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Research Article

Temporal HRV Feature Extraction Using QRS Peaks For Arrhythmia ECG Heart Disease Patterns

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ABSTRACT

Electrocardiogram (ECG) signals are commonly used to diagnose heart electrical activity and disorders. Many different heart ECG patterns are detected and used to make diagnoses. This makes it critical to classify the appropriate ECG pattern prior to diagnosis and treatment. This research sought to create an effective feature extraction strategy for ECG classification problem. Paper initially processes the raw ECG data employing the modified Pan Tompkins basic filtering technique to remove noise and artifacts. Then average filter is used to smooth the difference of notch filtered data and its 10th level wavelet approximation. The filtered data is used to detect the QRS wave peaks to be utilised as a criterion for further classification. Paper proposed an adaptive threshold selection based ECG peak detection method. The temporal ECG features are extracted based on the detected peaks. Rich set of 8 time domain heart rate variability (HRV) features are considered and extracted for each ECG pattern. The algorithm is tested over the MIT-BIH ECG database signal with 10 ECG data for each of four patterns. Machine learning (ML) classification algorithms can be employed to recognize distinct ECG disease patterns based on the QRS set of features detection. The basic proposed method correctly recognizes the ECG signal peaks including the Q, R, and S peaks. The visual results indicate the ECG's QRS detection efficiency in the case of artifacts.

Keywords: ECG, ECG artifacts patterns, Pan Tompkins, Adaptive Threshold Peak Detection, QRS Complex, HRV, SDNN, and ECG Classification.

Introduction

The diagnosis and treatment of numerous diseases depend heavily on the examination of the heart's electrocardiogram (ECG) signals. Several cardiac disorders result in varying heart rate variability (HRV), as well as consequently, varying electrocardiogram (ECG) patterns. The most prevalent rhythms are Normal Sinus Rhythms (NSR), Atrial-Premature-Beat (APB), Atrial Flutter (AFL), and Atrial Fibrillation (AFib). Every one of these ECG pattern corresponds to a distinct heart procedure.One of the most crucial phases in the treatment of ECG signals is the interpretation as well acquisition of the complex QRS [1]. Significant variations in QRS complex in abnormal ECG patterns is observed this makes the R wave crucial for both the assessment of HRV along with the identification of abnormal cardiac rhythms (HRV). Feature set employed in the ECG signal classification consists of outcomes of peak detection techniques. Noise has a major effect on how accurately features are extracted. The filters may change the nature of true ECG and therefore causes wrong features this leads to wrong false positives. Under the heart disease significant amplitude and feature variations are observed in ECG patterns. The ECG patterns may contract or expand in time domain. Thus efficient feature extraction is still a critical field of research. This manuscript presents filtering employing the standard Pan Tompkins method [2] as the first stage in the ECG processing. It is suggested to adapt the Pan and Tompkins method for better baseline wandering problem with the goal to remove line noise.is offered in a step-by-step manner. The Pan Tompkins approach to peak detection is used for extracting temporal time domain characteristics. In this paper the method of feature set extraction is suggested for use in machine learning (ML) classification of the different ECG illness patterns. ECG signals are used by medical

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professionals to diagnose heart illness and pinpoint issues with the electrical supply of the heart. The electrical activity of the heart is represented graphically in ECG signals throughout the cardiac cycle.

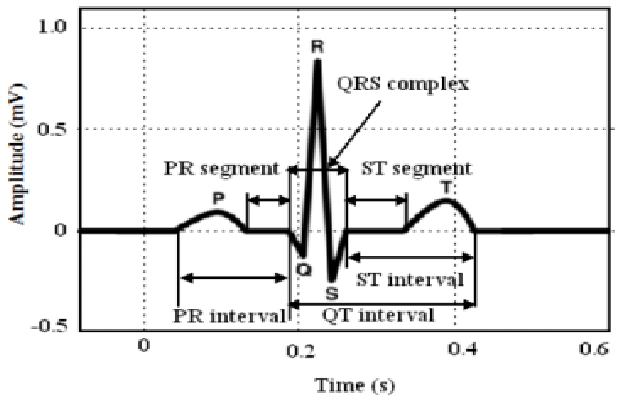


Figure 1 basic ideal structure of QRS ECG wave

Figure 1 displays the essential structure of a normal human ECG QRS pulse. The ECG rhythm peak is represented by the R. Additionally Q and S represents the SR and PR sections, respectively. The RR interval represents the whole pulse time between R to R. The RR interval is calculated using methods for identification ECG QRS peaks. But it is observed that in case of any heart disease the significant variation in the QES peak and RR intervals is observed. Therefore efficient and simultaneous detection of QRS peaks is the critical phase of the feature extraction. Thus this paper is aimed to tune the optimal adaptive threshold for accurate R peak detection.

In earlier work [2] the ECG signal obtained from the MIT-BIH arrhythmia dataset is filtered utilizing a threshold decision combined with mixtures of a Hilbert transformation with Wavelet transform for determine R-peaks [3]. Some of recent methods have used complex optimization method for HRV detection [4]. There were certain variability analysis methods, designed for Atrial Fibrillation (AFiB) Nguyen A, [7]. The time and frequency domain based HEV measurement analysis is presented by Chakrabarty, et al [8]. The feature extraction parameters are calculated and evaluated for the specific case of AFiB as by Kirti K, et al [9]. There are many modification of the Pan Tompkins methods were proposed as in [10]/ Since long back due to its efficiency and capability of handling baseline wondering problem method is a crucial part of recent ECG analysis. Our proposed strategy is expected to design the rich set of temporal features which may outperform over reported earlier findings on the basis of accuracy, sensitivity, classification efficiency. In this paper various ECG arrhythmia patterns are used to determine the extended set of features for measuring the HRV. The basic processing steps for the ECG classification are given in the Figure 2.

