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Cardiac Disease Detection Using Modified Pan—Tompkins Algorithm

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Abstract

The analysis of electrocardiogram (ECG) signals facilitates the detection of various abnormal conditions of the human heart. The QRS complex is the most critical part of the ECG waveform. Further, different diseases can be identified based on the QRS complex. In this paper, a new algorithm based on the well-known Pan–Tompkins algorithm has been proposed. In the proposed scheme, the QRS complex is initially extracted by removing the background noise. Subsequently, the R–R interval and heart rate are calculated to detect whether the ECG is normal or has some abnormalities such as tachycardia and bradycardia. The accuracy of the proposed algorithm is found to be almost the same as the Pan–Tompkins algorithm and increases the R peak detection processing speed. For this work, samples are used from the MIT-BIH Arrhythmia Database, and the simulation is carried out using MATLAB 2016a.

Keywords: ECG signal, QRS complex, R-R interval, Heart rate, Tachycardia, Bradycardia

1. INTRODUCTION

Cardiac disease is one of the main causes of death and disability worldwide. The prevention of these deaths requires long-term monitoring and manual inspection of ECG signals, which is a time-consuming process. The prediction and diagnose of cardiac diseases such as tachycardia, bradycardia, atrioventricular block (AVB), and right bundle branch block (RBBB) through electrocardiogram (ECG) plays a major role in the field of medical science and biomedical engineering [1]. Consequently, a wearable system that can automatically categorize beats is essential.

An ideal ECG signal indicates the P wave, QRS complex (a group of waves in the electrocardiogram), and sometimes the T wave, as shown in Figure 1. The descriptions of wave functionalities are given in Table 1.

In ECG, the electrical activity of the heart is measured using the potential difference between different leads placed on the body. A typical healthy ECG heartbeat can be seen in Figure 1. An ECG beat consists of four typical complexes: P, QRS, T, and U. The U wave cannot be distinguished most of the time; hence, it is generally not illustrated. The P wave indicates the contraction of the atrial rooms of the heart, the QRS complex shows the contraction of the ventricular rooms, and the T wave represents the relaxation of the ventricular rooms. The shape and size of these waves vary

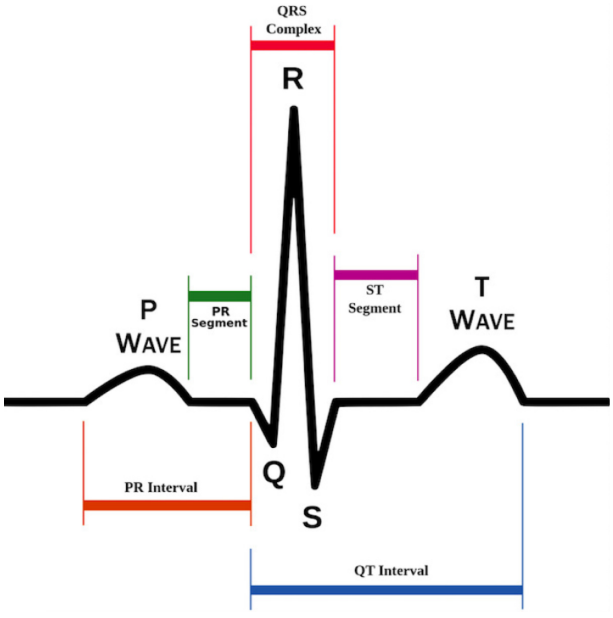

Fig. 1. ECG of a single heartbeat in normal sinus rhythm

Table 1. Functionalities of different waves.

P wave	Atrial Depolarization
QRS complex	Ventricular Depolarization
T wave	Ventricular Repolarization

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depending on the lead from which the signal is being observed.

