

International Journal of Computational Vision and Robotics

ISSN online: 1752-914X - ISSN print: 1752-9131

<https://www.inderscience.com/ijcwr>

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DOI: [10.1504/IJCVR.2025.10067737](https://doi.org/10.1504/IJCVR.2025.10067737)

Article History:

Received:	01 November 2022
Last revised:	10 December 2022
Accepted:	15 March 2023
Published online:	02 December 2024

Detection of cardiac abnormalities in ECG signal using time-based signal processing algorithm

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Abstract: Electrocardiograms are bioelectrical signals that provide information regarding the normal and abnormal physiology of the heart. Early detection of cardiac irregularities in cardiac patients prevents strokes and sudden deaths. The effective functioning of the heart in each individual is dependent on the amplitude and interval values of the P-QRS-T segment. In this work, a modified Pan-Tompkins algorithm is used for identifying the characteristic points. Various signal characteristics, including R-R interval, T-amplitude, and QRS duration, were meticulously quantified and compared with NSR to

determine ECG cardiac problems. Further, different cardiac abnormalities such as atrial fibrillation (AF), right bundle branch block (RBBB), cardiac ischemia (CI), left bundle branch block (LBBB), bradycardia, and tachycardia are detected using the time and amplitude features of the ECG. The suggested method was evaluated on three major online Physionet ECG databases (the AFDB, NSR, and MIT-BIH Arrhythmia databases) to assess its generalisability.

Keywords: electrocardiogram; ECG; cardiac abnormalities; signal processing; bradycardia; tachycardia; atrial fibrillation; AF; left bundle branch block; LBBB; right bundle branch block; RBBB.

Reference to this paper should be made as follows: Patro, K.K., Prakash, A.J., Tummalapalli, G., Kumari, P.L. and Rao, M.J.M. (2025) 'Detection of cardiac abnormalities in ECG signal using time-based signal processing algorithm', *Int. J. Computational Vision and Robotics*, Vol. 15, No. 1, pp.59–74.

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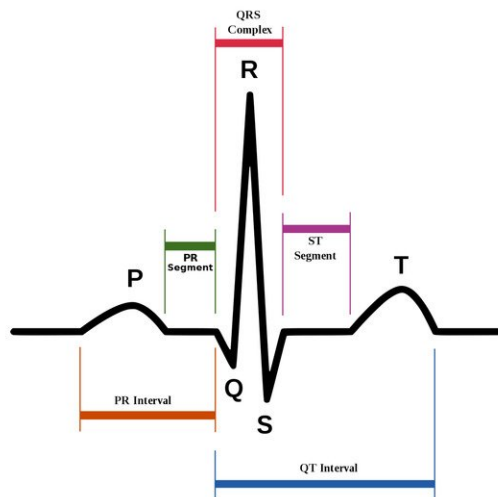
1 Introduction

The World Health Organization identifies cardiovascular disorders as the leading cause of death across the globe (<https://www.who.int/news-room/fact-sheets/detail/noncommunicable-diseases>). The majority of deaths from non-communicable diseases

(NCD), around 17.9 million individuals per year, are attributed to cardiovascular diseases (<https://www.who.int/news-room/fact-sheets/detail/noncommunicable-diseases>). So, in recent years, medical researchers have put a lot of effort into studying heart health. This has led to an increased emphasis on preventative, medical, and technological advancements. The electrocardiogram, often known as an ECG, is an extremely helpful diagnostic tool that assesses the electrical activity of the heart. It offers understanding of the many heartbeat stages and the numerous abnormalities that may influence them. ECG is a simple, cost-effective, and risk-free screening method for evaluating the current state of cardiac health (Aras et al., 2005). Long-term monitoring and the manual inspection of electrocardiogram data, both of which are time-consuming processes, are required in order to reduce the number of deaths caused by cardiovascular disease. Moreover, biomedical engineers and medical experts rely heavily on ECG readings for the diagnosis and prognosis of heart conditions such as normal sinus rhythm (NSR), atrial fibrillation (AF), right bundle branch block (RBBB) and left bundle branch block (LBBB) (Haque and Ahmed, 2016).

The electrical potential between several leads on the body is measured to generate an ECG. As depicted in Figure 1, the standard ECG wave consists of the P wave, QRS complex, ST segment, and T wave. The relationship between P waves and QRS complexes may assist in the identification of various heart abnormalities. In general, the P wave indicates that the atrial chambers of the heart are contracting, the QRS complex demonstrates that the ventricular chambers are contracting, and the T wave indicates that the ventricular chambers are relaxing. The shape and magnitude of these waves shift in response to the change in the position of the lead from which the signal is being monitored.

