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Detection of Ventricular Tachycardia, Paced Rhythm and Idioventricular rhythm through QRS complex Analysis

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Abstract— **ECG signal plays a necessary part in the perception and study of heart diseases. Detection and monitoring of RR interval and QRS complex is a vital method in the analysis of ECG patterns to diagnose abnormal behavior of the heart. Abnormalities in the patterns are used to detect arrhythmia arising out of atypical electrical flow in the functioning of the heart. The rate and rhythm of these patterns render information that can be correlated with normal values to detect and categorize conditions of arrhythmia. While theoretical models exist for extraction of arrhythmia information from ECG, real-time analysis and detection have remained a challenge. An algorithm based on the Pan-Tompkins method is used to detect R peaks, from which we can measure heart rate using average R-R interval, was used. Detection of QRS duration, which is also a factor to identify the different types of arrhythmia. As a further step, uncertainity in the QRS duration and uncertainity in position of peaks helps to eliminate AWGN noise reducing false detections. The algorithm is implemented considering both arrhythmia screening and real-time monitoring applications. For validation of the algorithm, data from different internationally published databases like to MIT-BIH, with known arrhythmia conditions like Ventricular Tachycardia, Paced rhythm and Idioventricular rhythm and PTB, ESTST samples with known number of peaks have been used as reference signals and corresponding published results are compared with expected outcomes.**

Keywords— ECG, RR interval, QRS complex, DWT, arrhythmia.

I. INTRODUCTION

Arrhythmia is the irregularity associated with the heartbeat. A small variation in this can lead to serious problems. To diagnose a heart disease, it is necessary to review ECG for the presence of abnormal patterns like irregular heartbeat, QRS width variation, and so on. The heart may beat too fast (tachycardia), or too slow (bradycardia). The typical range for the normal heart rate is 60 to 100 beats per minute. If the heart rate in an adult is less than 60 beats per minute then it is considered to be Bradycardia. The condition is called Tachycardia when the heart rate is greater than 100 beats per minute. In our paper, we determine heart rate by testing R-R interval and QRS duration, in order to identify arrhythmias like Paced rhythm, Ventricular Tachycardia and idioventricular rhythm.

Electrocardiogram (ECG) has been one of the most regularly documented physiological signals and a vital component of all diagnostic analysis associated with cardiac status. The ECG signal comprises a report about the electrical activity of the heart. The ECG signal has a regular pattern (as shown in Figure 1) that produced at every beat of the heart. Of the numerous morphological markers of the ECG, the QRS complex and the R-peak is the most useful in detection of arrhythmia and other measurements of the heart function. The frequency of the R peaks is related to the pumping rate of the heart (beats per minute) [8]. It could range from 60 to 100 bpm in normal human conditions. The QRS complex pattern yields significant information such as heart rate variability and cardiac cycle classification [7]. Its duration could range from 0.06 to 0.1 sec for a normal person.

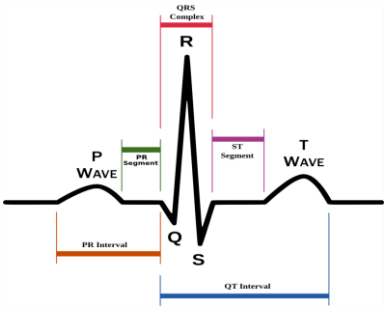

Figure 1 ECG signal [9]

The spectral density of QRS complex is more between the frequencies of 5 to 15Hz compared to the rest of the waves present in a single ECG waveform. These spectral characteristics give more information on the associated variability, shape and energy of the signal which are vital to detection of anomalies in the functioning of the heart. However, in real life conditions, the measurement of ECG signals is subjected to distortions caused by electrical noise induced from power-line and radiation from nearby electrical appliances. Further, there are also spiky artifacts and muscle noise induced due to minor muscular activities while recording the ECG, with typical electromyography interference and T wave interference. Also, the baseline of the whole signal itself wanders due to long term variation of body potential. All these distortions have to be suppressed to the highest extent possible to yield the required accuracy and to avoid false alarms for the automatic detection of arrhythmia.

Several methods have been proposed to detect arrhythmias by extracting characteristic points of ECG based on neural networks [14], independent component analysis [12] which are computationally complex. Wavelet analysis [13-14] gives flexibility to detect characteristic points but false selection of mother wavelet is catastrophic. Time domain approach has more advantages because of its less computational complexity and simple algorithms suitable for real time environment [15]. Several independent

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methods are considered [1]-[8] but a combination of methods could lead to a more reliable detection.

