Volume 3, No. 3, May-June 2012
ISSN No. 0976-5697
International Journal of Advanced Research in Computer Science
RESEARCH PAPER
Available Online at www.ijarcs.info

Heart Rate Determination with RR Interval and PP Interval Time Series

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Abstract: The efficient heart rate determination leads to dependable heart health diagnosis. The ECG signal is constituted by P-QRS and T waves. The heart rate is generally determined by detecting R peaks and calculating the RR intervals. This is because R peak has highest amplitude among various wave components of the ECG signal and therefore it is easier to detect the R peak locations. The heart cycle actually starts from P wave , so the PP interval series constitutes the actual heart rate time series. In the present paper the ECG features and the PP series and the corresponding RR time series have been detected and the heart rate was evaluated. The results of heart rate computed using PP and RR time series were compared and the results were in close approximation with each other for various MIT/BIH and fantasia database.

Keywords: Electrocardiogram; QRS complex; P wave; T wave; Threshold detection; PP interval time series; RR interval time series.

I. INTRODUCTION

The ECG signal contains information about electrical activity of the heart. Clinical diagnosis depends mainly on a patient's history, and to a lesser extent on the physical examination. The ECG can provide evidence to support a diagnosis, and in some cases it is crucial for patient management. It is, however, important to see the ECG as a tool, and not as an end in itself. The ECG is essential for the diagnosis, and therefore management, of abnormal cardiac rhythms. It helps with the diagnosis of the cause of chest pain, and the proper use of thrombolysis in treating myocardial infarction depends upon it. It can help with the diagnosis of the cause of breathlessness.Electrocardiogram (ECG) is the most commonly recorded physiological signal.

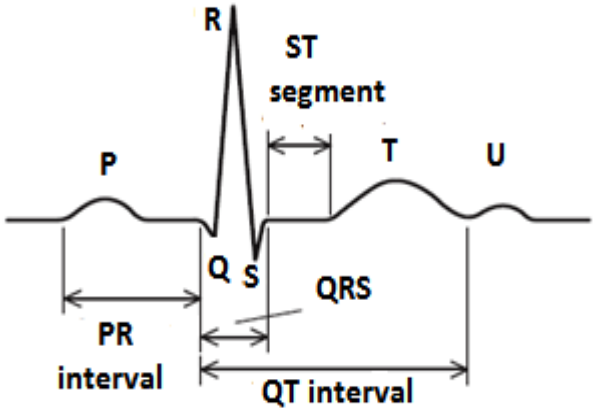

Figure 1. An ECG waveform

It is a crucial component of all diagnostic tests involving cardiac health. A number of ECG parameters are also used as primary and secondary endpoints in drug and device trials. The ECG signal has a characteristic pattern that repeats with every beat of the heart. Of the many morphological markers of the ECG, the QRS complex and the R-peak are the most significant – with the contribution of the R-peak to the R-R interval being a driving factor. The number of R peaks in a specific time interval translates to the heart rate (in beats per minute). It is a graphical record of the direction and magnitude of the electrical activity of the heart that is generated by depolarization and repolarization of the atria and ventricles. ECG provides information about the heart rate, rhythm, and morphology. The importance of the Electrocardiography is remarkable since heart diseases constitute one of the major causes of mortality in the world.

ECG varies from person to person due to the difference in position, size, anatomy of the heart, age, relative body weight, chest configuration and various other factors. The ECG is characterized by a recurrent wave sequence of P, QRS, T and U wave associated with each beat. The QRS complex is the most striking waveform, caused by ventricular depolarization of the human heart. Figure.1 depicts the basic shape of a healthy ECG heartbeat signal with P, Q, R, S, T and U characteristics and the standard ECG intervals QT interval, ST interval and PR interval.

To determine heart rate with RR and PP interval time series, the first step is to detect the R peak and P peak of an ECG signal A number of techniques have been devised by the researchers to detect the characteristics in ECG. Different delineation approaches are found in literature. Many of these approaches delineate either P or T-waves of ECG waveforms, whereas a few approaches delineate both P and T-waves. Thakor and Zhu [1] used adaptive filters for delineation of P-waves. Pietka [2] used a combination of syntactic methods and methods based on measurement vectors by applying the attribute grammars. Trahanias and Skordalakis [3] used attribute grammar for the detection of P and T-waves. Murthy & Niranjan [4] used discrete Fourier transform (DFT) to delineate P and T waves.