Figure 1 Typical ECG beat (see online version for colours)



An irregular heartbeat, also known as arrhythmia, can be caused by the heart beating too quickly, too slowly, too early, or in an uneven pattern. When the electrical signals to the heart that coordinate heartbeats are not functioning properly, arrhythmias occur. Many heart arrhythmias are harmless, but if they are very unusual or are caused by a weak or

damaged heart, they can cause serious and even life-threatening symptoms. Some of the most common heart problems are bradycardia, tachycardia, AF, RBBB, CI and LBBB. Bradycardia is characterised by a heart rate that is slower than normal. At rest, humans' hearts typically beat between 60 and 100 times per minute. When a person has bradycardia, their heart beats less than 60 times per minute. In case of tachycardia, it is considered as a common form of abnormal cardiac rhythm (arrhythmia) in which the heart beats quicker than usual at rest. It is common for an individual's heart rate to increase during physical activity or as a physiological response to stress or disease (sinus tachycardia). In tachycardia, however, the upper or lower chambers of the heart, or both, pulse faster than normal at rest. Both bradycardia and tachycardia are characterised by anomalies in the ECG signal. Table 1 shows the conditions of the heart abnormalities in ECG signal.

Table 1 Cardiac abnormalities in ECG signal

<i>S. no.</i>	<i>Heart abnormalities</i>	<i>Conditions</i>
1	Tachycardia	Heart rate > 100 BPM
2	Bradycardia	Heart rate < 60 BPM
3	AF	Irregular R-R intervals
4	RBBB	Greater S wave duration
5	CI	Inverted T wave

In ECG signal, detection of QRS complex is very much important for finding other signal parameters. Numerous QRS detection algorithms have been developed, including those based on conventional methods like mathematical morphology and the Hilbert transform (Sathyapriya et al., 2014). The majority of QRS detection algorithms are divided into two steps: the pre-processing stage and the decision stage, each of which is broken down into multiple smaller stages. During the preprocessing stage, the signal is subjected to a variety of processing methods, including smoothing, linear and nonlinear filtering, and linear filtering. When comes to making a decision, determining the appropriate thresholds is the most crucial responsibility. Real-time QRS complex detection from an ECG signal was presented by Pan and Tompkins (1985), in which the band is restricted to 50 Hz using an analogue filter, and the sampling frequency is set at 200 times per second. The processed signal is squared before being sent to a moving window integrator. Dual threshold approach is utilised to retrace lost beats. Adaptive threshold modification and RR interval change enhance the efficiency of QRS complex detection.

Fernandez et al. (2005) combined Pan-Tompkins (PT) and wavelet algorithms for QRS detection. QRS is recognised using filter threshold. In wavelet approach, ECG is split into discrete scale components. Primary scale is high-frequency noise and R peaks. Secondary scale includes low-frequency information and T-wave. R peaks are found by matching scale values and PT algorithm uses filter threshold to identify QRS. The QRS detection method relies on more complex digital filters reported in Wang et al. (2010) that is characterised by large amplitude and effectively detects R-wave in the time domain by employing the threshold technique of ECG signal with first or second order derivative. The filters function as notch filters, affecting the wave and causing data loss. In Chen et al. (2006), a real-time QRS complex detection approach that is based on the temporal Cross-correlation is described. The sophisticated QRS detection approach is

provided together with an implementation using a modified delay-coordinate mapping technique in Singh and Sunkaria (2011).

Rana and Kim (2019) used a modified version of the Pan-Tompkins algorithm in their study to detect heart diseases. For the simulation, samples from the MIT-BIH Arrhythmia Database were used. The QRS complex is originally extracted in the study that has been proposed by first eliminating the background noise. After that, the R-R interval and heart rate are calculated to determine if the electrocardiogram is normal or if it has certain anomalies like tachycardia and bradycardia. The authors came to the conclusion that the suggested approach found approximately the same results as the Pan-Tompkins algorithm and speed up the R-peak detection processing. In this research, a time-dependent signal processing approach was proposed, which proved successful in pinpointing the defining features. Furthermore, timing and amplitude aspects of ECG are used to detect a variety of cardiac disorders, including AF, RBBB, CI, LBBB, bradycardia and tachycardia.

At this time, several researchers have introduced various machine learning (Prakash et al., 2022) and deep learning approaches (Patro et al., 2022) for automatic classification of biomedical signals and image analysis for the purpose of disease diagnosis. In recent years, strategies including artificial intelligence and specific algorithms have been shown to be useful for detecting a variety of medical diseases, including ECG arrhythmias (Asif et al., 2022), breast cancer categorisation (Alhussan et al., 2021; Samee et al., 2022c), breast lesion diagnosis (Samee et al., 2022a), COVID-19 detections (Samee et al., 2022b), and many more. The Pan-Tompkins QRS detection algorithm (Pan and Tompkins, 1985), which has been utilised to a great extent in earlier studies, makes use of the most recent methodologies that are capable of rapidly adapting to the changes in the signal and obtaining good QRS recognition even in noisy signals (Álvarez et al., 2013). In order to accelerate the R-peak detection procedure, this work focuses on a modification of the Pan-Tompkins algorithm in which some processing steps are modified. The primary contributions of the work as follows:

- for accurate detection of QRS complex and other signal peaks, a modified time-based signal processing technique is suggested and tested
- various signal parameters, including R-R interval, T-amplitude, and QRS duration, were carefully calculated and compared with NSR in order to diagnose ECG cardiac abnormalities
- the proposed approach tested with significant online Physionet ECG databases including MIT-BIH Arrhythmia database, NSR database, and Atrial Fibrillation (AFDB) for generalisation capability of the proposed approach.