In practical scenarios, a significant source of signal corruption is EMG noise. It is very important to remove this noise before estimation since it varies from DC to 10KHZ which corrupts overall signal significantly. In our approach, a new step was added in the time domain signal processing chain prior to R-peak detection in Pan-Tompkins method [11] (which is sensitive to noise as it uses adaptive thresholds to detect peaks). Based on the detected R peaks, QRS duration is calculated by Windowing method and arrhythmias are detected by simple decision rule (computationally simpler than algorithms such as Support Vector machines (SVM) and Hidden Markov Models (HMM) which require training sets). The EMG noise filter is implemented using Discrete Wavelet Transform (DWT) followed by a band pass filter (BPF) to lower other noise sources and thereby boosting the signal-to-noise ratio [8]. In this paper, MIT/BIH database has been taken as standard reference input of ECG data to validate the performance of our method.

The rest of the paper is classified as follows: Segment II and III explain the signal processing algorithm and implemented steps. Segment IV is concerned with experimental outcome and finally, conclusions are drawn in Segment V.

II.PAN-TOMPKINS METHOD

Pan-Tompkins method [11] is literally a linear-filtering technique for QRS detection. In the preprocessing stage, the signal-to-noise ratio is boosted by applying a band-pass filter. Then, the outcome signal is differentiated and then squared to further amplify the amplitude of the QRS complex. In the decision stage, QRS complexes are detected by using an adaptive thresholding method.

III.PROPOSED METHOD

The block diagram of the algorithm is as shown in Fig (2).

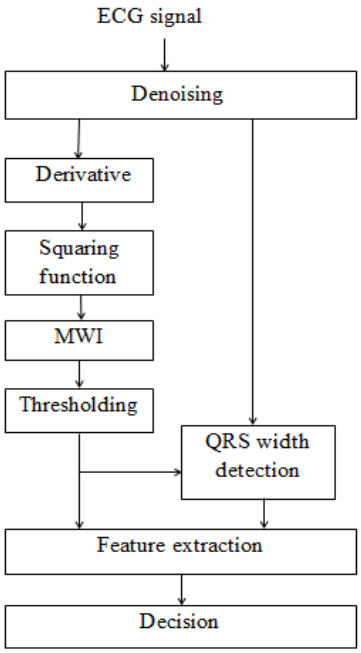

Figure 2 Block diagram of proposed method

3.1 ECG signal: To test our method, we used some of the selected records from 48 documented signals present in MIT-BIH Arrhythmia database, each of 30 minute span and having two leads (modified limb lead II and one of the leads V1, V2, V4 or V5), with the sampling rate of 360 Hz[8].

3.2 De-noising: Noise sources consist of power-line interference, baseline wander, electromyography noise. In our approach, to suppress this noise bior2.4 at level 4 is used to scale down the domination of EMG noise and also band pass filter (BPF) which lowers other noise sources and thereby boost the signal-to-noise ratio. Thus, for the ECG signal x(t), we can relate the filtered signal to the original signal as:

$$y(t)= DWT_{bior2.4}(x(t);a=2^4) \quad (1)$$

3.3 Derivative filter: After de-noising, the signal is to be differentiated to provide the QRS complex slope information and emphasize rapid transition regions in the signal. A 4-tap differentiator was employed in our method, with difference equation as follows:

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

where x(T) and y(T) are the input and respectively. (2)

3.4 Squaring function: After differentiation, the signal is converted to a unipolar pattern and its slope contrast is further emphasized by squaring the signal as:

$$Y(nT)= [x(nT)]^2 \quad (3)$$

This makes all data points positive and does amplifies the output of previous stage in non-linear manner, thus emphasizing the transition of R and other peaks in the signal.

3.5 Moving-Window Integration(MWI): It is necessary to filter the waveform over a moving-average window to clean the Signal of unwanted spiky artifacts and features embedded in the signal which also would have been amplified in the previous steps. The smoothing function employed in this method is a moving average window that integrates the signal as

$$y(nT)= (1/N)\ [x(nT- (N–1)T) +x(nT-(N-2)T)+…+x(nT)] \quad (4)$$

where N is the number of samples in the width of the integration window (N can be varied to get best results).

3.6 Thresholding: An appropriate threshold is selected to detect the QRS complex successfully. Thresholding is done same as Pan Tompkins method [11].

3.7 QRS Width detection: The QRS duration is determined. The de-noised signal is inverted first to find QRS duration. Depending upon the location of R peak, Q and S points are determined by finding maximum amplitude point to the left and to the right of R peak respectively. From this width, the duration is estimated as

QS_duration = (Avg_dist_of_QS/360)

3.8 Feature extraction: Here the average R to R interval is calculated between R peaks in seconds, and related to heart rate as

Heart Rate (HR, bpm) = 60/RR interval in sec.