A fuzzy clustering technique using asymmetric basis function network approach, is presented by Geva [6]. Sovilj et al. [7] used multistage methodology enabled by Wavelet Transform to delineate the ECG signal and develop a sensitive and reliable P-wave detector. Wong et al. [8] applied Discrete Wavelet Transform (DWT) analysis, employing Haar Wavelet detecting the T-wave peak and the T-wave end. Martinez et al. [9] presented a generalized and robust method for delineation of P and T waves. Mehta et al. [10] proposed a method for the recognition of P and T waves in electrocardiograms using fuzzy theory. Carlson et al. [11] proposed classification method for P-wave morphology. Botter et al. [12] used a neural network with asymmetric basis functions to extract the features of the P

waves. Yang et al. [13] proposed approximating functions for P waves recognition. Vila et al. [14] presented an algorithm for the detection of T -waves based on its mathematical modeling. Strumillo [15] proposed nested median filtering for detecting T-wave offset in ECG.

II. METHODOLOGY

One way of looking at the ECG is the classification of the signal in two parts, namely, QRS-complexes and non-QRS regions. The QRS-complexes being the most prominent parts of the signal are detected first. Already detected QRS-complexes become a reference for detection of P and T-waves. The ECG signal part between each successive pair of QRS-offset and the subsequent QRS-onset constitute non-QRS regions. Since the detection of P and T-waves is done with reference to QRS onset and offset, therefore a good QRS-detection rate is a pre-requisite and is fulfilled by the algorithm for QRS-detection [16]. Figure.2 shows the description of the algorithm for detection of ECG components.

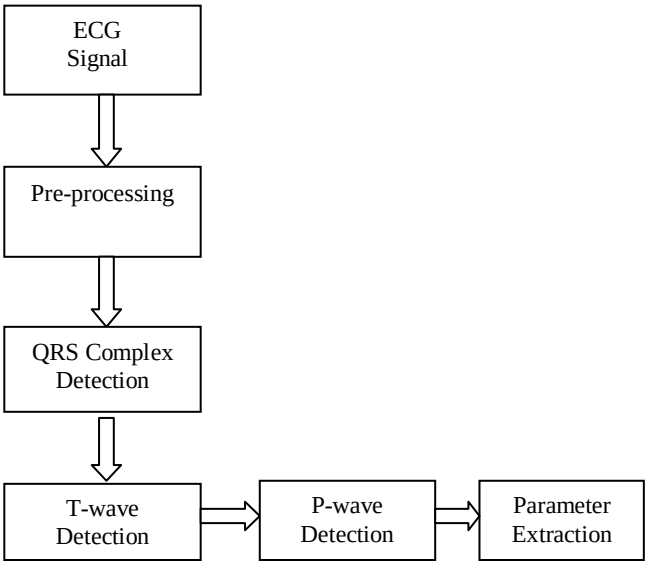

Figure.2. Description of the algorithm for detection of ECG components.

A. QRS Complex Detection:

The QRS complex represents activation of the ventricle. Special conducting bundles spread the wave of depolarization rapidly over the ventricle. Pre-processing of an ECG signal is of vital importance to remove the unwanted noises like 60Hz line interference, baseline wander and muscle noise [18]. Figure.3 shows the description of the algorithm for detection of QRS complex. An analog filter bandlimits the ECG signal at 50 Hz. An analog-to-digital converter (ADC) samples the ECG. The resulting digital signal passes successively through a sequence of processing steps that includes three digital filters implemented in software. First is a bandpass filter composed of cascaded low-pass and high-pass filters. Its function is noise rejection. Next is a filter that approximates a derivative. After amplitude squaring process, a proper threshold is applied to detect the R peaks. The number of R peaks in a specific time interval translates to the heart rate. Figure.3 shows the description of the algorithm for detection of QRS complex.