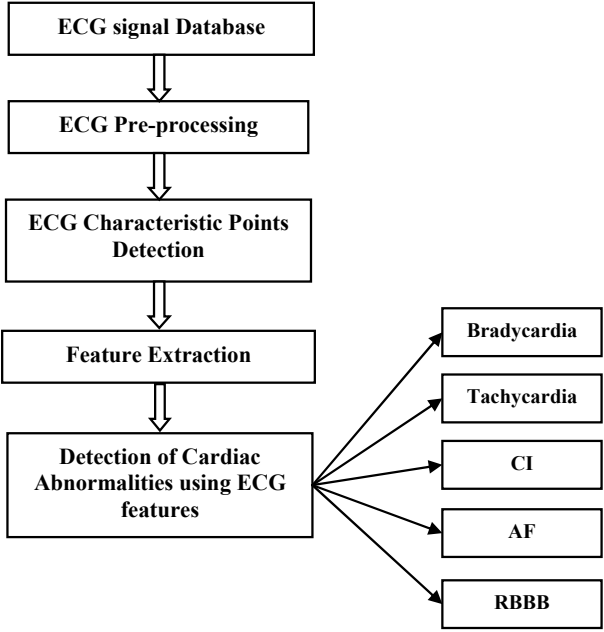
This paper's remaining sections are structured as follows: in Section 2, the materials and methods of the proposed algorithm for QRS detection is explained. In Section 3, experimental findings are discussed. Finally, the Section 4 concludes the paper with a conclusion.

2 Materials and methods

The proposed method for locating cardiac anomalies on an ECG concentrated primarily on the identification of the QRS complex as well as other peaks and durations. The

suggested technique includes a variety of stages, such as an ECG database, pre-processing, identification of characteristic points, feature extraction, and the detection of abnormalities, as shown in Figure 2.

Figure 2 Proposed methodology for cardiac abnormalities detection



2.1 ECG signal database

The ECG signals are obtained from the Physionet database (Goldberger et al., 2000), which is accessible online. This database has numerous records of the various biomedical signals with annotation files. The MIT-BIH Arrhythmia Database (Khalaf and Mohammed, 2021) was the first publicly accessible collection of standard test material for evaluating cardiac abnormalities, and it has been utilised for both that purpose and basic research into heart dynamics. In addition to this, NSR database (Sharma et al., 2012), and AFDB (Dash et al., 2009) were also acquired from Physionet for ECG signal processing.

2.2 Modified Pan-Tompkins algorithm

The time-based signal processing technique suggested for QRS detection shown in Figure 3 comprises of multiple phases, including filtering, derivation, squaring, average and threshold, peak identification, and QRS detection.

The purpose of the pre-processing of an ECG signal is to eliminate unnecessary noise. As a result of various electrical interferences or noises, such as power-line interference, baseline wandering, and electromyography, the acquired database signals get distorted after being collected (Patro and Kumar, 2015). In this preprocessing method, a band pass filter is employed to eliminate both high frequency and low frequency noise. The band

pass filter with lower cutoff frequency 5 Hz and upper cutoff frequency 40Hz is designed since power line interference has the frequency at 50 Hz, this can also be removed using the above band pass filter. Figure 4 represents the typical ECG signal for a normal sinus rhythm. ECG signals are obtained from NSR signals database in physionet.org with a record number 16265. The signals are exported in .mat format from Physionet organisation. In the figures X-axis represents the number of samples and the Y-axis represents the amplitude of the ECG signal and amplitude is taken in millivolts.

Figure 3 Modified Pan-Tompkins algorithm

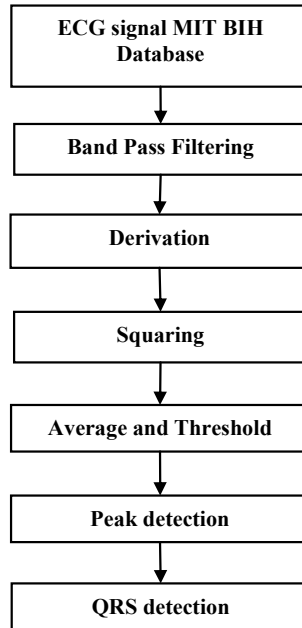


Figure 5 depicts the electrocardiogram (ECG) signal that was obtained by applying a band pass filter on the NSR signal in order to suppress the numerous noises that can have an effect on the ECG.

The typical method for locating high slopes is known as the 'derivation' method. This method also determines the direction in which the slope of the signal is moving and differentiates QRS complexes from other ECG waves. Figure 6 depicts the ECG signal obtained by applying the derivative procedure to the NSR signal with record number 16265.

The signal values are changed so that they are positive after being squared, and the output of the stage before it is amplified. It lowers the amplitude of the P and T waves while raising the frequency of the higher frequency components of the QRS complex. The ECG signal produced by applying the squaring approach to the NSR signal with record number 16265 is depicted in Figure 7.