3.9 Arrhythmia Detection: Following assumptions [10] as used as guidance factors for arrhythmia detection:

1. The typical range for normal HR is 60 - 100 bpm
2. Bradycardia in an adult with a HR < 60 bpm
3. Tachycardia with a HR >100 bpm
4. Ventricular Tachycardia: HR>100bpm,QRSwidth> 0.1s
5. Paced rhythm: HR ~ 72bpm, QRS duration> 0.1 sec.

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The proposed algorithm is implemented as shown in Figure 3.

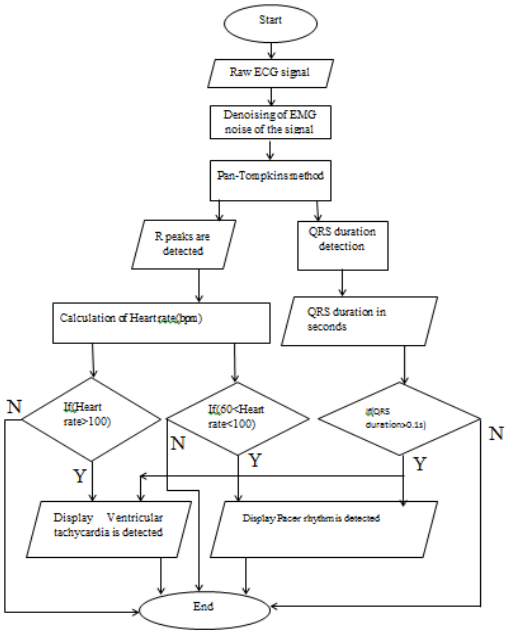

Figure 3 Flow chart of proposed method

II. TESTS AND RESULTS

Raw dataset to test the algorithm was taken from Massachusetts Institute of Technology-Beth Israel Hospital (MIT-BIH) database, the European ST-T database and from the Physikalisch-Technische-Bundesanstalt (PTD) database. Specific cases with and without arrhythmia was selectively fed to the system and the outcomes measured for correct detection; false detection (missing a present arrhythmia as well as flagging arrhythmia when no arrhythmia) was recorded. The raw estimates of HR, Number of peaks detection, QRS duration and arrhythmia detection results are summarized. Table 1 describes that proposed algorithm is susceptible to false alarms when normal sinus rhythm of duration 30 min except the record no. 101 of the MIT-BIH samples (specific samples are selected) is fed to the algorithm. Table 2 validates the algorithm in terms of number of peaks against the PTB database. Table 3 validates the algorithm in terms of number of peaks against the E ST-T database Table 4 compares the heart rate calculations between MIT-BIH database and proposed algorithm. Table 5 shows heart rate, QRS width duration calculations with uncertainty in QRS duration in seconds. Table-6 shows arrhythmia detected based on Heart rate and QRS duration for particular types of arrhythmia given in MIT BIH arrhythmia database directory. MIT-BIH arrhythmia database directory is available at physionet.org in which specified points of interest for particular arrhythmia are given from that we are selecting few records to check the algorithm out of which some records showing paced rhythm and other records with ventricular tachycardia and only one record has Idioventricular rhythm. The processed signal for record no. 102 and 213 of MIT-BIH records are shown figure 4 where first and second figures are raw ECG signal and third and fourth are processed signal in those black coloured line representing QRS on MWI signal and noise level, red colour line represents the signal level and green coloured line represents an adaptive thresholding. This is the part of the 30 min signal which is available in MIT BIH arrhythmia database.