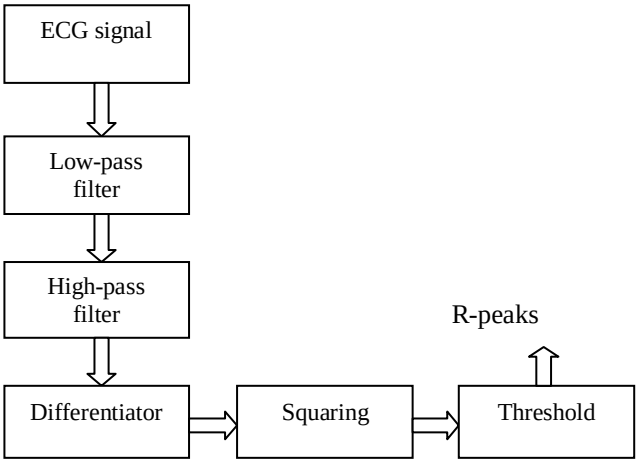

Figure.3. Description of the algorithm for detection of QRS complex.

a. Bandpass Filter:

The bandpass filter [17] reduces the influence of muscle noise, 60 Hz interference, baseline wander, and T-wave interference. The desirable passband to maximize the QRS energy is approximately 5-30 Hz. A bandpass filter is the cascading of lowpass and highpass filter. The difference equation of the lowpass filter is

$$y(nT) = 2y(nT-T) - y(nT-2T) + x(nT) - 2x(nT-6T) + x(nT-12T) \quad (1)$$

where x(T) and y(T) are the input and output signals respectively.

The difference equation of highpass filter is

$$y(nT) = 32x(nT-16T)-[y(nT-T) + x(nT) - x(nT - 32T)] \quad (2)$$

where x(T) and y(T) are the input and output signals respectively.

b. Derivative Filter:

After filtering, the signal is differentiated to provide the QRS complex slope information. The difference equation of the differentiator is

$$y(nT) = (1/8\ T)\ [-x(nT - 2T) - 2x(nT - T) + 2x(nT + T) + x(nT+ 2T)] \quad (3)$$

where x(T) and y(T) are the input and output signals respectively.

c. Squaring Function:

After differentiation, the signal is squared point by point.

$$y(nT)=[x(nT)]^2 \quad (4)$$

This makes all data points positive and does nonlinear amplification of the output of the derivative emphasizing the higher frequencies (i.e., predominantly the ECG frequencies).

d. Thresholding And Decision Making:

After the squaring process, an appropriate threshold is selected to detect the QRS complex successfully. Threshold should be such that it does not miss any of the QRS complexes in the ECG signal. Application of thresholding is possible because the amplitude of R wave is maximum among the characteristics of the ECG signal. Figure.4 represents the QRS detection algorithm processing steps for a normal ECG. The low-pass and high-pass filters together form a band-pass filter that can be implemented with integer arithmetic to provide for real-time operation. This is followed by differentiation and squaring. The normalized ECG signal is passed through a low-pass filter to reduce

muscle noise and 60-Hz power line interference. The next stage is a high pass filter to reduce baseline wander in the ECG. Baseline wander is a low frequency variation caused by patient movement during recording. The next stage is the derivative filter. A derivative filter helps in identifying a change in direction in the slope of the signal which is indicative of a peak in the signal.

