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DEVELOPMENT OF AN AUTOMATIC HEART ABNORMALITY DETECTION SYSTEM

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Abstract- *The* ***e****lectro****c****ardio****g****ram (ECG) is the electrical activity of heart. It helps to detect the condition of the heart. It gives necessary information about the cardiovascular system. The ECG interpretation is necessary for detecting heart abnormalities. Conventional visual technique requires time and experience. There is possibility of missing vital information. Therefore, computer based heart abnormalities detection system is very helpful for diagnostics purpose. Here we have developed a system that would detect the heart abnormality automatically. For this we use samples from the MIT-BIH arrhythmia database. Then we processed the samples and calculate the heart rate (which is an indicator of heart condition) using Pan Tompkins method in MATLAB. The normal heart rate is 60-100 beats per minute (bpm). If the heart rate if less than 60bpm, the abnormality is bradycardia and if it is greater than 100, the abnormality is tachycardia. Here we also detect these two abnormalities.*

Keywords: ECG, Heart Rate, Abnormality, Bradycardia, Tachycardia

1. INTRODUCTION

ECG (the electrical activity of heart) is an effective and more accurate way for detecting the heart abnormality. Many lives could be saved through proper treatment if the heart abnormalities are detected early. Conventional techniques for ECG interpretation require time as well as experience where there is possibility of missing vital information. Computer based (automatic) heart abnormality detection system can be a solution of it. A typical ECG signal is shown below-

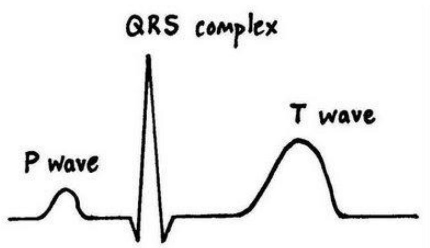

Fig. 1: a typical ECG signal

The heart abnormality detection can be divided into a sequence of stages. First one is acquisition of ECG signal and second one is detection of QRS complex which is a very important parameter of ECG and used for calculating the heart rate. Finally detecting the heart abnormality (sinus tachycardia and sinus bradycardia) based on heart rate. In this paper samples from the MIT-BIH arrhythmia database is used. Then the signal is processed (de-noised) to calculate the heart rate (which is an indicator of heart condition) using pan Tompkins method in MATLAB. The proposed heart abnormality detection system is a low cost system as well as portable. It can be easily used for premedical purpose or primary care treatment.

2. LITERATURE REVIEW

Many techniques have been proposed to detect ECG patterns for detecting heart abnormalities. Wavelet transform is used effectively in many works to detect ECG patterns. Moreover, frequency domain features, autocorrelation and time frequency analysis have been used. Time-frequency analysis is used in [1] to detect normal condition, first degree heart block, second degree heart block type 1, second degree heart block type 2, third degree heart block, right bundle branch block and left bundle branch block. Among many techniques neural network is the most effective one. Neural network is used in many applications successfully to detect abnormalities as it has great predictive power. Recurrent neural network has been used in [2] to classify normal beat, congestive heart failure beat, ventricular tachyarrhythmia beat and atrial fibrillation beat. In [3] adaptive wavelet network has been proposed to detect normal beat, atrial premature beat, premature ventricular contraction , right/left bundle branch block beat, paced beat and fusion of paced and normal beat. Combined neural network model is used to detect normal beat, congestive heart failure beat, ventricular tachyarrhythmia beat, atrial fibrillation beat in [4]. In [5], it is shown that SOM network shows better performance than BP and LVQ network to detect normal sinus rhythm, premature ventricular contraction, atrial premature beat and left bundle branch block beat. Combination of many models is also used in many works to detect ECG patterns. In this paper, a heart abnormality detection system to detect heart abnormality is proposed. It helps to recognize normal heart condition, tachycardia and bradycardia. Sinus Bradycardia is the indication of various fatal heart abnormalities like heart block, heart tissue damage, obstructive sleep apnea, congenital heart defect, sick sinus syndrome, hypertension etc. [6,7]. Moreover, sinus tachycardia indicates various heart abnormalities including heart failure, risk of stroke, risk of sudden cardiac arrest or death, excessive thyroid hormone, low blood oxygen level, heart valve disease etc. [8]. So, detecting sinus tachycardia and sinus bradycardia heart abnormality can be confirmed. It is a low cost and effective heart abnormality detection system that can be easily used for premedical purposes.