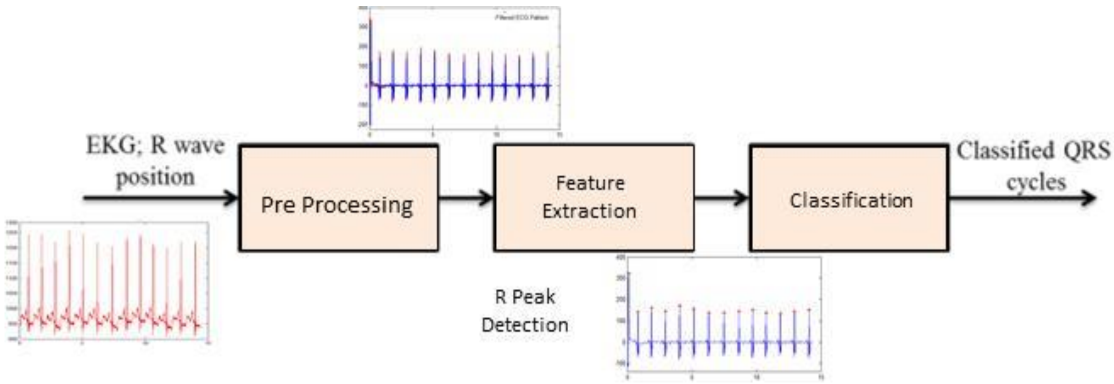


Figure 2 basic processing step used for the proposed ECG classification system

The preprocessing is performed using Pan Tompkins method. For feature extraction the ECG R peaks are determined then temporal features are calculated using the provided ECG patterns data. Furthermore, different classification strategies of ECG pattern recognition can be applied and evaluated. Thus the accuracy of any classification method highly depends on the feature extraction part.

2. Motivation of Work

ECG data that has been captured is susceptible to line frequency disturbances brought on by changes in acquisition time. Baseline wondering is therefore a crucial component of early ECG signal processing. There were numbers of methods were proposed in past out of which some techniques could be more susceptible to noise than others. The accuracy of method may be less due to insufficient or wrong feature extraction. The noisy ECG may leads to wrong features and thus in turn compromise on accuracy. Mostly poor electrode placement and movements may cause noisy interfering ECG signals. The frequency domain features are mostly specific to kind of ECG pattern or disease pattern. Thus recognize the ECG patterns and disease classification is an open field of research. The motivation is to highly improve the efficiency of existing pre-processing and feature extraction methods systematic design methodology

3. Literature Review

The broad classification of various feature extractions and classification methods used for ECG pattern detections are represented in the Figure 3.

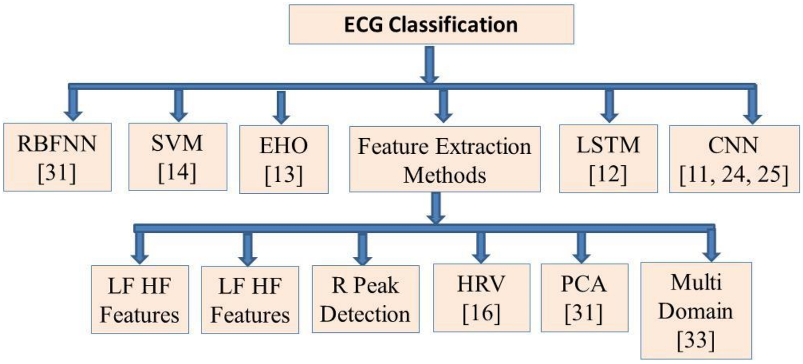


Figure 3 Various ECG features extraction and classification methods

Zhao, K: et al [1] have proposed a wearable ECG sensors based QRS detection and R-peak identification algorithm. They proposed a bilateral threshold technique and QRS watchdog significantly increase the robustness and accuracy of detection. However, the primary drawback of wearable device-based ECG systems lies in the fact of only capable to record one or a small number of leads of ECG data. M. A. Z. Fariha et al [2] have proposed to design the Pan Tompkins method for ECG analysis task. Method efficiently eliminates the impact of noise and the interference issue called base line wondering problem. Abdullah et al [3] have put forward a proposition a better R peak detection for ECG signals employing dynamic mode selected energy (DMSE) and Adaptive Windows Size Approaches with Decision Tree (DT) analysis. He, R. et al. [4] has proposed particle swarm optimization (PSO) method for ECG peak detection. The nearest neighbours are optimally determined for R peak detestation. But method was computationally complex and probabilistic in performance. Eduardo José et al [5] have proposed the HRV based classification of the ECG arrhythmia data. They have surveyed various pre- processing methods for ECG analysis, and discussed their limitations and scope,Eduardo also described various AAMI standard databases/ they stated the MIT-BIH database is mostly being used for ECH studies. And classification accuracy is highly depended on size and patterns of ECG data. M.J. Reed, et al [6] had presented the specific case of ventricular arrhythmias classification using HRV evaluation. Ventricular arrhythmias may causes low blood pressure (BP) and suss cardiac attacks. Nguyen A, et al. [7] has analysed AFib ECG patterns using the HRV study. They stated that it is critical to correctly categorise ECG recording segments for AFib patterns. They used numerical, frequency, geometric and entropy variables to classify AFiB and non-AFiB ECG patterns. Chakrabarty et al. [8] have used time – frequency features for ECG patterns detection. Along with temporal features the frequency domain LF/HF ratio is used as features for ECG arrhythmia. Wavelet (Symlet5) is used for R peak detection for classification of 40 ECG patterns 10 in each of four classes. Kriti K. et al [9] have used the ANOVA, (Analysis of Variance) tool for ECG AFiB patterns analysis and classification. Sathyapriya, et al; [10] have proposed a modified Pan Tompkins approach for the processing and R peak detection for the ECG data. The modification in standard Pan Tompkins method is based on noise filtering, and peak detection process with goal to minimize false peaks.