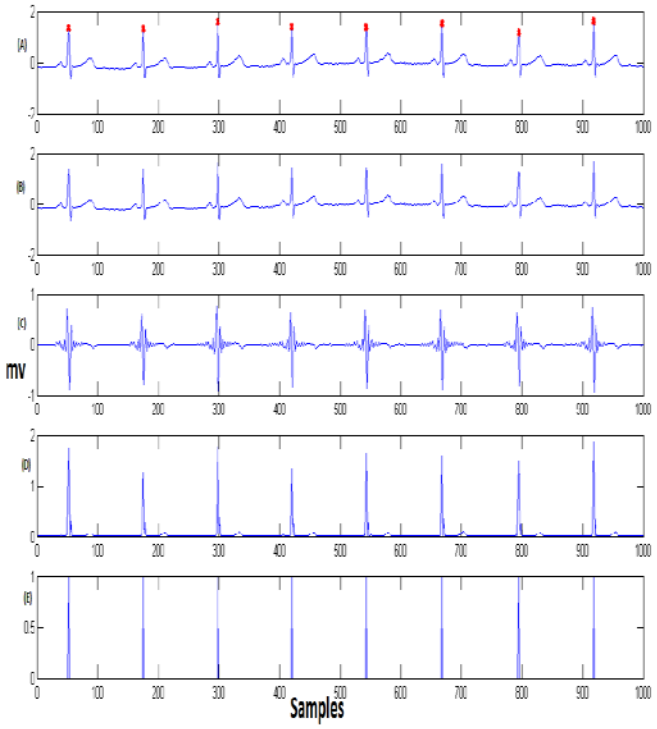

Figure.4 QRS detection algorithm processing steps for a normal ECG (a) Original signal. (b) Output of band-pass filter. (c) Output of differentiator. (d) Output of squaring process. (e) Output detected R-peaks.

The next stage, a simple squaring function, helps not only in making all the signal values positive but also amplifies the output of the previous stage in a nonlinear manner thus emphasizing the R peaks in the signal. The final stage is to apply the appropriate threshold to the squared signal to detect the R wave from the ECG signal. The QRS complex and the R-peaks are the most significant – with the contribution of the R-peak to the R-R interval being a driving factor. The number of R peaks in a specific time interval translates to the heart rate.

B. P-wave Detection Algorithm`:

The P wave represents the spread of electrical activity over the atrium. The normal depolarization begins at the sinoatrial (SA) node near the top of the atrium. This section describes an algorithm developed for the detection of P-wave. The QRS-complexes being the most important parts of the signal are detected first. Already detected QRS-complexes become a reference for detection of P and T-waves.

Step 1: A raw digitised recorded ECG signal of a patient is acquired. Figure.5(a) shows raw signal of record 04048.

Step 2: A raw ECG signal is often contaminated by disturbances such as power line interference and baseline wander. Pre-processing is done to remove all the contaminations from the ECG signal and a filtered ECG is obtained as shown in Figure.5(b).

Step 3: QRS detection algorithm is applied to detect the R-peaks as discussed in Figure.4. These QRS complexes are removed from the ECG signal by replacing them with a baseline corresponding to the R-peak location shown in Figure.5(c). The signal without QRS complexes is displayed in Figure. 5(d).

Step 4: The slope at every sampling instant is calculated to enhance the signal in the region of T-waves. The slope is used as an important criterion because slope of the signal is much more in the T wave region than in the region of P wave.

Step 5: A sliding window is moved forward by one sampling instant over the slope curves. When the window lies in the region of T-waves, the desired output of the window is set to 1 for the mid of T-peaks and when it lies in the other region, the desired output is set to 0. The locations of the T wave are shown by the curve Figure. 5(e)

Step 6: The T waves present in the ECG signal are removed by replacing them with a baseline. The ECG signal without the QRS complexes and the T-waves is shown in Figure. 5(f).

Step 7: A sliding window is moved forward by one sampling instant over the signal without the QRS complex and T-wave. When the window lies in the region of P-waves, the desired output of the window is set to 1 for mid of P-peaks and when it lies in the other region, the desired output is set to 0. Figure.5(g) shows the detected P waves.

The heart rate is generally determined by detecting R-peaks and calculating the RR intervals. This is because R peak has highest amplitude among various wave components of the ECG signal and therefore it is easier to detect the R peak locations. The heart cycle actually starts from P-wave, so the PP interval series constitutes the actual heart rate time series. PP interval series is extracted from the already detected P waves and is compared with RR interval series to calculate whether there is any difference in the heart rate obtained with RR and PP interval time series individually