Figure 4 ECG signal obtained from MIT-BIH ECG Database NSR signal (Record no. 16265) (see online version for colours)

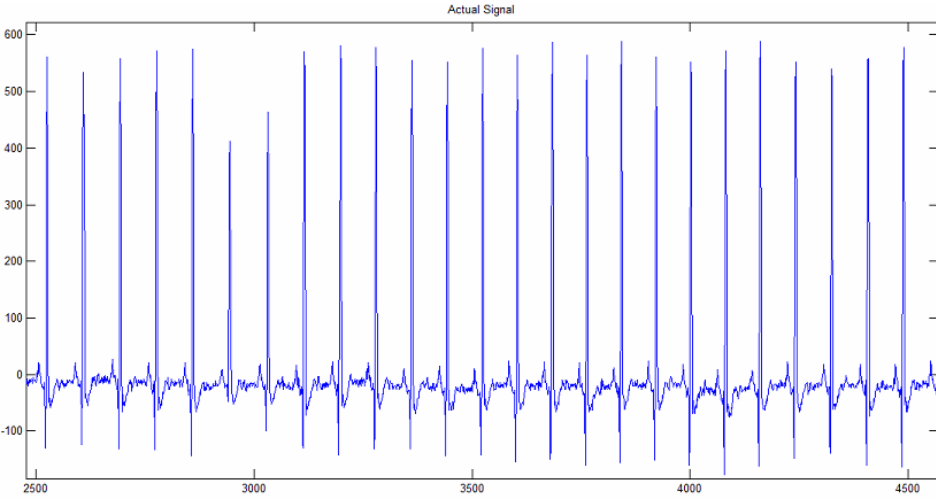


Figure 5 Result after band pass filtration of ECG signal (Record no. NSR 16265) (see online version for colours)

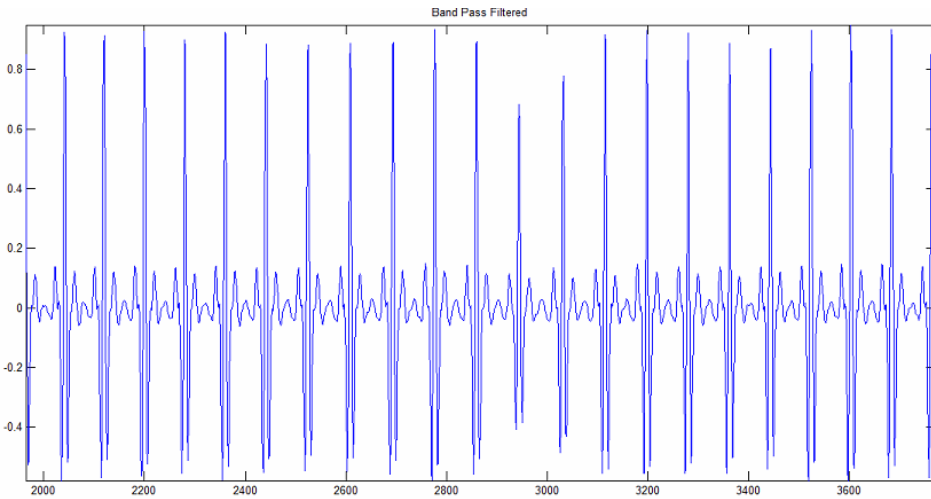
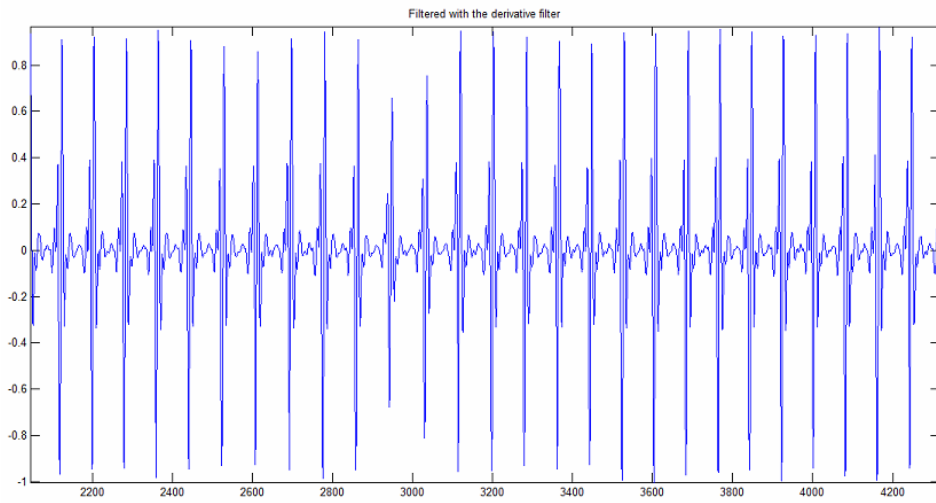
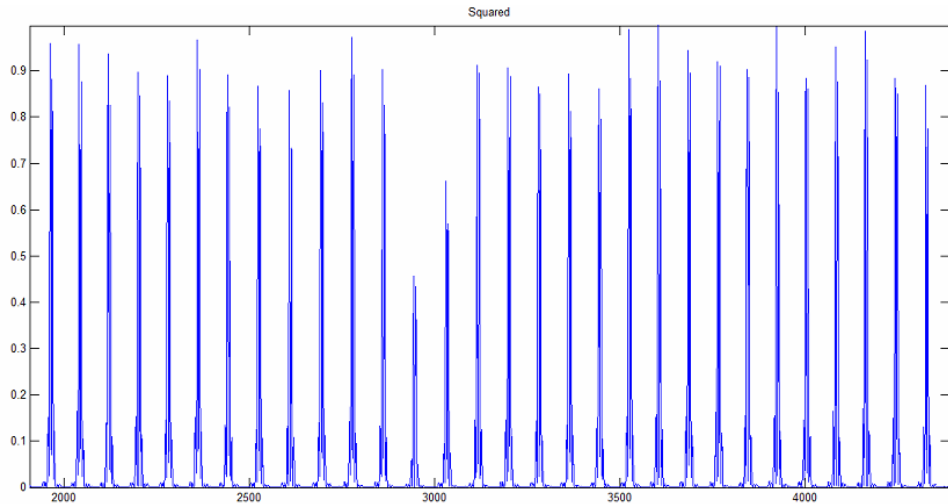