III. OBSERVATIONS AND CONCLUSION

The proposed algorithm determines the heart rate and QRS width duration. Using these we have attempted to detect three types of arrhythmia, i.e., ventricular tachycardia where there is rapid heartbeats because of an inappropriate electrical activity of the heart, paced rhythm where there is a wide QRS complex and idioventricular rhythm where electrical impulses cannot reach ventricles because of block in the conduction. From table 1 we can observe that when the data has no arrhythmia the algorithm is susceptible to false alarms in one case among available normal sinus rhythm cases in MIT-BIH arrhythmia database. Table 2 and 3 validates the algorithm in terms of number of peaks against two other databases where all the peaks are detected correctly. Table 4 compares the heart rate calculations of proposed algorithm with heart rates specified in the MIT-BIH database of some selected records where heart rate was deviated from reference in two cases. This accuracy is also a function of threshold selected for determination of arrhythmia. From table 5, we observe that algorithm correctly identifies the arrhythmia types in all cases when validated with arrhythmias specified in MIT-BIH database. In Table-6 corresponding heart rates and QRS widths are calculated with respect to records selected in Table 5 to detect arrhythmias. Presence of additive white Gaussian noise in input signal will affect the accuracy of measurement of position of peaks and hence result in uncertainty in QRS widths. As shown in the Table 6 where the calculation of uncertainty in QRS width and peak positions due to the noise help to set correct threshold to reduce false detection, as was the case found in record number 200 for ventricular tachycardia detection specified in the MIT-BIH database. The work can be extended to process the signals for detection of other parameters as needed to determine multiple classes of arrhythmias. The accuracy obtained with limited test cases considered here is good enough for screening applications, but one can expect the smaller fraction of false detections or missed arrhythmia over a statistically larger number of cases one would obtain in typical real life applications.

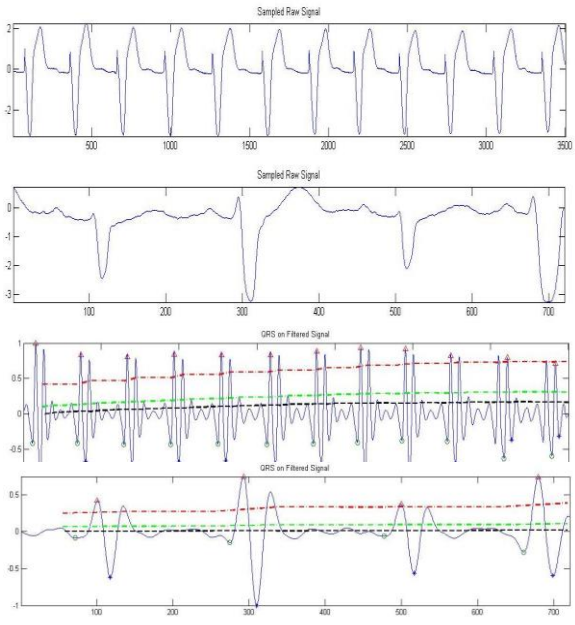

Figure 1 Processed signals for 102 and 213 records

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APPENDIX

Nomenclature:

1. Normal sinus rhythm = NSR
2. Ventricular tachycardia = VT
3. Paced Rhythm = PR
4. Accelerated idioventricular rhythm = AIR

Table 1

Record no.	According to MIT(Selected samples)	Our Results
100	NSR	NSR
101	NSR (33480:34200)	VT
103	NSR	NSR
112	NSR	NSR
122	NSR	NSR

Table 2

Record no	No. of peaks (E ST-T)	Our Results
e0103	10	10
e0104	12	12
e0105	9	9
e0108	9	9
e0110	10	10

Table 3

Record no	No. of peaks(PTB)	Our Results
s0010_rem	13	13
s0014lrem	14	14
s0015lrem	13	13
s0016lrem	14	14
s0017lrem	13	13

Table 4

Record no.	Heart rate(According to MIT)	Our Results
100	70-89	75.41
101	55-79	53.54
102	68-78	72.63
103	62-92	70.05
104	69-82	74.54
105	78-102	87.65
107	68-82	70.54
108	44-78	59.54
109	77-101	83.59
111	64-82	70.53
112	74-91	84.37
117	48-66	50.99
122	67-97	82.13
123	41-65	50.37
210	88-114	88.89
230	63-99(NSR) 59-93(Pre excitation)	79.41 69
232	24-48	59.51

Table 5

Record no.	Arrhythmia type (MIT)	Number of samples selected	Our Results
102	PR	351000 to 358200	PR
103	NSR and APC	1 to 650000	Correctly detected as no VT or PR
104	PR	579600 to 580320	PR
107	PR	15120 to 18720	PR
200	VT	535260 to 536400	VT
205	VT	106560 to 108720 (10 beats)	VT
213	VT	319680 to 320400	VT
214	AIR	115200 to 115920	AIR
215	VT	62640 to 63720	VT

Table 6

Record no.	Heart rate(bpm)	QRS duration(uncertainty in sec)
102	75.56	0.1374(±0.1699)
103	70.05	0.0907(±0.3542)
104	76.59	0.1417(±0.0039)
107	70.23	0.1289(±0.0053)
200	92.80	0.1428(±0.0280)
205	136.44	0.1331(±0.0065)
213	107.46	0.1292(±0.0092)
214	69.23	0.1250(±0.0867)
215	116.37	0.1444(±0.0186)