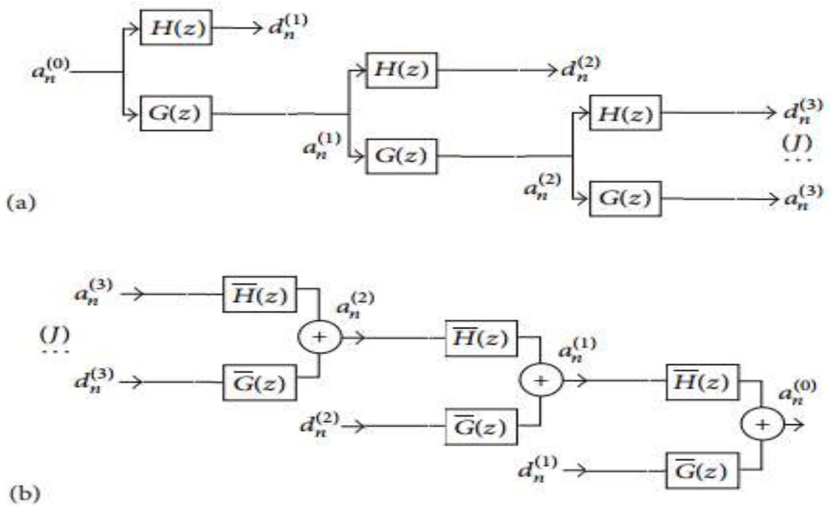

Fig. 1. Undecimated wavelet transform, (a) analysis filter bank and (b) reconstruction filter bank.

To further remove the noise from the ECG, UWT is employed to decompose the signal at various levels. For an N level UWT, we have N detail sub-bands (W). All the W sub-bands are used for de-noising purpose. An adaptive threshold selection using principle of Stein's Unbiased Risk Estimator [6] is used to calculate the threshold value. Then, soft thresholding [7] is used to remove the noise. Finally, the noise-free ECG is obtained by taking the inverse UWT.

C. Feature Extraction

The UWT based peak detection method is implemented using ECG Feature Extractor VI which firstly detects all beats (R waves) in the signal then extracts characteristics for every beat. Thus the accuracy of detecting R waves is very important. For normal ECG signals, they can be easily detected, while abnormal morphology makes the detection difficult for ECG from patients with some specific heart diseases. Thus we need to perform some signal enhancement (pre-processing) before features extraction which usually contains two steps:

1) The filtering: since the R wave of human ECG has usually a frequency between 10-25Hz we have used a bandpass filter with the following characteristics: fstop1= 2Hz, fpass1= 10Hz, fpass2= 25Hz, fstop2= 48Hz. Ripple specification= 0, 1. Design method: Dolph-Chebyshev Window.
2) The rectification: Calculates the average rectified value of the ECG.

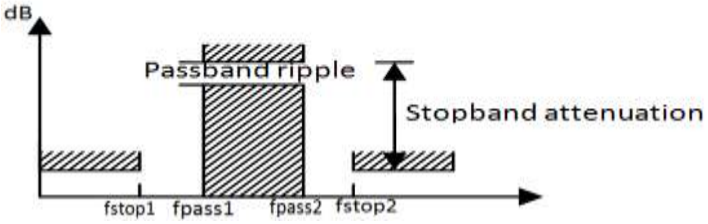

Fig. 2. Filter's characteristics

The pre-processed ECG signal is used to detect position of R waves. After that, all other characteristics will be extracted using original signal, because the signal enhancement may change these features.

Thus the R waves can be more obvious and easily detected after filtering and absolute rectification. Fig. 3 shows the hyperkalemia ECG signal with weak R peaks and a stiff rise of T waves. After improvement all the R waves can be easily detected.