Figure 8 illustrates the ECG signal that was acquired by applying the moving integration procedure to the NSR signal at record number 16265. The performance of this process results in the creation of windows that can be used to locate the distinctive points in the ECG signal.

Figure 6 ECG signal (NSR) after derivation (see online version for colours)**Figure 7** ECG signal (NSR) after squaring technique (see online version for colours)

The width of the integration's moving-window is crucial. Typically, the width of the window should be comparable to the largest conceivable QRS complex. Since the number of samples in the width of the QRS complex is dependent on the sampling frequency and the width of the broadest QRS complex will always be less than 150 ms, N is taken as a function of sampling frequency that meets the 150 ms width requirement. By performing averaging and thresholding to the obtained signal from previous step we can depict the R peak and R-R interval from which heart-rate can be calculated. Figure 9 depicts R peaks detected in actual ECG signal by using Pan-Tompkins algorithm.

Figure 8 ECG signal (NSR) after moving window integration (see online version for colours)

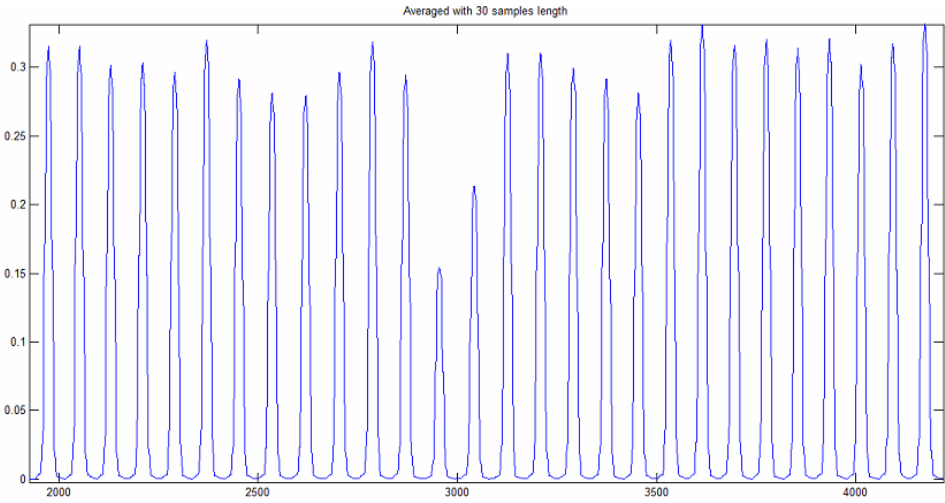
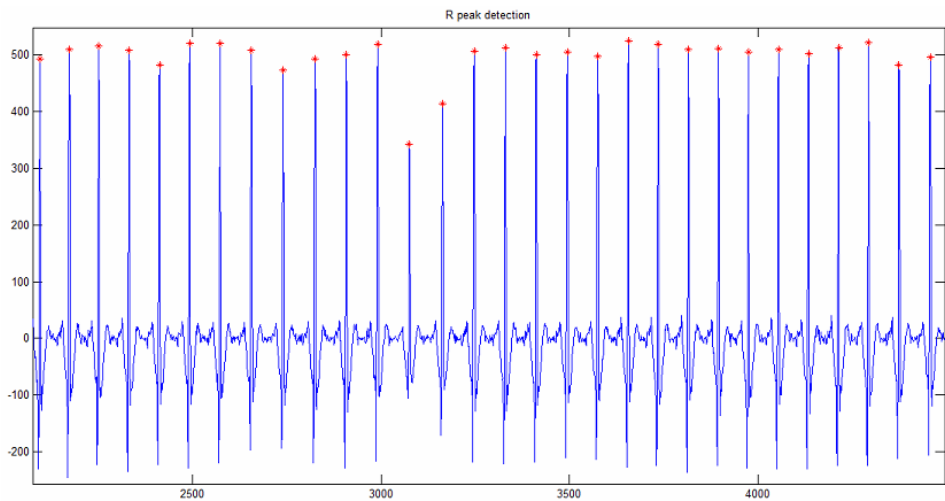
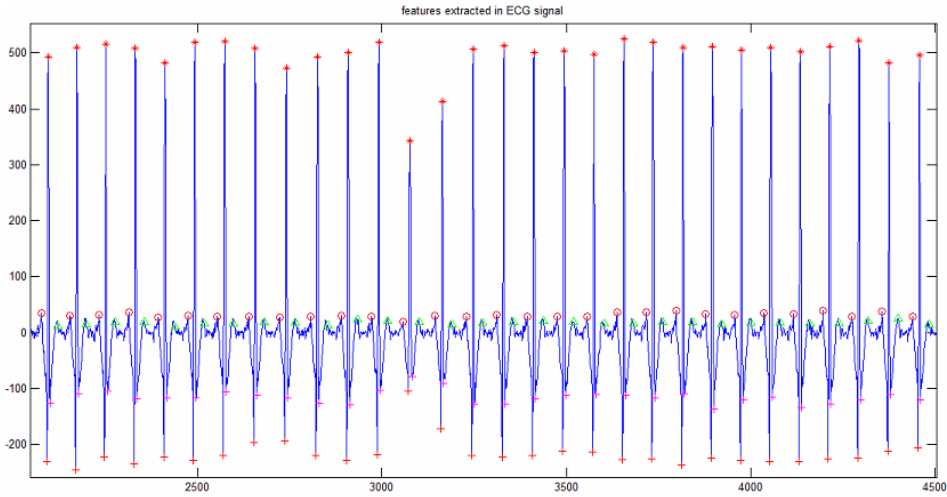