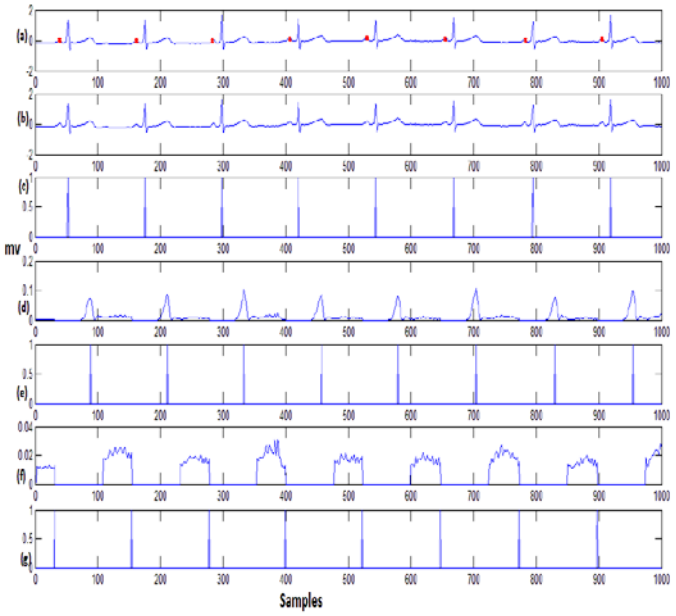

Figure. 5 Results obtained at each step of the algorithm for MIT/BIH atrial fibrillation database record 04048 (a) Raw ECG, (b) Filtered ECG, (c) R -peak locations,(d) Enhanced ECG signal without QRS, (e) T-peak locations, (f) Enhanced ECG signal without QRS and T waves, (g) Detected P waves.

Figure.6 represents the flow-chart for the detection of P-wave and comparison of PP and RR interval time series. R peak locations become the reference for detection of T waves and finally the P-waves. Thresholding step is a very important step in the feature extraction of ECG. Thresholding step depends on the sampling frequency of the raw data. If proper outputs are not obtained in any step, the adjustment of the threshold is done to obtain the desired output as the output of one stage becomes the reference for the input in the next stage. PP and RR interval time series are calculated with already detected P and R-peaks. Heart rate comparison is done in the last step to reach to a consensus.