Many QRS detection algorithms have been introduced, including those based on traditional techniques such as mathematical morphology and the Hilbert transform [2]. In most QRS detection algorithms, there are two stages: pre-processing and decision, which consist of several sub-stages. In the pre-processing stage, different techniques are applied to the signal, such as linear and nonlinear filtering, and smoothing. In the decision stage, the most important task is the determination of thresholds. The Pan–Tompkins QRS detection algorithm [3], which has been used extensively in previous research, uses the latest techniques that can quickly adapt to the signal changes and obtain good QRS detection even in noisy signals [4]. This paper focuses on modifying the Pan–Tompkins algorithm, in which some processing steps are excluded to increase the R-peak detection processing speed.

The remaining parts of this paper is organized as follows: The proposed algorithm for the R-peak detection is described in Section 2. Simulation results are discussed in Section 3. Finally, conclusion and references are provided in Sections 4 and 5, respectively.

2. Proposed Algorithm

The schematic flow of the proposed R-peak detection algorithm is shown in Figure 2. The whole process is divided into four main stages: (1) filtering, (2) derivative, (3) squaring, and (4) peak detection. After the detection of R peak, the R-R interval between two consecutive points is calculated, and the heart rate is obtained. Based on these two parameters, the system can detect the normal and diseased (tachycardia, bradycardia) ECG signals.

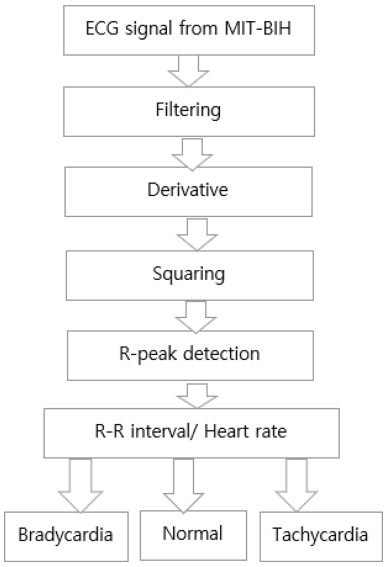

Fig. 2. Proposed R-peak detection algorithm

2.1 Filtering

The raw input ECG signal, as shown in Figure 3, is initially preprocessed using a band-pass filter to reduce the influence of different types of noises such as the baseline wander and muscle noise. In this work, low and high band-pass filters are cascaded to form a band-pass filter that can automatically remove both high and low frequency noises.

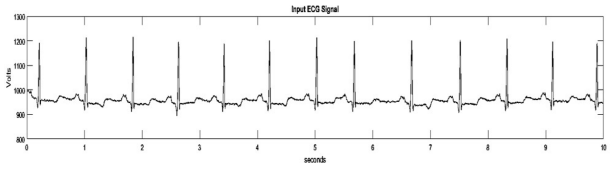

Fig. 3. Raw input ECG signal

2.2 Derivative

To acquire the slope of the QRS complex, the noise-free signal is made to pass through differentiation, as shown in Figure 4. This mainly suppresses the low frequency components of P and T waves, and provides a large gain to high-frequency components arising from the high slopes of the QRS complex.

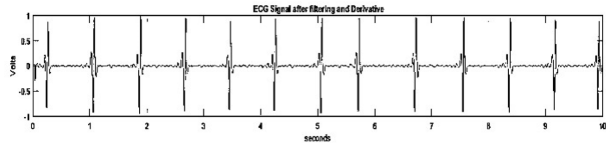

Fig. 4. ECG signal after filtering and derivative

2.3 Squaring

As shown in Figure 5, after derivative the output signal is squared sequentially. Consequently, all data points become positive, and the derivative output is amplified nonlinearly. This shows the higher frequencies in the signal, which are mainly due to the QRS complex.