Figure 9 R peak detection using Pan-Tompkins algorithm (see online version for colours)



By using R peak as reference the other characteristic points are detected and in the Fig.10 the characteristic points are marked with different symbols such as R peak with star '*' in red, P peak with a circle 'o' in red, T peak with a triangle '^' in green, Q and S peaks are marked with plus signs '+' in red and magenta respectively.

Figure 10 ECG signal with the extracted features using the Pan-Tompkins's algorithm (NSR) (see online version for colours)



3 Experimental results

The time-based signal processing technique was tested using the Physionet database. In this work, five cardiac abnormal cases such as bradycardia, tachycardia, AF, CI, RBBB were tested along with NSR database (128 Hz sampling frequency). The database of ECG signals with AF, sampled at 250 Hz, the CI and RBBB person database (Arrhythmia database) signals also obtained with sampling frequency of 360 Hz. All the records are collected and stored in .mat format. These files are read from MATLAB software and further processing of ECG signal is done in MATLAB 2021a. After application of the modified Pan-Tompkins algorithm (Section 2) all the abnormal characteristic features of the ECG signal were calculated. Figure 11 depicts the output of the characteristic wave identification for AF person for record number 'afdb04647.m'. The irregularity of the R peaks can be seen in the illustration. Due to the fact that the QRS complex indicates the synchronisation between the atria and ventricles, the irregularity of the R peak represents the irregular excitations that occur during atrial fibrillation.

Figure 12 depicts the output of the characteristic wave identification for the CI individual with the record number 'stdb305m' (Aras et al., 2005). The inverted T wave indicates ischemia in the ventricles in this figure. Due to the fact that the area of ischemia in the heart does not propagate the electrical pulses, the T wave is inverted as a result. The result of the characteristic wave identification for RBBB person with record number 'rbbdb118' is illustrated in Figure 13. In addition to having a QRS complex with a longer duration than a normal ECG, it has a characteristic S wave of longer duration than the R wave. After using the time-based signal processing technique, the heart rate can be estimated based on the R-R interval in order to detect abnormalities such as bradycardia and tachycardia for five different databases reported in Table 2.

Figure 11 Result for AF person (record no. afdb04647m) (see online version for colours)

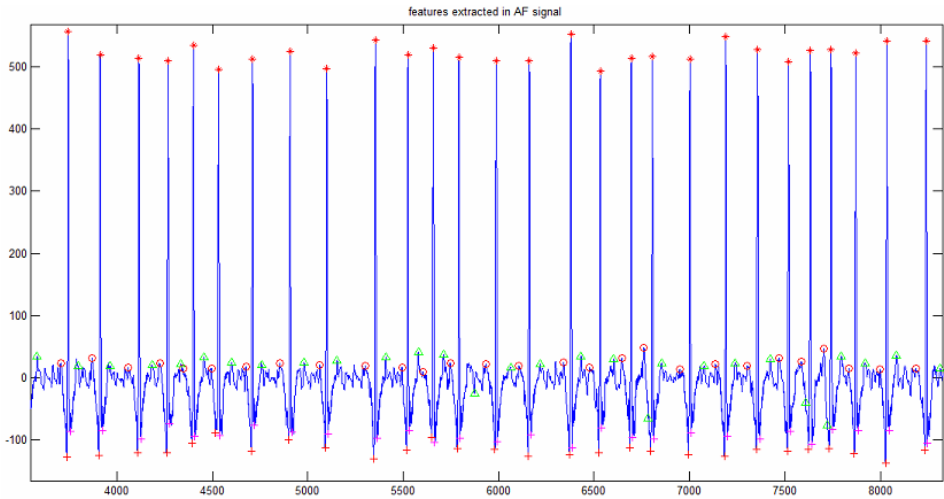


Figure 12 Result for person having cardiac ischemia (record no. 305) (see online version for colours)