M. M. Rahman Khan et al [11] proposed a deep learning 1-D CNN (convolutional neural network) suggested for categorising five different forms of cardiac arrhythmia automatically from ECG. The ECG data underwent a number of pre-processing processes (filtering, peak identification and heartbeat segmentation) to perform better. SaeedSaadatnejad et al. [12] proposed a unique long-term-short=term LSTM-based ECG classification algorithm that outperforms for their specific ECG data in terms of classification performance. AzmiShawkatAbdulbaqi et al.[13] have discussed about the de-noising of an ECG signal using the Dual-Tree (CWT) approach is covered in this publication. This article also covers the extraction of several aspects from the suggested designated and reconstructed signal, including measures of time intervals, morphological analysis, and object identification point localisation. NajlaaJannah et al [14] has an objective to demonstrate the superiority of complex CSVM over traditional SVM in concurrently recognising various arrhythmia types using multi-lead recordings after signal compression in the Fourier domain. Additionally, MATLAB was used to develop the algorithm. IbraheamFathail et al. [15] have presented a method to digitise the ECG and automatically detecting R peaks, computing the average heart rate, and sending SMS to the physician through cloud in the event of detection of abnormalities. System works by uploading an ECG image, using the

MATLAB programming language to reduce its dimensions, extract its features as digital signals/ Er. J.S Dhir et al. [16] have researched about a reliable R-peak detection. The study of ECGs and the identification of R-peaks are the topics of this paper. For the other ECG performance phases, the determined position of R peak's accuracy is crucial. S. Sathishkumar et al. [17] have researched studied about R-R interval is the primary goal of this effort. Different strategies are used to examine the obstruction, which makes computation simple and accurate. The data were retrieved from the dataset created by MIT-BIH. Both healthy and unhealthy ECG signals can be found in the retrieved data. JuhoLaitala et al. [18] have studied about a novel LSTM-based method for R-peak detection from ECG data in this study. Our approach provides more reliable R peak recognition when compared to conventional approaches, both with real-world ECG data and ECG data that has been augmented with Gaussian noise. Our approach was created with the idea that it will be used offline. Goodfellow, J. et al [19] article outlines a unique method for identifying R peaks in ECGs with a focus on both samples with normal sinus rhythm (NSR) and those with atrial fibrillation. Kavitha, R. et al [20] has described a method for analysing electrocardiogram (ECG) signals using features derived from the classification of heartbeats. Data on ECG signals is gathered from the MIT-BIH database.

Parák, Jakubet al [21] have studied about the digital ECG signal filtering described in this work. The goal of the filters that were created was to get rid of breathing muscle artifacts and supply network 50 Hz frequencies. Additionally, this work describes three ECG heart rate frequency detection techniques.Aziz, S. [22] has studied about the R, P, and T peaks, a fusion algorithm based on FrFT and TERMA was suggested. Conventional wavelet transform techniques were utilised to de-noise the signals, however the performance of the peak identification step in the TERMA algorithm was significantly improved by the inclusion of FrFT. Nikan, S. [23] provides a pattern recognition technique for identifying arrhythmias. One of the main causes of sudden cardiac mortality worldwide is irregular heart electrical activity (arrhythmia). Anita Desiani [24] studied about to identify and categorise a normal, aberrant, or arrhythmic beat, convolution neural network (CNN) was integrated with R-peaks of ECG signals in this study. A reliable classification technique for data with several dimensions is CNN. Pan, J.[25] researched to create a Z80 assembly language implementation of our online real-time QRS detection algorithm. This technique utilises slope, amplitude, and width data to accurately identify QRS complexes.

Kai ZHAO [26] had studied the robust QRS detection technique presented in this research can both detect QRS complexes and correctly identify R-peaks. Laxmi S. Sargar [27] have worked on estimation of cardiovascular function can be done using the examination of these described features. Discrete Wavelet Transform (DWT) has been used to create an algorithm for the detection of ECG peaks. Ibrahim Patel [28] has studied about a method of the ECG's QRS, T, and P waves in there paper. Additional research will be needed for the extraction in various methodological areas. The long-term ECG signal takes less time with this method of detection, which is its main advantage.

Mayank Kumar Gautama et al. [29] have to extract features from an ECG signal, many approaches and transformations have been presented in the literature. This report also offers a comparative analysis of various techniques for retrieving the feature from an ECG signal. Varshney, M., [30] has discussed various methods for removing features from an ECG signal that have been previously proposed in the literature. This research also presents a comparative analysis of the techniques used to evaluate the overall system's correctness. R. Rodríguez et al. [31] have studied the ECG feature extraction and peak detection using adaptive thresholding and principal component analysis (PCA). D' Aloia, M. [32] have presented a successful method for peak point localization and detection in noisy electrocardiogram (ECG) signals

Table 2 Summary of related literature review

S. No	**Author's**	**Methodology**	**Evaluation Parameter**	**Classifier**
1.	Zhao, K: et al [1]	Design wearable ECG sensors based QRS detection and R-peak identification	Bilateral threshold for peak detection and RR intervals	No
2.	M. A. Z. Fariha et al [2]	Design the Pan Tompkins method for MIT-BIH ECG patterns analysis task.	Sensitivity (Se) calculated for evaluation under different SNRs.	No
3.	He, R. et al. [4]	Proposed R Peak detection and used PSO with the nearest neighbor approach	RR interval and peaks	N
4.	Nguyen A, et a; [7]	Have proposed AFiB detection using single lead ECG numerical, geometric and entropy features	Accuracy and precision are evaluated	Linear and RBF SVM
5.	Sathyapriya, et al; [10]	Proposed a modified Pan Tompkins for R peak detection	Using filtered ECG for R peak detection determine RR interval and SDNN	No
6.	M. M. Rahman Khan et a; [11]	ECG Heartbeat classification for the detection of Cardiac Arrhythmia.	classification using MIT-BIH Arrhythmia dataset and accuracy is compared using R peak detection	CNN
7.	NajlaaJannaha et al, [14]	Proposed multi-lead ECG analysis and classification of arrhythmia	Fourier domain analysis of signal compression, and	CSVM and SVM