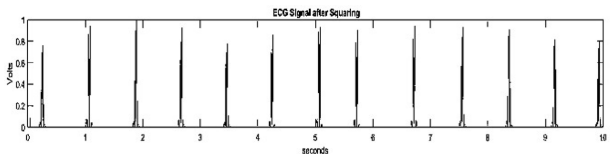

Fig. 5. ECG signal after squaring

2.4 Peak detection

The common necessity for signal processing is to identify specific peaks in a signal and determine their characteristics. A peak is determined when a signal changes direction within a certain time interval [6][7]. After all preprocessing steps, this algorithm can robustly detect R peaks, as shown in Figure 6.

In the following sections, the R-R interval and heart rate, which are the essential parameters used to differentiate a diseased ECG signal as either tachycardia (heart rate above normal) or bradycardia (heart rate below normal), are described. Figure 7 shows the pseudo code used in the proposed algorithm for disease detection.

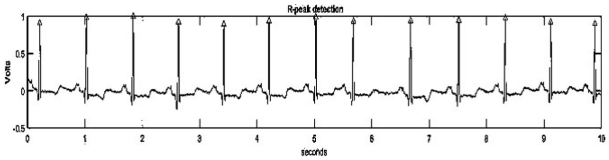

Fig. 6. ECG signal after R-peak detection

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Pseudo code for disease detection
if (heartrate > 60 & heartrate< 90)
disp ("Healthy person")
end
if (heartrate<60 )
disp("Person is suffering from Bradycardia")
elseif(heartrate>90)
disp("Person is suffering from Tachycardia")
end
```

Fig. 7. Pseudo code for disease detection

2.4.1 R-R interval

The R peak is the longest peak in the ECG signal. It can be calculated by dividing the number of samples between two R peaks and sampling frequency of the signal [5]. It also plays a vital role in identifying the abnormalities of a given signal. In the of abnormal ECG signals, the R-R interval in consecutive R peaks changes significantly. The normal R-R interval time period ranges from 0.6–1.2 s.

This paper describes the major role of the R-R interval in detecting diseases.

2.4.2 Heart rate

Once the R-R interval has been calculated, the heart rate is easy to calculate. The formula for calculating the heart rate is shown in equation 1.

$$\text{Heart rate} = 60/\text{R-R interval in seconds} \quad (1)$$

Based on the value of the heart rate, it is possible to distinguish whether an ECG signal is normal or has some abnormalities.

3. Simulation Results

The simulations are performed both for the existing Pan–Tompkins algorithm and the proposed algorithm. The results are explored using MATLAB 2016a.

The proposed algorithm, based on the Pan–Tompkins algorithm, was applied to the ECG records of the Massachusetts Institute of Technology-Beth Israel Hospital (MIT-BIH) Arrhythmia Database. Table 2 provides brief information about the sample ECG signals and the cardiac diseases that were detected.

Table 2. Conditions for heart abnormalities.

Serial No.	Heart Abnormalities	Conditions
1	Tachycardia	Heart rate>90
2	Bradycardia	Heart rate<60

The performances of the Pan–Tompkins algorithm and the proposed algorithm for the disease detection can be analyzed using Tables 3 and 4, respectively.

The detection accuracy of the proposed algorithm was as good as the Pan–Tompkins algorithm. The results of disease detection are shown in Figure 8, 9, and 10. From the results of the detection of the heart rate, it was confirmed that the heart rate was extracted without a large error. The accuracy of the proposed algorithm is almost same as the Pan–Tompkins algorithm and increases the R-peak detection processing speed.