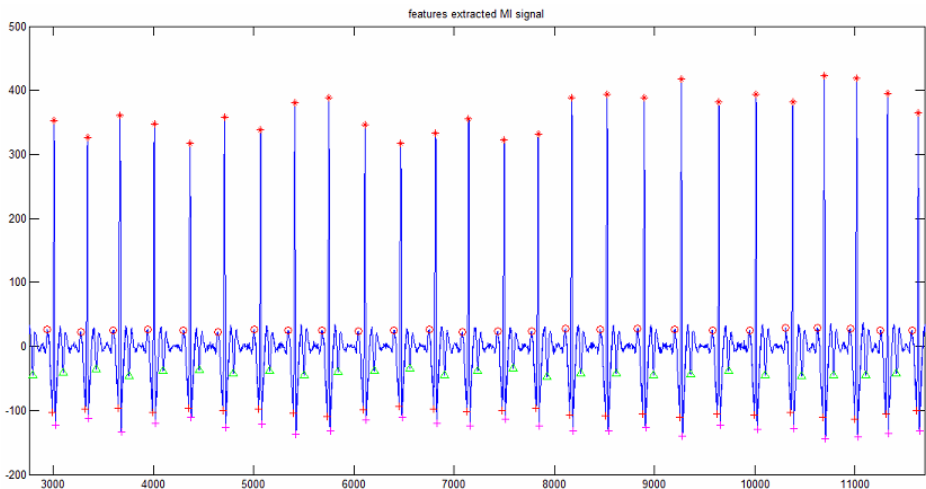
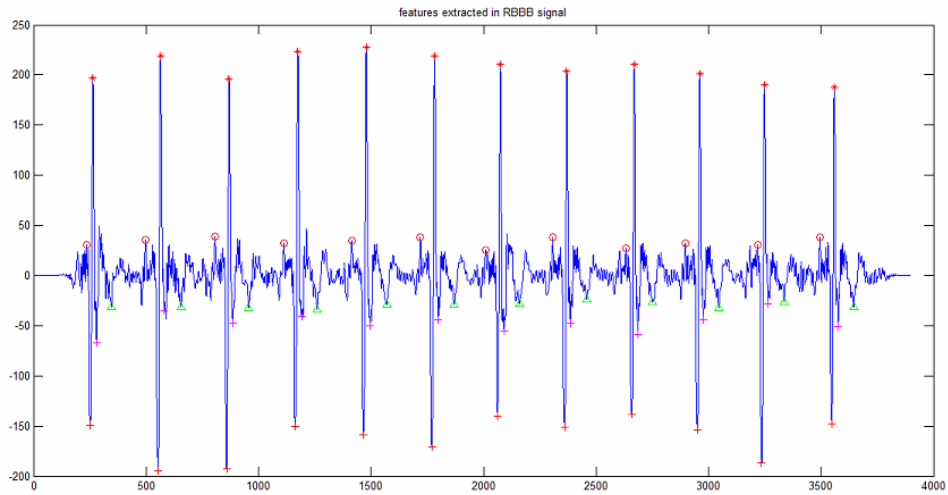


Table 3 illustrates the typical values of a NSR signal, also known as the typical ECG readings. The abnormality or arrhythmia can be diagnosed by comparing the standard values to the affected person's ECG data and then determining the deviations in specific values. In Table 4, the ECG feature values for a person who is affected by atrial fibrillation are listed. After clear examination of comparing these values with standard normal values in Table 3, we may determine where the signal deviates from normal. It is evident from a comparison of the data in Tables 3 and 4 that the R-R interval differs in each situation. This leads us to the conclusion that someone with atrial fibrillation will have irregular R-R intervals.

Figure 13 Result for person RBBB (record no. 118) (see online version for colours)**Table 2** Heart rates for different ECG records

Database	Record no.	R-R interval (mean) (sec)	Heart rate (60/R-R)	Detection
NSR	16265.m	0.8214	73	NORMAL
	18184.m	0.8034	75	NORMAL
	16272.m	1.0230	58	BRADYCATRDIA
AF	04647.m	0.3030	198	TACHYCARDIA
	04048.m	1.1342	52	BRADYCARDIA
	04126.m	0.2250	266	TACHYCARDIA
Arrhythmia	118.m	1.306	45	BRADYCARDIA
	124.m	0.6104	98	NORMAL
	125.m	0.9239	64	NORMAL
CI	302.m	0.8423	71	NORMAL
	305.m	0.6120	98	NORMAL
	304.m	1.1258	53	BRADYCARDIA

Table 3 Features for normal sinus rhythm (NSR)