			filtering, accuracy	
8.	JuhoLaitala et al. [18]	R-peak detection method that is based on the Long Short-Term Memory (LSTM) network.	.classification accuracy and peak detection sensitivity and precision	LSTM
9.	Jonathan Goodfellow1 et al [19]	Algorithm could discriminate between segments presenting normal sinus rhythm and those presenting atrial fibrillation based on RR interval data derived from the R-peak detection method.	Efficacy of R-peak detection for NSR and AFIB was assessed via sensitivity, productivity (P) & accuracy. 99.61%, 99.88% and 99.50% respectively.	No
10.	Aziz, S et al [22]	Fusion of FrFT and TERMA was proposed to detect R, P, and T peaks. Wavelet transform were used to de noise ECG.	Automatically classify heart disease, train a machine-learning model. The F1 score and accuracy are measured	MLP and SVM are compared
11.	Pan, J et al [25]	Designed a real-time QRS detection algorithm and implemented using Z80 assembly language, It detects QRS peak by amplitude, slope, & width information.	Have used MIT/BIH arrhythmia database to evaluate. The database consists of 48 half-hour recordings for a total of 24 h of ECG data.	No
12.	Kai ZHAO et al. [26]	Detected "R" peak locations, which has an impact to HRV accuracy. By optimizing the parameters of the proposed R-QRS algorithm	evaluating 9 PhysioNet databases, and achieves Se = 99.99%, +P = 99.98%, shown better or comparable performance,	No
13.	Ibrahim Patel	Presented algorithm for the detection of QRS, T and P waves of ECG. The key gain of this method of detection is that the long-term ECG signal takes less time.	QRS complex was detected by maximum slope threshold. The P waves and the T waves can also be detected from QRS comples.	No
14.	Qaisar, S.M et al, [39]	Wavelet based de noised ECG is applied k-nearest neighbor classification for arrhythmia detection	Accuracy of 98.2 % and specificityof 0,95 is achieved	KNN
15.	ShikhaDhyaniey al. [40]	Used SVM classification using R Peaks for China physiological signal challenge (CPSC) ECG	Precision and accuracy is calculated for different SVM methods	SVM and complex SVM

4. Proposed Methodology of ML based ECG Classification.

QRS peak detection plays an important role in illness detection including the recognition of HRV. The ultimate goal of paper is to design time domain features analysis of the various ECG patterns for HRV detections. Paper contributed in three part first Pan Tompkins method is used for filtering and pre-processing. This is combination of low pass filter and band- pass followed by the derivative high pass filter. Average filter is used to smooth the difference of notch filtered data and its 10th level wavelet approximation. In the second pass for improving accuracy of the R peak detection the adaptive threshold is set for eliminating outlier peaks and improving the true positives of peak detection. Finally paper has proposed to determine the ECG signals feature set based on the HRV parameters measurements. The classification of ECG disease patterns based on classification using machine learning (ML) methods is propose for efficient disease identification from ECG signals. The time series and frequency series features are required to design the extended feature set .and then the classifiers are applied for training and testing of the database. Proposed block diagram of the expected ECG signal processing methodology is given in the Figure 4.

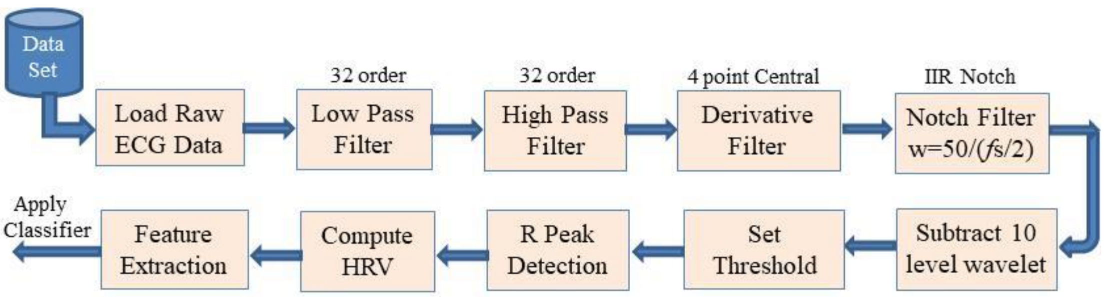


Figure 4 Proposed block diagram of the ECG feature extraction system

As it is clear from the Figure 4 that suitable window size and the threshold selection is proposed to improve the peak detection efficiency as per the ECG patterns. Since the Q and S peaks are having less amplitude thus are ignored in this work and R peaks are used for finding the HRV. It is proposed to extract the time domain and statistical features.

5. Results and Validations

The ultimate goal of this work is to efficiently apply peak detection for the four class of ECG This section preseted the results in three parts. First part describes the detail of the dataset under consideration. Then results of the various pre-processing stages for Pan Tompkins method are presented for different filters. The final section preseted the result of the extracted features for the ECG data.

5.1 ECG datasets Used for Validation

Total 60 ECG data of 10 persons of different type of ECG rhythms and age groups are considered for analyses in this study are NSR, APB, AFL, and AFlB

NSR: is consider as the normal sinus rhythm and is generally consider as healthy 60 to 100 BPM. Normally represent good health of cardiovascular patterns.

APB: Atrial premature beats (APBs), also known as atrial and supraventricular extra systoles, are atrial de polarizations that occur before the anticipated sinus node stimulation, usually from a location outside the sinus node

AFL: Atrial flutter (AFL) is a frequent source of irregular cardiac rhythm that begins in the heart's atrial chambers. It's frequently coupled with a fast heart rate when it first happens, and it's classified as a sort of supraventricular tachycardia. The heart beats unusually fast but also in a regular pattern with people having AFL

AFiB: is termed as Atrial Fibrillation is serious cardiac disorder and must be cure earlier..

The data of 6 ECG class under the each category are preseted in the Figure 5 for comparison.