Table 3. Performance of the existing Pan—Tompkins algorithm for disease detection.

Patient id	Age /Gender	R-R Interval	Heartrate	Detection	Accuracy
100	69/M	0.80	74	Normal	95%
103	84/F	0.83	72	Normal	95%
105	73/F	0.71	85	Normal	90%
106	24/F	0.90	66	Normal	95%
212	32/F	0.6	91	Tachycardia	95%
215	81/M	0.56	106	Tachycardia	90%
119	51/F	1.1	54	Bradycardia	80%
213	61/M	0.62	97	Tachycardia	80%

Table 4. Performance of the proposed algorithm for disease detection.

Patient id	Age /Gender	R-R Interval	Heartrate	Detection	Accuracy
100	69/M	0.80	74	Normal	95%
103	84/F	0.85	70	Normal	90%
105	73/F	0.71	83	Normal	90%
106	24/F	0.99	60	Normal	90%
212	32/F	0.6	91	Tachycardia	95%
215	81/M	0.5	106	Tachycardia	90%
119	51/F	1.03	58	Bradycardia	80%
213	61/M	0.6	100	Tachycardia	85%

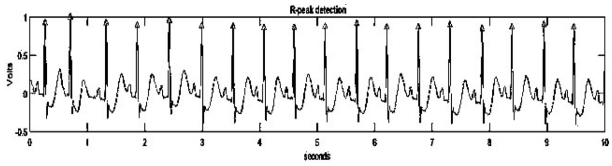

Fig. 8. Tachycardia detected from the patient ID 213 in 2.55 s.

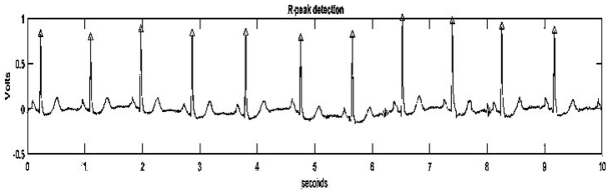

Fig. 9. Normal ECG signal from patient ID 101.

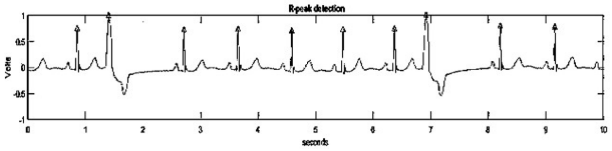

Fig. 10. Bradycardia detected in test signal 119 in 8.93 s.

4. CONCLUSIONS

The proposed algorithm demonstrated 90% accuracy in the detection of two types of diseases among eight ECG data samples. It successfully distinguished tachycardia and bradycardia from the given records. This work was based on certain parameters such as the R-R interval and the heart rate of the ECG signal for disease detection. For future work, more parameters will be added to detect abnormal signals. Further, the focus will be on developing an efficient and robust P and T wave detection algorithm to detect severe diseases (such as myocardial infraction and atrial fibrillation) with better accuracy.

REFERENCES

[1] E. Haque, F. Ahmed, “ECG Signal Based Heart Disease Detection System for Telemedicine Application1”, 1st Int’l Conference on Advanced Information and Communication Technology, pp. 1-4, May 2016.

[2] L. Sathyapriya, L. Murali, T. manigandan, “Analysis and detection R-peak detection using Modified Pan-Tompkins algorithm,” 2014 IEEE International Conference on Advanced Communications, Control and Computing Technologies, pp. 483-487, May 2014.

[3] J. Pan and W. J. Tompkins, “A real-time QRS detection algorithm”, IEEE Transactions on Biomedical Engineering, Vol. BME-32, No.3, pp. 230-236, March 1985

[4] Raul Alonso Alvarez, “A comparison of three QRS detection algorithms over a public database”, Procedia Technology, pp. 1159-1165, September 2013.

[5] P. Tirumala Rao, S. Koteswarao Rao, G. Manikanta and S. Ravi Kumar, “Distinguishing Normal and Abnormal ECG Signal”, Indian Journal of Science and Technology, Vol. 9, No. 10, pp. 1-5, March 2016.

[6] Y. Ferdi, J. P. Herbeuval, A. Charef, B. Boucheham, “R wave detection using fractional digital differentiation”, ITBM-RBM, Vol. l.24, pp.273-280, December 2003

[7] C. Mani and M. Singh, “Detection and Analysis of Heart Rate during Arrhythmia”, Journal of Biological Engineering Research and Review, pp. 14-19, September 2017