S. no.	Record	T amp (mean) (mV)	T amp (S.D)	R-R interval (mean) (sec)	R-R interval (S.D)	QRS du (mean) (sec)	QRS du (S.D)	Detection
1	16265.m	0.1269	0.02058	0.8214	0.6183	0.07969	0.01665	NSR
2	18184.m	0.24304	0.02957	0.8034	0.8902	0.09722	0.00416	NSR
3	16272.m	0.61766	0.06294	1.0230	1.3198	0.06031	0.00922	NSR
4	19090.m	0.1100	0.14296	0.7842	0.71732	0.0733	0.01235	NSR
5	18184.m	0.24304	0.02957	0.9682	0.9809	0.09722	0.00416	NSR

Table 4 Features for atrial fibrillation (AF)

<i>S. no.</i>	<i>Record</i>	<i>T amp (mean) (mV)</i>	<i>T amp (S.D)</i>	<i>R-R interval (mean) (sec)</i>	<i>R-R interval (S.D)</i>	<i>QRS du (mean) (sec)</i>	<i>QRS du (S.D)</i>	<i>Detection</i>
1	04647.m	0.2726	0.44564	0.3030	0.20425	0.0902	0.03098	AF
2	04048.m	0.2565	0.23077	1.1342	0.18285	0.12707	0.04092	AF
3	04126.m	0.0615	0.04017	0.2250	0.3942	0.14554	0.04324	AF
4	04908.m	0.0371	0.15505	0.3101	0.22593	0.12193	0.02662	AF
5	04936.m	0.2253	0.01899	0.2864	0.02569	0.148	0.03816	AF

The ECG values for a patient with RBBB are listed in Table 5. By comparing these feature values to normal typical features (NSR), we may determine where the signal deviates from the normal signal (NSR). Comparing the values in Tables 3 and 5, it is evident that the QRS complex interval in each instance differs. From this, it can be extrapolated that a patient with right bundle branch block will have irregular QRS complexes, with the S-peak lasting longer than the R-peak.

Table 5 Features for right bundle branch block (RBBB)

<i>S. no.</i>	<i>Record</i>	<i>T amp (mean) (mV)</i>	<i>T amp (S.D)</i>	<i>R-R interval (mean) (sec)</i>	<i>R-R interval (S.D)</i>	<i>QRS du (mean) (sec)</i>	<i>QRS du (S.D)</i>	<i>Detection</i>
1	118.m	0.2801	0.6411	1.306	0.0275	0.13889	0.02838	RBBB
2	124.m	0.5401	0.14513	0.6104	0.1264	0.10625	0.01786	RBBB
3	125.m	0.2677	0.01395	0.9239	0.4590	0.08472	0.0042	RBBB
4	212.m	0.3571	0.10945	1.2034	0.5335	0.15667	0.0175	RBBB
5	231.m	0.3684	0.06894	1.1065	0.4534	0.07361	0.01934	RBBB

The ECG readings for a person with cardiac ischemia are shown in Table 6, and by comparing these values to normal typical values, we may determine where the signal deviates. When comparing the feature values from Tables 6 and 3, it is obvious that the T wave's amplitude differs in each situation. Therefore, it follows that a person suffering from cardiac ischemia will have an inverted T wave.

Table 6 Features for cardiac ischemia (CI)

<i>S. no.</i>	<i>Record</i>	<i>T amp (mean) (mV)</i>	<i>T amp (S.D)</i>	<i>R-R interval (mean) (sec)</i>	<i>R-R interval (S.D)</i>	<i>QRS du (mean) (sec)</i>	<i>QRS du (S.D)</i>	<i>Detection</i>
1	302.m	-0.0499	0.10000	0.8423	0.02498	0.06288	0.00814	CI
2	305.m	-0.4186	0.03765	0.6120	0.05118	0.08919	0.01093	CI
3	304.m	-0.8293	0.13587	1.1258	0.11984	0.06183	0.01293	CI
4	324.m	-0.4003	0.02812	0.6842	0.04453	0.04943	0.00154	CI
5	325.m	-0.4186	0.03765	0.5984	0.05118	0.08919	0.01093	CI

In this study, the suggested time-based signal processing algorithm functioned effectively for a variety of cardiac disorders, including bradycardia, tachycardia, AF, congestive heart failure, and RBBB. Nonetheless, random noise impairs the performance of the suggested approach. In this algorithm, some R-peaks with a low level below the threshold may be ignored. In the future, authors will work more prominently and with the assistance of artificial intelligence-based techniques to overcome all constraints.

4 Conclusions

In this work, a time-based signal processing approach is suggested to determine the ECG cardiac cycle's P, Q, R, S, and T characteristic points. To determine the heart rate, the intervals between R-R samples, are utilised. ECG signals can be categorised as normal (if heart rate is between 60 and 100 beats per minute), bradycardia (if heart rate is less than 60 BPM), or tachycardia (if heart rate is greater than 100 BPM) based on the heart rate. This work is primarily concerned with determining ECG signal features such as R-R interval, T wave amplitude, and QRS duration in order to detect significant cardiac abnormalities. Different ECG signals, including NSR, AF, CI, and RBBB, from the Physionet online database were chosen for testing, and the MATLAB 2021a software is used to assess the findings. More parameters for automated classification of ECG cardiac anomalies will be introduced in the future.

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