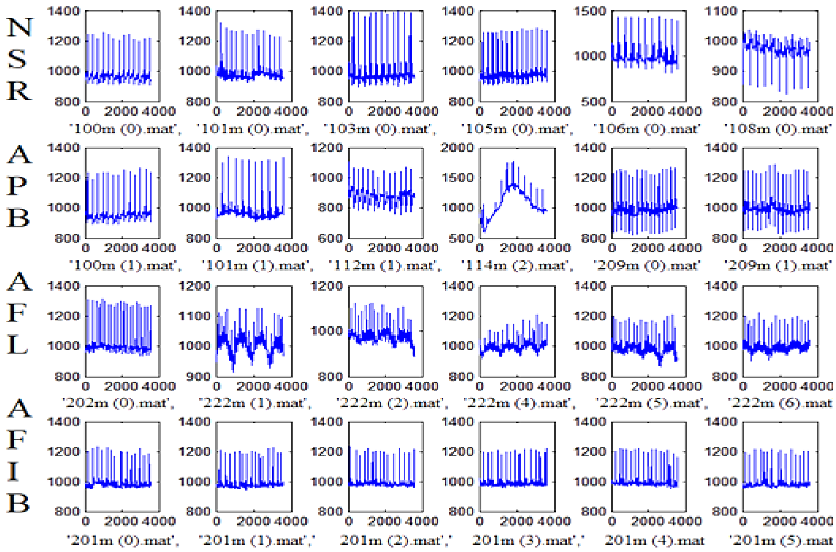


Figure 5 plot of six ECG channels in each of four categories of the ECG data base.

. This study used a set of 40 ECG data as shown in Figure 5 from people in various age categories and the MATLAB framework to complete the categorisation. Due to mathematical problems, the times mentioned as initial 3600 samples of ECG data as .mat files will be used for the evaluation in thins work. The databases used are MIT-BIH .mat file data available on PhysioNet site. Since there are significant variations in the PQRST complex of the ECG patterns thus to understand the definitions of all four patters the close initial 500 samples are plotted in Figure 6 for comparisons.

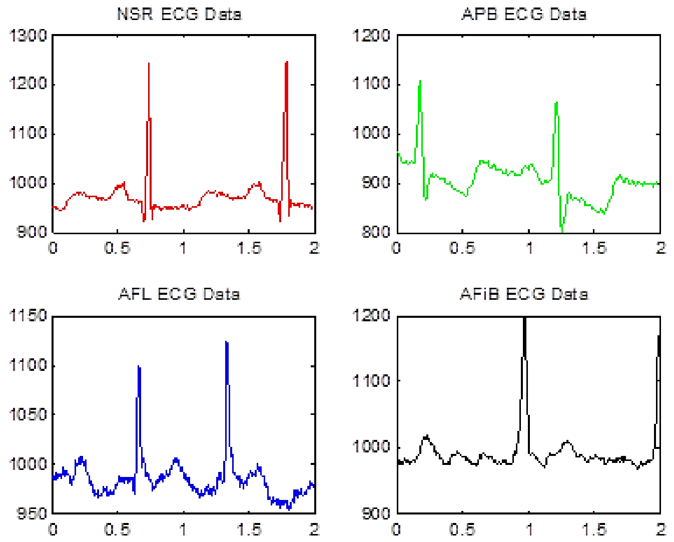
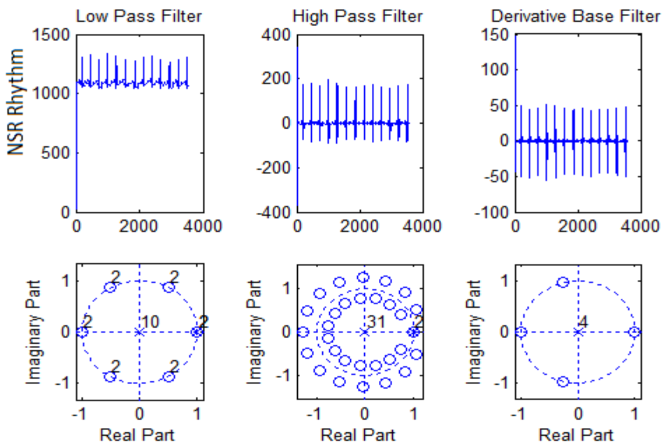


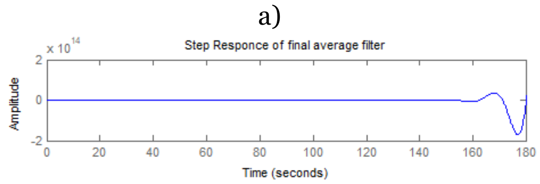
Figure 6 comparisons of four ECG patterns representing variation in PQRST positions.

5.2 Results of Pre-Processing

This section have preseted the stage wise results of the various filters for different Pan Tompkins steps. The results of .ECG pre-processing of normal sinus rhythm and respective pole zero analysis is presented in the Figure 7. It can be clearly observed that pole zero plots shown in Figure 7 a) for low pass, high pass and derivative filters. The order of the filter is relatively reduced for the derivative filter and is used for the base line wondering (BLW) of ECG data. The order of filter is shown in the pole zero plots respectively. The four point central derivative of barrens is used as derivative filter for addressing BLW problem. The respective transfer functions of different filter are shown in the Table 3. The respective step responses are shown in the Figure 7 b).



a)