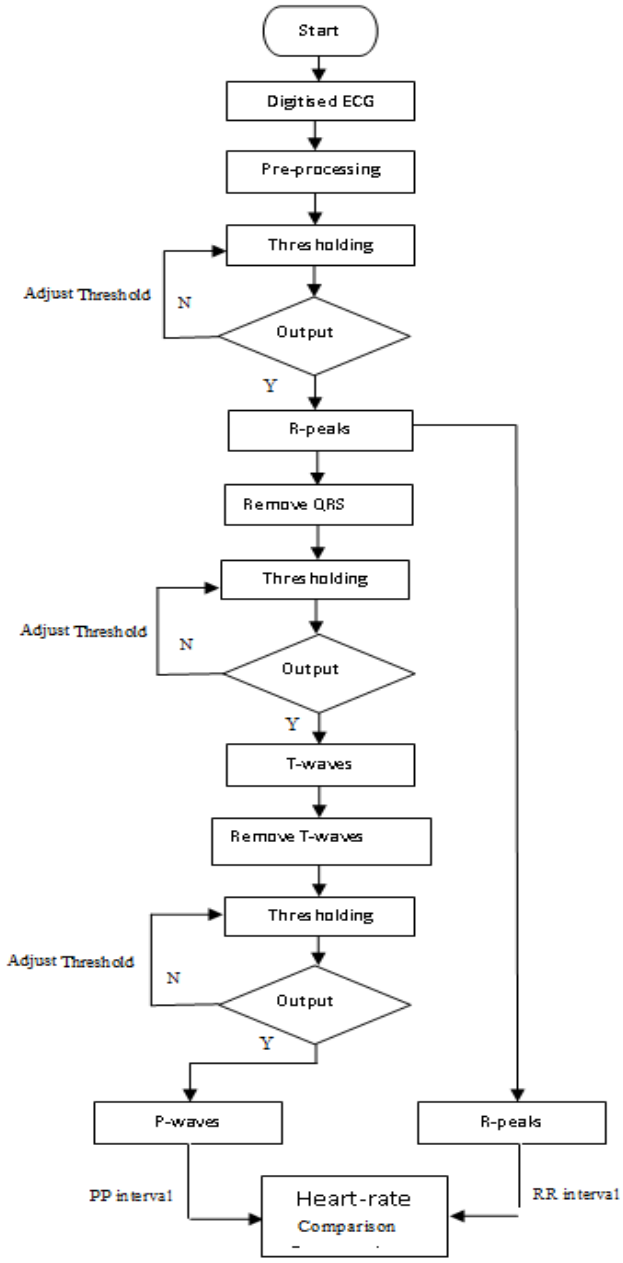

Figure.6 Description of the flow-chart for detection of P-wave and comparison of RR and PP interval time series

III. RESULTS AND DISCUSSION

The proposed algorithm is implemented in MATLAB language and has been applied to ECG segments for 1 minute duration samples taken from MIT/BIH and Fantasia database [19] to detect R peaks and P peaks. Firstly the R and P-peaks detection results are given in tabular form. Then PP and RR interval time series are compared to achieve the main target and conclusion.

A. Detection Results:

Table.1 R-peak detection with MIT/BIH normal sinus rhythm database for 1 minute duration samples

Record number	Total R-peaks	Detected R-peaks	Missed peaks	Detection Rate
16272	62	62	0	100
16483	96	94	2	97.91
16420	93	92	1	98.92
16773	74	71	3	95.95
16786	72	71	1	98.61

Table.2 R-peak detection with MIT/BIH supraventricular arrhythmia database for 1 minute duration samples

Record number	Total R-peaks	Detected R-peaks	Missed peaks	Detection Rate
800	46	45	1	97.83
803	68	68	0	100
806	98	95	3	96.94
809	82	81	1	98.78
811	48	48	0	100

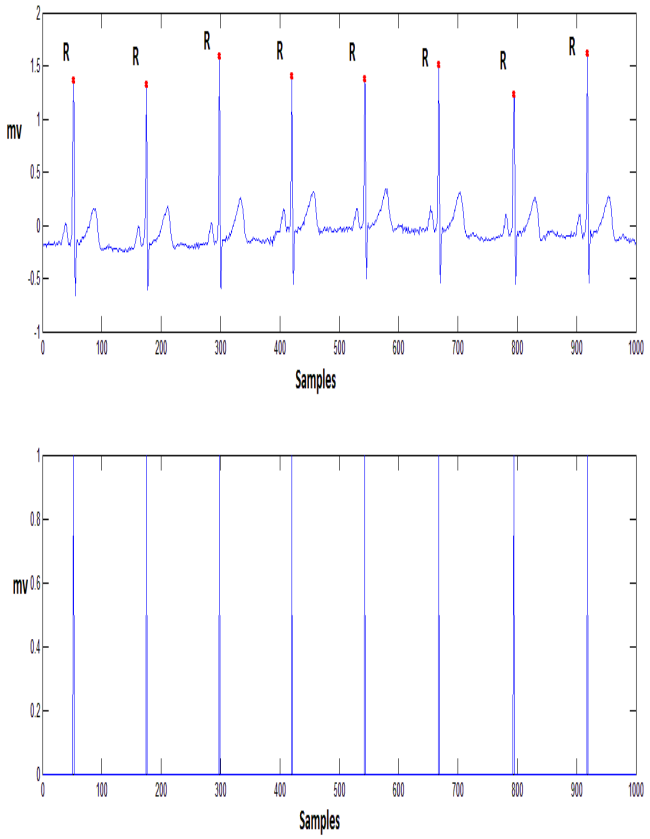

Figure.7 Detection of R peak with MIT/BIH normal sinus rhythm database Record 16272 and Sampling frequency 128 samples/sec.

Table 1 presents the number of actual R-peaks, number of R-peaks detections, missed R-peaks and the detection rate for the MIT/BIH normal sinus rhythm database each for one minute duration samples. Table 2 presents the number of actual R-peaks, number of R-peaks detections, missed R-peaks and the detection rate for the MIT/BIH supraventricular arrhythmia database each for one minute duration samples.