3. HEART ABNORMALITY

Any deviation from heart normal condition can be treated as heart abnormality. Heart rate is one of the indicators of heart abnormality. The normal resting adult human heart rate ranges from 60–100 bpm (beats per minute) [9]. Bradycardia is a slow heart rate, defined as a resting heart rate below 60 bpm. Tachycardia is a fast heart rate, defined as above 100 bpm at rest [10].

4. Bandwidth of ECG Signal

Bandwidth of ECG signal is very important for accurate recording and processing of ECG signal. Normally, the frequency range of an ECG signal is of 0.05–100 Hz [3]. There are many application of detection of QRS-complex. QRS-complex is a vital portion of ECG signal. It is very important for clinical purpose such as diagnosis, defibrillation etc. Detection of QRS is complex because it vary man to man as well as there are various noise that affect the ECG signal such as power line interference, electrode pop or contact noise, baseline drift etc. The slope of R wave is an important feature to locate QRS-complex. The desirable passband to maximize the QRS-energy is approximately 5-15Hz [4].

5. NOISE SOURCE

The ECG signal is affected by various noise and artifacts. There are various sources of noise and artifacts. Some of them are-

- Power line interference
- Electrode contact noise
- Patient–electrode motion artifacts
- Electromyographic (EMG) noise
- Instrumentation noise generated by electronic devices.
- Baseline drift
- Data collecting device noise
- Electrosurgical noise etc.

6. Methodology

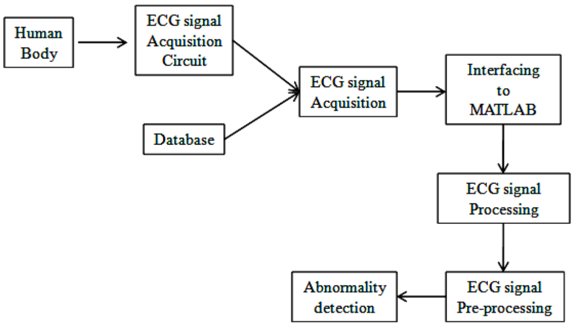

Fig. 2: Steps of total process

We divide the process in three steps.

1. Acquisition of ECG signal
2. Pre-processing
3. Abnormality detection

5.1 Acquisition of ECG signal

ECG signal can be achieve directly from human body or one can use database for this purposed. Here the MIT-BIH arrhythmia database is used for ECG signal.

5.2 Pre-Processing

In this step the ECG signal is de-noised. Here we used butterworth filter of order 3 with cut-off frequency 0.05Hz and 100Hz. Here we also eliminate the DC offset voltage and remove the power line noise. After that we use band pass filter of 5-15 Hz for detecting the QRS-complex.

5.2.1 Pan-tomkins method

We need to detect the QRS-complex in the ECG signal to calculate the Heart Rate (HR). We detect the QRS-complex by Pan-Tompkins algorithm [12-13]. Pan-Tompkins provides a real-time QRS detection algorithm based on slope, amplitude and width of the QRS complexes. Fig. 3 shows the steps of Pan-Tompkins algorithm.

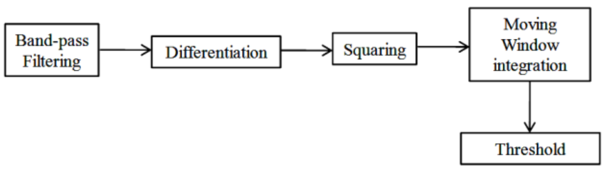

Fig. 3: Sequence of Pan-tomkins method

Step I: Band-pass filtering

It reduces the effect of muscle noise, 50/60Hz noise, baseline wander, T-wave interference. The desirable pass-band to maximize the energy of QRS-complex is approximately 5-15Hz. The filter implemented in this algorithm is composed of cascaded high pass and low-pass Butterworth filters [12].