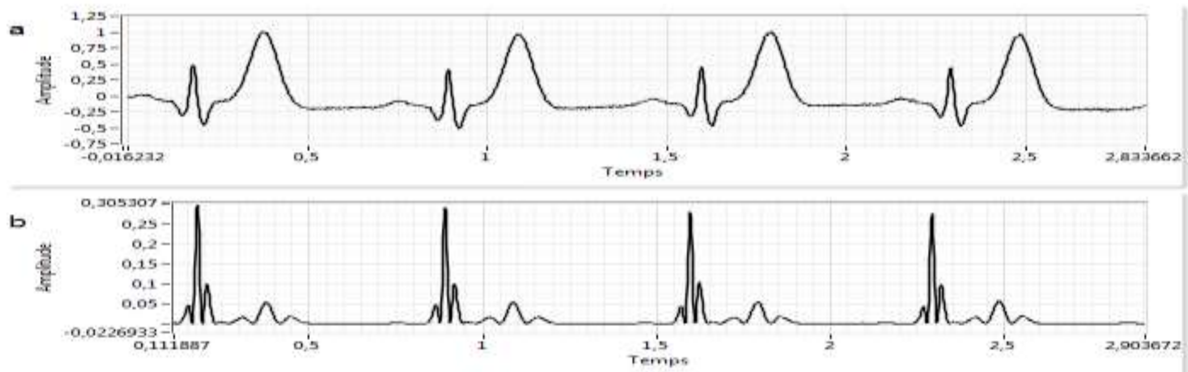

Fig. 3. Signal enhancement. **(a)** The hyperkalemia ECG signal. **(b)** The hyperkalemia ECG signal after filtering and absolute rectification.

After the extraction of the features, viz. amplitude of the QRS wave, QRS onset, QRS offset, P onset (the beat start time), T offset (the beat end time), T onset, P offset and the time of the R waves. the application calculates the time between the onset of atrial depolarization and the onset of ventricular depolarization (PR interval), The duration of the ventricular depolarization (QRS complex which occurs very rapidly), the time of isoelectric period (ST segment) at which the entire ventricle is depolarized following the QRS complex and the time for both ventricular depolarization and repolarization (QT interval).

For the time of corrected QT interval (QTc), who allows an assessment of the QT interval that is independent of heart rate, is calculated by Bazett's formula, as in

$$QTc = QT / \sqrt{RR} \tag{1}$$

Fig. 5 exposes parameters calculations method which treats characteristics extracted (FOR loop), then calculates the parameters by using Std Deviation and Variance VI.

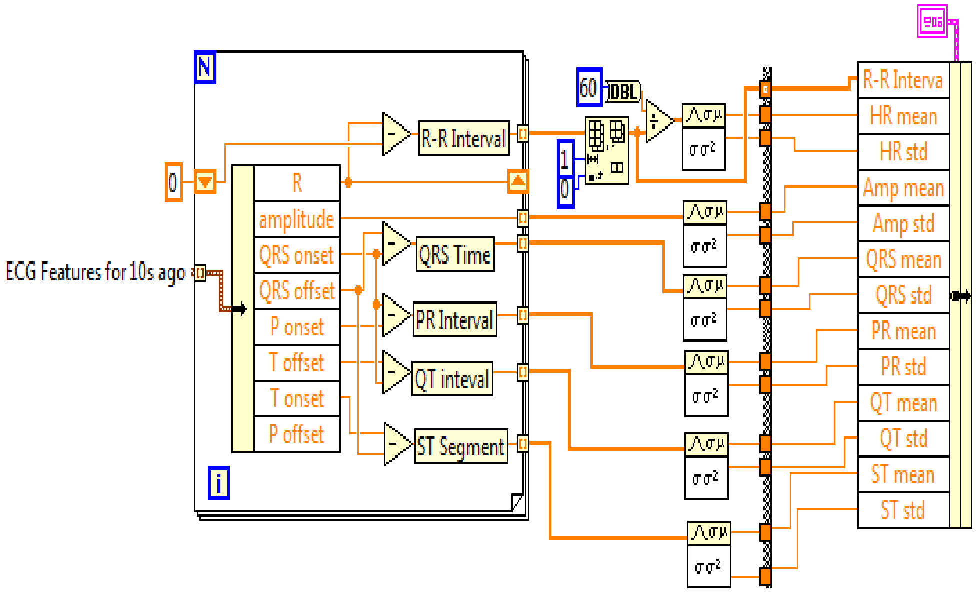

Fig. 4. The features extraction and parameters calculation

D. Heart rate variability analysis

Measurement of Heart Rate Variability (HRV) is a noninvasive approach based on ECG monitoring that allows an indirect evaluation of cardiovascular autonomic control [8]. HRV analysis is the ability to assess overall cardiac health and the state of the Autonomic Nervous System (ANS) responsible for regulating cardiac activity [9].