Table 3 P-wave detection with fantasia database for 1 minute duration samples

Record number	Total P-waves	Detected P-waves	Missed waves	Detection rate
f1o02	62	61	1	98.38
f1o04	48	48	0	100
f1o06	48	47	1	97.92
f1o10	68	65	3	95.95
f2o10	82	79	3	96.34
f1y03	70	68	2	97.14
f1y04	46	45	1	97.82
f1y05	62	58	4	93.54
f2o02	55	55	0	100
f2o03	61	60	1	98.37
f2o04	63	60	3	95.24

Similarly, Table 3 presents the number of actual P-waves and number of P-wave detections, missed waves and the detection rate for Fantasia database each for 1 minute duration samples. Figure.8 and Figure.9 shows the detection of T and P waves from Fantasia database record f1o04.

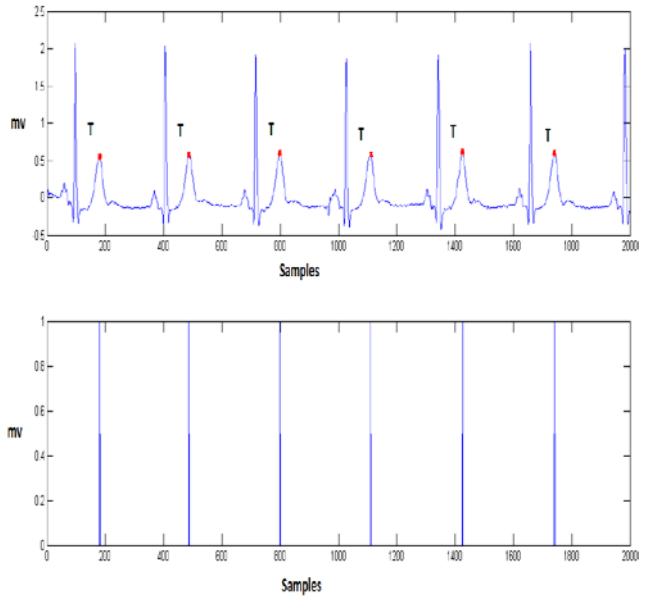

Figure.8 Detection of T-wave (Fantasia database Record f1o04)

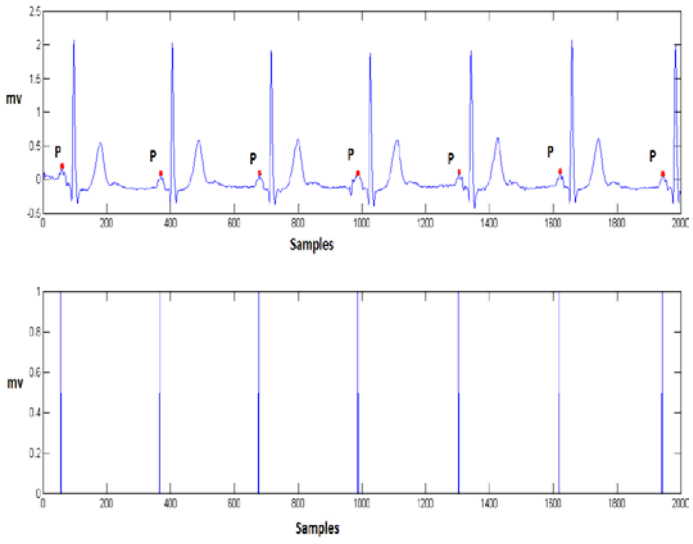

Figure.9 detection of P-wave (Fantasia database Record f1o04)

B. Comparison Results:

Table 4 Heart rate comparison from RR and PP interval time series for MIT/BIH Normal Sinus Rhythm database for 1 minute duration samples

Record number	Average RR interval (SEC)	Heart rate H_{RR}	Average PP interval (SEC)	Heart rate $H_{PP`}$	Difference $\lvert H_{PP} - H_{RR} \rvert$
16272	0.9705	61.82	0.9702	61.84	0.02
16483	0.6276	95.60	0.6276	95.60	0.00
16420	0.6502	92.28	0.6500	92.30	0.02
16773	0.8173	73.41	0.8178	73.36	0.05
16786	0.8316	72.15	0.8312	72.18	0.03