Low-pass Filter

$$H(z) = \frac{(1-z^{-6})^2}{(1-z^{-1})^2} \ldots\ldots\ldots (1)$$

High-pass filter

$$H(z) = \frac{-1+32z^{-16}+z^{-32}}{1+z^{-1}} \text{.........} \quad (2)$$

Step II: Differentiation

After filtering the signal is differentiated for QRS-complex slop information. The derivative procedure suppresses the low frequency components of P and T waves, and provides a large gain to the high-frequency components arising from the high slopes of the QRS Complex [14].

Derivative filter

$$H(z) = (1/8T)(-z^{-2} - 2z^{-1} + 2z + z^{2}) \text{........} \quad (3)$$

Step III: Squaring

After the differentiation the signal is squared point by point. The squaring operation makes the result positive and emphasizes large differences resulting from QRS complexes; the small differences arising from P and T waves are suppressed. The high frequency components in the signal related to the QRS complex are further enhanced. This is a nonlinear transformation that consists of point by point squaring of the signal samples [14].

$$y(n) = x(n)^2 \text{.........} \quad (4)$$

Step IV: Moving window integration

The squared waveform passes through a moving window integrator. This integrator sums the area under the squared waveform over a suitable interval, advances one sample interval, and integrates the new predefined interval window [14].

Moving average filter

$$Y(nT)=\frac{1}{N}[x(nT-(N-1)T)+x(nT-(N-2)T)+....+x(nT)]......(5)$$

Step V: Adaptive Thresholds

Adaptive thresholds discriminate the location of the QRS-complex. After adaptive thresholds we will get stream of pulses making the location of QRS-complexes [12].

5.3 Abnormality Detection

We know,

$$HR = \frac{60}{RR}\, bpm\text{.........} \quad (6)$$

Here, HR=heart rate.

RR=interval between R wave.

So, heart condition is-

Normal for $60 \leq HR \leq 100$

Abnormal for $HR \leq 60$ or $HR \geq 100$

Again if abnormal, it is-

Bradycardia for $HR \leq 60$

Tachycardia for $HR \geq 100$

6. RESULT

Sample 100m: HR is 74.42 and normal

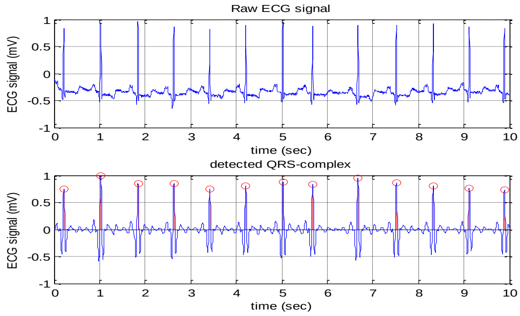

Fig. 4: Raw ECG signal and QRS-complex

Here fig. 4 shows the raw ECG signal as well as the detected QRS-complex. And fig. 5 shows whether the heart is in normal or abnormal condition.

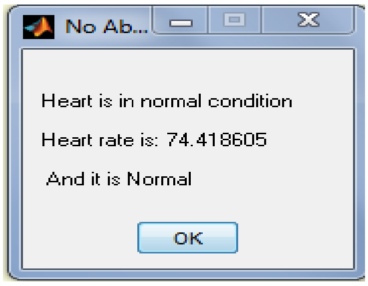

Fig. 5: Heart rate and abnormality

Sample 123m: HR is 47.41 and bradycardia (abnormal)