There are different methods of HRV analysis [10].

1) Time domain analysis

For time series analysis, time domain measurements are commonly used to extract much information from the HRV signal to show changes in the ANS. From the original RR intervals a number of parameters are calculated:

-RR Mean and standard deviation (Std) of all RR intervals.

-RMSSD is Square root of the mean of the sum of squares of differences between adjacent RR intervals, as in

$$RMSSD = \sqrt{\frac{1}{N-1}\left(\sum_{i=1}^{N-1}\left((RR)_{i+1} - (RR)_i\right)^2\right)} \tag{2}$$

Where N is number of RR interval terms

-NN50 is defined as the mean number in which the change in consecutive normal sinus (NN) intervals exceeds 50 in all the measurements.

-pNN50 is the number of successive difference of intervals which differ by more than 50 ms expressed as a percentage of the total number of ECG cycles analyzed, as in

$$\text{pNN50} = (\text{NN50 count}) / (\text{total NN count}) \tag{3}$$

The pNN50 measure has proved very useful in providing diagnostic and prognostic information in a wide range of conditions.

2) Frequency analysis

The spectral analysis of the signal is a very powerful technique for assessing autonomic nervous activity and allows the separation of the frequency bands related to the sympathetic and parasympathetic branches of the nervous system. The power spectrum may be divided into three bands, namely:

Very low frequency (VLF): Power from 0 Hz to 0.04 Hz.

Low frequency (LF): Power from 0.04 Hz to 0.15 Hz.

High frequency (HF): Power from 0.15 Hz to 0.40 Hz.

Calculated power spectrum for the RR interval of each band is expressed using different units as shown in table I. Also the ratio of low frequency to high frequency which is a good method of detecting alterations in nervous system activity is also calculated.

The developed application provides for frequency-domain analysis:

- Fast Fourier Transform (FFT), as in

$$\mathrm{fft}(x) = \sum_{j=1}^{N} x(j)\exp[-2\pi i(j-1)(k-1)/N] \tag{4}$$

Where X is the input and N is the size of X.

Autoregressive method (AR), as in

$$X_t + a_1 X_{t-1} +,\ldots,+ a_n X_{t-n} = e_t \tag{5}$$

Where n is the AR order, X_t is a univariate time series, e_t is a Gaussian white noise series with a mean of zero and $a_1 \ldots a_n$ is AR coefficients.

Using both of these methods consists of the following three steps:

1) Sub-sampling the RR interval signals at 2Hz.

2) Estimating the PSD of the RR interval signals.

3) Computing frequency-domain parameters from the PSD.

The RR interval data along the time axis are not equally spaced and we need to resample the raw RR intervals first at 2 Hz, the fast Fourier transform and autoregressive methods used by the virtual device also accept signals that are already resampled.

III. EXPERIMENTAL RESULTS

In order to show of the benefits of the applied technique, a separate study of noise suppression has been carried out using reel ECG signal from the MIT–BIH databases and a comparison study between decimated wavelet-based method, Butterworth lowpass filtering method and UWT method was carried out as shown in Fig. 5, also we have implemented this technique in a signal processing package software in the parallel graphical language.

Simulation

To start the analysis, one must, first of all, selects the desired recorded file by choosing the path of the desired ECG file. This file will be charged and the ECG signal will be denoised (Fig. 6).

Fig. 7 shows the heart rate, PR interval, QRS interval, ST interval, QT interval, QTc interval and QRS amplitude. The value standard deviation is calculated for each parameter, viz. heart rate std, PR interval std, QRS interval std, ST interval std, QT interval std, QTc interval std and QRS amplitude std

The program uses the heart rate variability as the base signal for the linear and frequency analysis. Fig. 7 shows the statistical and geometrical measures of variability that provide valuable prognostic information about patients, also shows the frequency analysis which describes how the power is distributed over the different frequencies.