Table 5 Heart rate comparison from RR and PP interval time series for MIT/BIH Supraventricular Arrhythmia database for 1 minute duration samples

Record number	Average RR interval (SEC)	Heart rate H_{RR}	Average PP interval (SEC)	Heart rate $H_{PP`}$	Difference $\lvert H_{PP} - H_{RR} \rvert$
800	1.3138	45.67	1.3135	45.68	0.01
803	0.8785	68.29	0.8790	68.26	0.03
806	0.6078	98.71	0.6078	98.71	0.00
809	0.7294	82.26	0.7293	82.27	0.01
811	1.2448	40.20	1.2448	40.20	0.00

Table 4 presents the heart rate comparison from PP and RR interval time series for MIT/BIH normal sinus rhythm database each for one minute duration samples. Table 5 presents the number heart rate comparison from PP and RR interval time series for the MIT/BIH supraventricular arrhythmia database each for one minute duration samples. Last column in tables IV and V represents the difference in the heart rate calculated with RR and PP interval time series individually which is negligible as compared to the actual heart rate.

Table 6 Heart rate comparison from RR and PP interval time series for Fantasia database for 1 minute duration samples

Record number	Average RR interval (SEC)	Heart rate H_{RR}	Average PP interval (SEC)	Heart rate $H_{PP`}$	Difference $\lvert H_{PP} - H_{RR} \rvert$
f1o02	0.9745	61.57	0.9745	61.57	0.00
f1o04	1.2571	47.73	1.2569	47.74	0.01
f1o06	1.2400	48.38	1.2401	48.38	0.00
f1o10	0.8867	67.67	0.8863	67.69	0.02
f2o10	0.7291	82.29	0.7295	82.25	0.04
f1y03	0.8543	70.23	0.8543	70.23	0.00
f1y04	1.2972	46.25	1.2972	46.25	0.00
f1y05	0.9635	62.27	0.9633	62.28	0.01
f2o02	1.0830	55.40	1.0830	55.40	0.00
f2o03	0.9853	60.89	0.9850	60.91	0.02

Table 6 presents the heart rate comparison from PP and RR interval time series for Fantasia database each for one minute duration sample. The difference between heart rate calculated with RR interval and the heart rate calculated with PP intervals is almost negligible. Thus we can firmly conclude that the heart rate calculated with R-peak and the heart rate calculated with P-wave doesnot make any difference.

IV. CONCLUSION

The R-peak detection efficiency evaluated with the above algorithm is 98.50%. The R-peak is an important

fiducial point for further ECG signal analysis. An efficient R-peak detection algorithm has been proposed. This will lead to formulation of highly accurate R-R interval time series which helps in highly dependable cardiovascular variability studies. The calculated P-wave detection rate with the proposed algorithm is 97.33%. In the detection algorithm for P-wave, firstly T-wave is detected in reference to R-peak.

The detection rate for T-wave is 98.12%. The calculated results are in close approximation with the original results. Sampling rate of the ECG signal is a very important factor for the detection algorithm. This method is efficient, simple to implement and can be easily modified to adapt to different ECG waves. The algorithm was tested on several ECG segments extracted from MIT/BIH and Fantasia database. It is shown to accurately detect and delineate waves in very noisy ECG signals. Some parameters like PR-interval, ST-interval and QT-interval which are very important for heart health diagnosis can be extracted from already detected P, QRS and T waves. Most of the work reported in the literature either deals with P-wave detection or T-wave detection. Both P and T-wave detection, if found in the literature, generally use different approaches to delineate them. It is the effort of this work to detect and delineate both P and T-waves simultaneously with good detection rate. Heart rate from RR and PP interval series are compared for various MIT/BIH and fantasia database. It is concluded from comparison results that heart rate calculated from RR and PP interval time series individually is approximately same.

V. ACKNOWLEDGMENT

The authors are highly thankful to Department of Electronics & Communication Engineering and Director, Dr. B.R. Ambedkar National Institute of Technology, Jalandhar for providing all necessary help to carry out the present work.

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