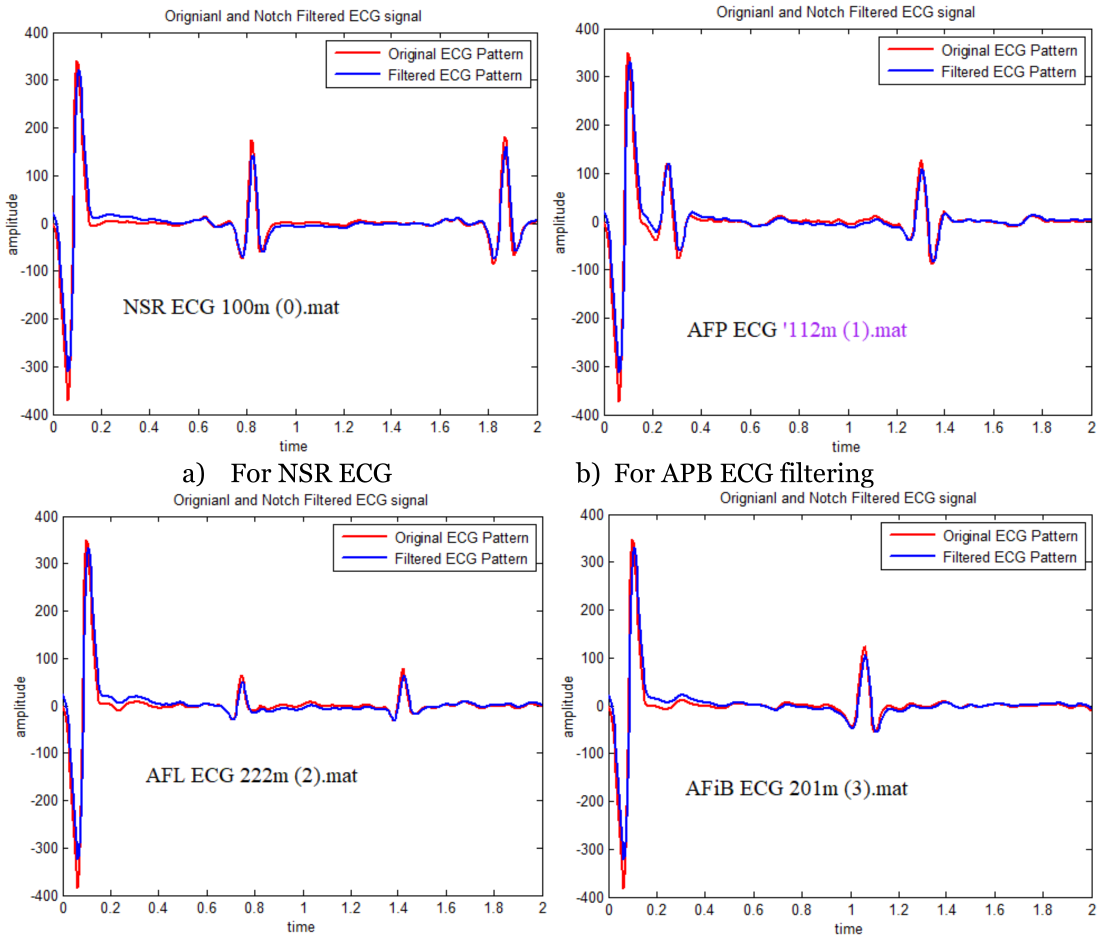


b) step response of final Notch filter

Figure 7 Result of Pan Tompkins pre-processing method and Pole zero analysis

Table 3 Transfer functions for proposed pre-Filters of proposed Pan Tompkins method

LPF	**HPF**	**Derivative Filter**	**Notch Filter**
$\frac{0.03125\,s\text{^}12 - 0.0625\,s\text{^}6 + 0.0312}{s\text{^}2\ -\ 2\,s\ +\ 1}$	$\frac{-0.03125\,s\text{^}32\ +\ s\text{^}16\ -\ s\text{^}15\ +\ 0.031}{s\ -\ 1}$	0.25 s^4 + 0.125 s^3 - 0.125 s - 0.25	$\frac{0.5792\,s^2 - 0.358\,s\ +\ 0.579}{s\text{^}2\ -\ 0.358\,s\ +\ 0.1584}$



a) For NSR ECG b) For APB ECG filtering

c) For AFL ECG d) ForAFiB ECG filtering

Figure 8 Result of Notch Filtering of ECG Pattern.

The results of filtered ECG signal for the first 500 samples are shown in the Figure 8 for the four different ECG patterns under consideration; it can be clearly observed that the filtered signal does not contain any base line noises. The variations in the ECG patterns clergy observed as contraction or expansion in time for all four cases as in Figure 8.

5.3 Results of R Peak Detection

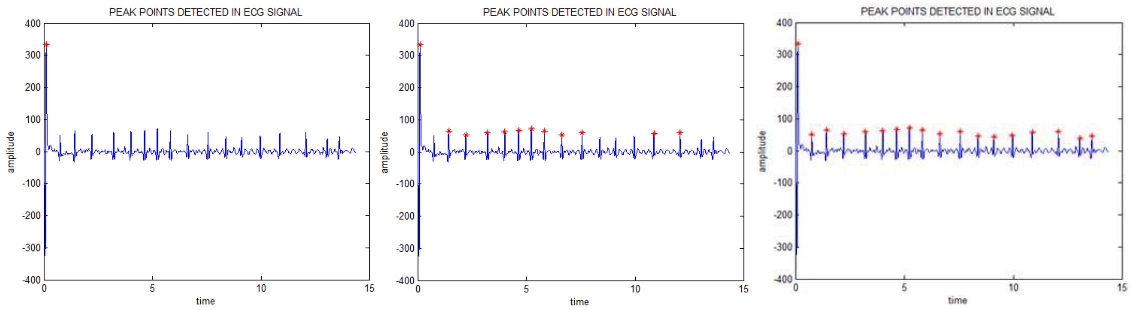
The peak detection is the most assentation step of the ECG signal processing. Since accuracy of the peak detection is the deciding factor for the precise ECG classification. For the ECG peak detection the threshold for notch filter smoothening in this work is set as

$$th = 0.1 * max(ECG_{smooth}) \quad (1)$$

Where ECG_{smooth} is the filtered ECG signal matrix.
It is observed that the varying the threshold value is the responsible factor for eliminating the false negatives for peak detection.

$$RPeak_{ime(i)} = \frac{[i-1]}{f_s}; \quad (2)$$

Where i is the ith peak of ECG, and f_s is the sampling frequency set to 250 Hz.
The results of the detected R peaks for the different threshold values are shown in the Figure 9 for representing the accuracy of proposed adaptive threshold. As it is clear that wrong threshold may have missing true negatives (TN).



a) With th=0.3 b) with th=0.15 c) with th= 0.1 adopted for AFiB

Figure 9.Results of Peak Detection for different thresholds.