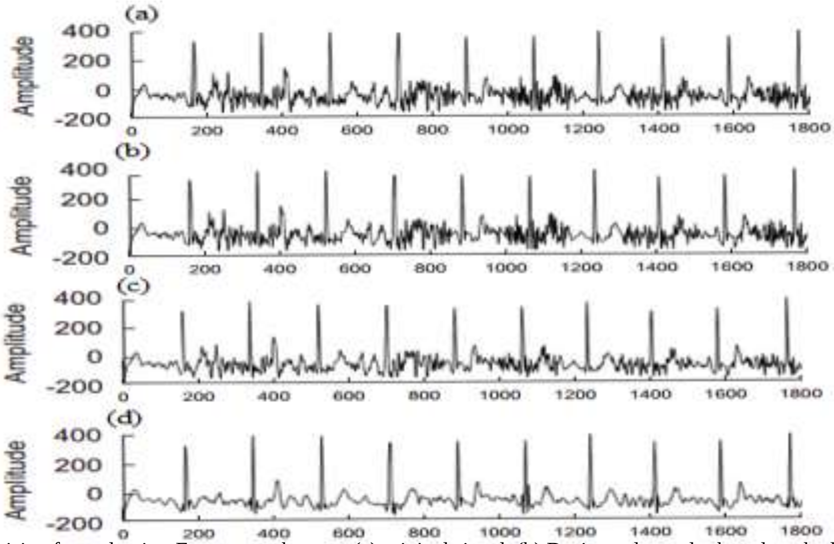

Fig. 5. ECG denoising for real noise. From top to bottom: (a) original signal, (b) Decimated wavelet-based method, (c) Butterworth lowpass filtering method, (d) Undecimated wavelet-based method.

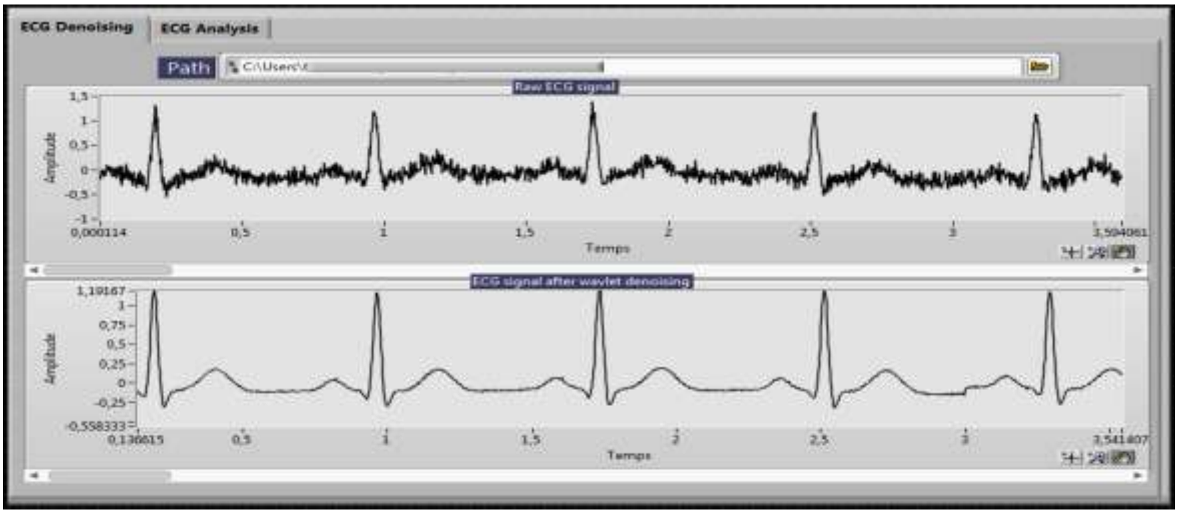

Fig. 6. ECG Denoising page

Fig. 7. ECG Analysis page

VI. CONCLUSION

ECG ECG signal enhancement is vital for accurate detection of cardiac arrhythmia. UWT based denoising method reduce noise from ECG signals more effectively compared to conventional algorithms. This paper analyzed reported denoising schemes in wavelet domains and verify their effectiveness in noise reduction using the MIT-BIH arrhythmia database.

The program has proven to be an essential tool in studying complex heart problems and provides the flexibility for biomedical researchers. This ECG-Analyzing system based on virtual instrument is helpful for improving the ECG analysis, also the developed GUI can be easily modified to suit the clinician needs.

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