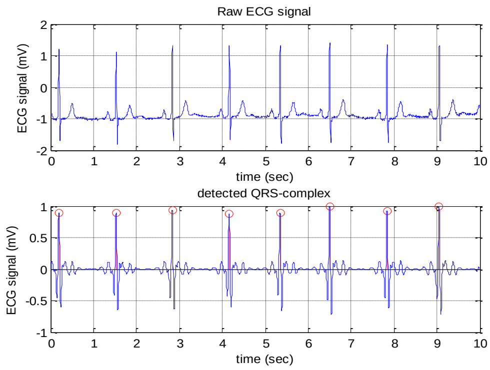

Fig. 6: Raw ECG signal

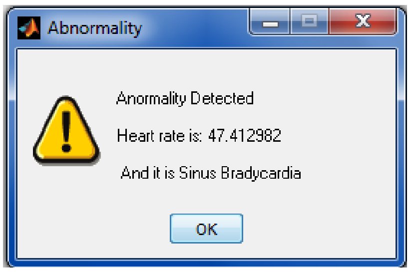

Fig. 7: Heart rate and abnormality

Sample 215m: HR is 112.12 and tachycardia (abnormal)

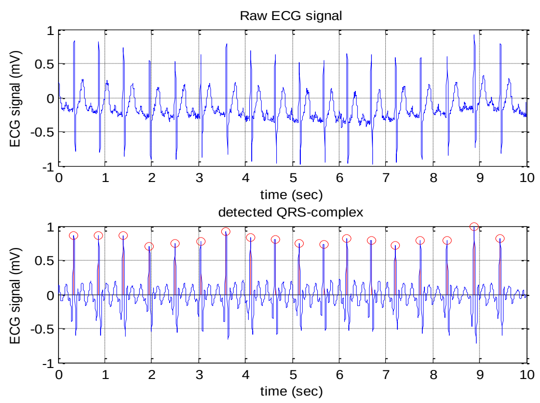

Fig. 8: Raw ECG signal

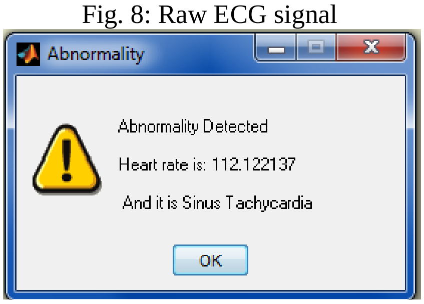

Fig. 9: Heart rate and abnormality

Table 1 shows the result of the entire samples that are collected from MIT-BIH arrhythmia database.

Table 1: Result of the samples from MIT-BIH arrhythmia database

Sample	HR(bpm)	Sample	HR(bpm)
100m	74.42	201m	84.81
101m	67.12	202m	53.32
102m	72.88	203m	115.54
103m	70.08	205m	89.87
104m	75.37	207m	59.11
105m	83.42	208m	96.09
106m	60.37	209m	94.50
107m	70.27	210m	95.10
108m	119.06	212m	90.67
109m	93.26	213m	110.84
111m	70.25	214m	74.79
112m	86.26	215m	112.12
113m	56.09	217m	71.12
114m	53.04	219m	82.10
115m	59.93	220m	71.72
116m	79.89	221m	78.43
117m	51.74	222m	75.35
118m	72.07	223m	80.00
119m	65.08	228m	73.29
121m	60.43	230m	81.94
122m	90.47	231m	60.02
123m	47.41	232m	58.70
124m	49.35	233m	98.88
200m	92.85	234m	90.87

6. CONCLUTION

This work will contribute to design and implement a reliable heart abnormality detection system. Here reliable computerized classifier is designed which will detect heart abnormalities. We tried to make the system more reliable with portability. In summary we completed this work in three stages. Firstly MIT-BIH database is used as ECG signal source, then the signal is processed to de-noise it and finally we detect the heart abnormality.

8. ACKNOWLEDGEMENT

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8. NOMENCLATURE

Symbol	Meaning	Unit
bpm	Beats Per Minute	
DC	Direct Current	Amp.
ECG	Electrocardiography	
EMG	Electromyography	
HR	Heart Rate	bpm
RR	Interval Between R Wave	Second