5.3.1 Parametric Evaluation

Corresponding to the different thresholds the parametric evaluation of accuracy is calculated. The main goal is to show that the suggested ECG peak detection and identification method improves the system's efficiency in classifying findings. This section will compute a few metrics such as sensitivity, specificity, accuracy, and precision to quantify efficiency and show efficacy.

When the approach fails to recognize a true beat, it generates a negative result (Fn). Fns are extracted from the matching annotation case within the MIT-BIH record. When a fake beat is discovered, it causes a false positive (Fp). True positive (Tp) signifies a precise beat detected by the specified method. True negative (Tn) beats are also known as correct not recognized beats. An equation is used to calculate these parameters.

$$Tn = \sum (Differ = 0 \; \& \; actual = 0) \tag{3}$$

$$Tp = \sum (Differ = 0 \; \& \; actual = 1) \tag{4}$$

$$Fn = \sum (Differ \sim = 0 \; \& \; actual = 1) \tag{5}$$

$$Fp = \sum (Differ \sim = 0 \; \& \; actual = 0) \tag{6}$$

Sensitivity: This is the percentage of precise beats which the algorithm properly detected during a specific recording session.

$$Se = \frac{Tp}{Tp + Tn} * 100 \tag{7}$$

Specificity: It is described as a capacity to successfully identify persons who do not have an illness by employing a test.

$$Sp = \frac{Tp}{Tp + Fn} * 100 \tag{8}$$

The accuracy and precision are numerically calculated as;

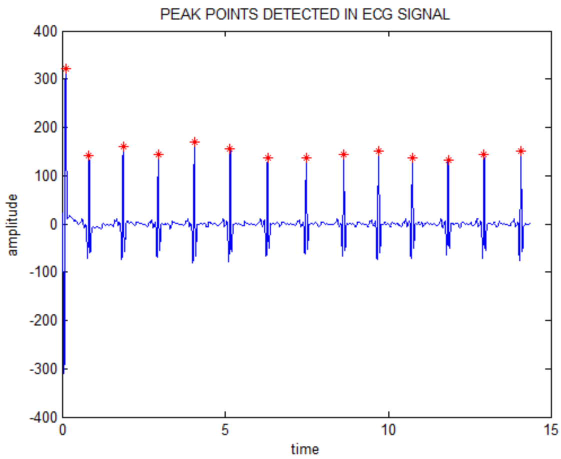
$$Accuracy = \frac{Tp + Tn}{Tp + Tn + Fn + Fp} * 100 \tag{9}$$

$$Precision = \frac{Tp}{Tp + Fn} * 100 \tag{10}$$

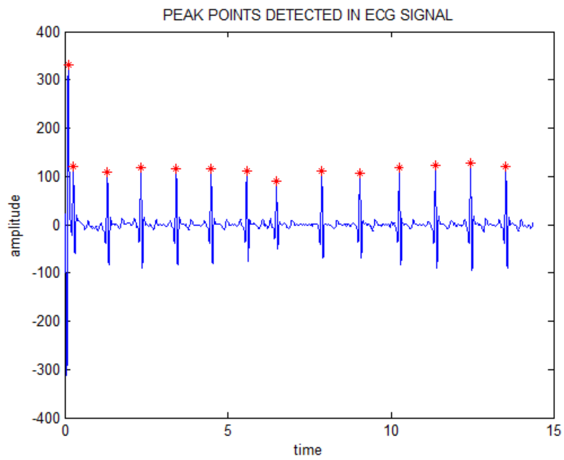
Tn, Tp, Fn, and Fp were analyzed in this paper utilizing several Pan Tompkins based peak detection with threshold ass illustrated above. The results of the accuracy of the proposed R peak detection method are represented in the Table 4. The proposed selected threshold works equally well for the all other four classes also and is capable of recognizing the R peaks with 100% accuracy.

Table 4 Results of the Accuracy of proposed peak detection for different threshold

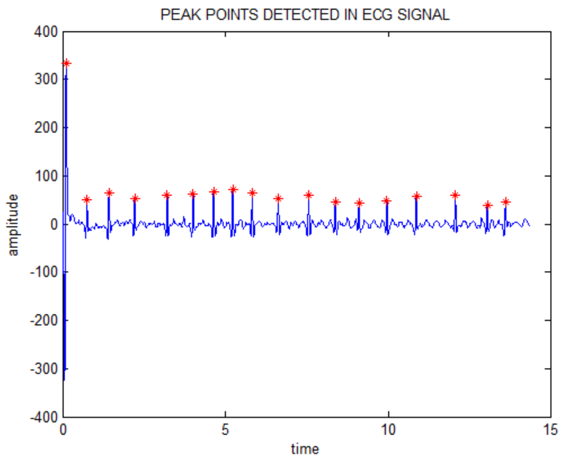
Parameter	With th=0.3	With th=0.15	With th=0.1
Tp	1	11	17
Fn	16	6	0
Accuracy	5.8824	64.7059	100



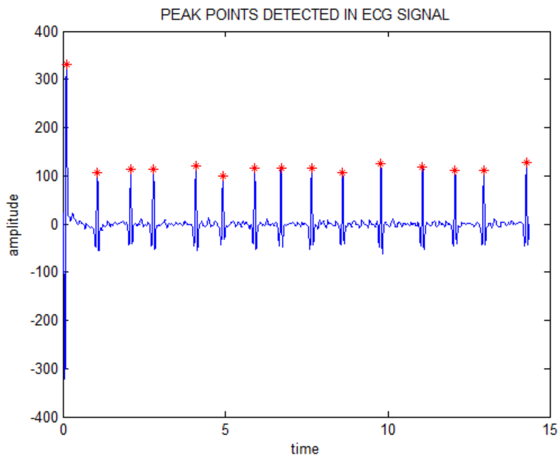
a) For NSR



b) For AFP



c) For AFL



d) For AFiB

Figure 10 Results of the proposed R Peak detection with th as in eq (1)

The results of the peak detection for NSR, AFP, AFL and AFiB ECG patterns are shown in the Figure 10 with the proposed method. It can be observed that all peaks are correctly detected and there is no false negative.

5.4 Time Domain HRV Feature Extraction

The suggested ECG classification and peak detection approach are based on investigations into time domain quantitative HRV properties. Various temporal domain parameters are calculated using the RR intervals used to investigate the ECG signal. The parameters used in the analysis of this research are listed as:

a) ***Standard Deviation (SD) for NN interval (SDNN):*** every pair of intervals of RR has a predetermined R-to-R time. The standard deviations (SD) for the RR periods are being used to determine the SDNN.

b) ***Root Mean Square value of SD (RMSSD):***The RMS value of SD is calculated using the RR intervals and the total of the squared differences between the derived approximation derivatives. The term "mathematically specified" relates to a theoretical relation given in eq (11).

$$RMSSD = \sqrt{\frac{1}{M}(diff(RR_{Region}).^{2})} \qquad (11)$$

Where parameter M is given length of RR interval vector here represented as RR_{Region}

c) ***NN50 Value:*** TThe percentage of R to R intervals that seem to be longer above 50 milliseconds is known as the NN50 value.

6.1.2 Time Domain HRV Parameter Analysis

The suggested ECG classification and peak detection approach is based on the analysis of time domain statistical HRV characteristics. Using the RR intervals used to analyze the ECG signal, various times domain characteristics are calculated. The following are the parameters used in this study's analysis:

a) ***Standard Deviation of NN interval (SDNN):***For each pair of RR intervals, the R to R time is determined. The SDNN is defined as the standard deviation (SD) of the RR intervals.

b) ***Root mean Square SD (RMSSD):***The RMSSD value is calculated using the RR interval and the sum of the square differences of estimated approximation derivatives. Mathematically, the term "mathematically defined" means "mathematic

$$RMSSD = \sqrt{\frac{1}{M}(diff(RR_{Region}).^{2})} \quad (12)$$

Where, M is the maximum length of RR period vector here represented as RR_{Period}

c) ***NN50 Measure:***The percentage of R -- R periods which appear to be greater than 50 mili-seconds is referred to as the NN50 value.

Statistical Features

d) Average (Avg): the statistical mean value of the filtered ECG signal

$$Avg = \frac{1}{S}\sum_{j=1}^{S} ECG_{smooth} \quad (13)$$

e) Peak to Peak Difference (PPD): positive to negative peak difference of ECG_{smooth}

f) SD: standard deviation of ECG_{smooth}signal

g) Min RR: is the minimum R-R period of ECG_{smooth}

h) Mas RR: Maximum R-R period of ECG_{smooth}

The estimated characteristics for the four different ECG patterns are 100m (0).mat for NSR, 112m (1).mat for AFP, 222m (2).mat for AFL, and 201m (3).mat for the AFiB ECG pattern. The numerical values for these patterns are presented in Table 5. The heart rate variability is calculated for the RR intervals and the mean HRV is used as feature in the table and is calculated as

$$Mean_{\mathrm{HRV}} = \left\lfloor mean\left(\frac{60}{RR_{Period}}\right)\right\rfloor_{abs} \quad (14)$$

Table 5 Numerical and Time domain HRV Features

Feature	**For NSR 100m (0)**	**For AFP** 112m (1).mat**)**	**For AFL** 222m (2).mat	**For AFiB** 201m (3).mat
NN50	3	7	8	12
HRV	56.6113	80.1229	69.3634	61.3054
SDNN	0.11447	0.28582	0.7818	0.19517
RMSSD	0.10218	0.30342	1.039	0.29585
Avg	0.1359	0.0864	0.2094	0.2678
SD	32.2632	30.2030	23.7782	30.2203
Min RR	0.7160	0.1560	0.5880	0.7000
Max RR	1.1800	1.3840	3.3360	1.3160

Thus using the feature set the classification of ECG patterns can be accurately achieved. And this may help in better disease diagnosis.

8. Conclusions and Future Scopes

This paper has proposed to design modified Pan Tompkins method in combination to accurate thresholding for the R peak detection of ECG patterns. The time series features are proposed to extract by using modified algorithm. Paper proposed to design and evaluation of ECG signal classification approaches for the heart disease classification based on the arrhythmiadatabase. The average filter is used to smooth the difference of notch filtered data and its 10th level wavelet approximation. The clipping threshold is adaptively selected for better R peak detection. The notch filter window size is tuned as per the sampling frequency. Results are evaluated for pre filtering and also the accuracy of R Peak detection is calculate n terms of Tp and Fpand is found to be 100 % stating proposed method determines all peaks efficiently. The novel extended time domain feature set is preseted for the ECG pattern classification. The Minimum and maximum of RR period are used as the additional time domain features. Based on the survey it is found that SVM and CNN are the two most frequently used classifiers in ECG context. Thus in future the proposed rich set of feature set will be used to apply and evaluate the efficiency of different classifiers. In future the LF and HF frequency domain features can also be combined for classification evaluation.

Declarations

• There was no funding received to help in the writing of this manuscript.
• We have NO connections with or engagement in any organisation or institution that has a financial or non-financial stake in the topic or materials covered in this work (including either professional or personal relationships, affiliations, expertise, or beliefs).

- Because no datasets were collected or analysed during the current study, data is available for free on MIT-BIH database at physionet site.
- This paper has not yet been submitted to, or is currently being reviewed by, any other journal or publishing venue.

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