International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

R-Peak Detection and HRV Analysis in ECG Signals: Overcoming Limitations in PQRST Complex Identification

Rabiya Bushra[1], Prof Rakesh Kumar Tiwari[2], Prof Mukesh Asati[3], Dr Vikas Gupta[4]

[1] Affiliations Department of Computer Science and Engineering, Technocrats Institutes of Technology & Science, RGPV, Bhopal, (M.P), India
Emails: **rabiya2420gmail.com**
[2] Affiliations Department of Computer Science and Engineering, Technocrats Institutes of Technology & Science, RGPV, Bhopal, (M.P), India
Emails: **rakeshktiwari80@gmail.com**
[3] Affiliations Department of Computer Science and Engineering, Technocrats Institutes of Technology & Science, RGPV, Bhopal, (M.P), India
Emails: asati.mukesh@gmail.com
[4] Affiliations Department of Computer Science and Engineering, Technocrats Institutes of Technology & Science, RGPV, Bhopal, (M.P), India
Emails: vikasgupta.bhopal@gmail.com

ABSTRACT:

Heart disease patterns have significantly increased during and after the COVID-19 pandemic, presenting a critical challenge in their identification and categorization. This research focuses on the peak detection method to extract features for classifying heart disease patterns using electrocardiographic (ECG) data. The detection of ECG peaks is essential for assessing cardiac health, identifying abnormal heart rhythms, analyzing wave shapes, evaluating heart rate fluctuations, and reducing signal interference. The proposed method utilizes the Pan-Tompkins algorithm for pre-processing ECG signals and efficiently detecting peaks and temporal features for four different ECG patterns: Normal Sinus Rhythm (NSR), Atrial Flutter (AFL), and Atrial Premature Beats (APB). The algorithm employs low-pass, high-pass, and derivative-based filters to isolate QRS complexes indicative of heart contraction. However, peak detection in ECG signals is challenging due to limitations such as low-amplitude waves, inconsistent rhythms, complex computations, threshold choice, sampling frequency limitations, starting point drift, inter-lead variability, morphological variability, noise sensitivity, and sensitivity to electrode placement. The proposed approach focuses on R-peak detection to determine time-domain features, as PQRST peak detection fails in cases like AFL and APB ECG patterns where no rhythmic pattern is ideally followed. The research validates the peak detection results using R-peaks and presents the variation in heart rates per ECG beat. A Poincaré plot is used to represent the heart rate variability (HRV) index, providing insights into the autonomic nervous system's regulation of heart rate. The proposed method aims to improve the accuracy and reliability of ECG classification, particularly when applied to the MIT-BIH Arrhythmia database.

Key Words: ECG, Peak Detection, PQRST Peaks, Heart Disease, Pan-Tompkins Algorithm, Arrhythmia Classification

Introduction

Over the past two years, a significant increase in heart disease patterns has been noted during and after the COVID-19 pandemic. Identifying and categorizing these heart disease patterns have become a critical challenge. This research primarily focused on the peak detection method to extract features for classifying heart disease patterns using electrocardiographic (ECG) data. The detection of ECG peaks in electrocardiograms (ECGs) is essential for various aspects of cardiac health assessment. This process enables the identification of abnormal heart rhythms, the analysis of wave shapes, the evaluation of heart rate fluctuations, and the reduction of signal interference.

It also facilitates adaptive threshold setting, comprehensive waveform examination, and the early detection of issues, automated analysis, tailored medical approaches, and scientific progress. Peak detection allows for the precise measurement of inter-beat intervals, recognition of wave-specific anomalies, and computation of heart rate variability metrics. Sophisticated algorithms eliminate noise and artifacts and enhance the peak identification in dynamic ECG signals. The use of adaptive thresholds helps accommodate changes in the QRS complex morphology during arrhythmias. Furthermore, improved peak detection techniques have contributed to in-depth arrhythmia studies, potentially leading to novel discoveries.

Identifying PQRST peaks in electrocardiogram (ECG) signals plays a vital role in evaluating cardiac function and in identifying heart-related disorders. Numerous techniques have been developed to precisely locate these key points, with particular emphasis on the R-peak, which is fundamental for assessing heart rate variability (HRV) (Bae & Kwon, 2021; Park et al., 2017). Algorithms for R-peak detection often encounter difficulties owing to the variable nature of the QRS morphology and interference in real-world ECG recordings (Manikandan & Soman, 2018; Manikandan & Soman, 2011). To overcome these obstacles, scientists have introduced methods, such as signal envelope filtering (SEF), Shannon energy envelope (SEE), wavelet transforms, and adaptive thresholding (Lee et al., 2018; Park et al., 2017; Qin et al., 2017).

These approaches aim to amplify the QRS complex while minimizing noise, thereby enhancing detection accuracy across various scenarios. Notably, certain strategies focus on identifying not only R-peaks but also other significant points within the PQRST complex. Bae and Kwon (2021) introduced a technique that considers the alteration of primary waves to accurately detect P-, Q-, R-, S-, and T-points. Furthermore, Ge et al. (2023) presented the ECG-MAKE method, which tackles both key point detection and morphological delineation, offering a comprehensive examination of ECG attribute knowledge. These innovations contribute to more precise and resilient ECG analysis, potentially enhancing early identification of cardiovascular diseases and real-time monitoring capabilities.

The example of true ECG pattern and respective basic QPRST ECG complex pattern is shown in the Figure 1.

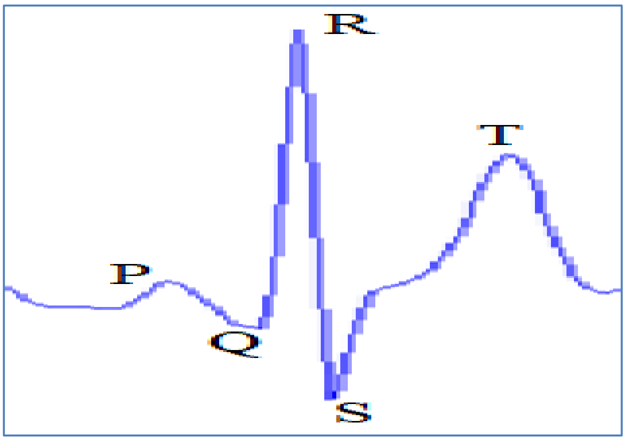


Figure 1 the representation of single PQRST ECG complex

Pan-Tompkins Method

The Pan-Tompkins algorithm is a widely used method for QRS complex detection in electrocardiogram (ECG) signals, particularly for R-peak detection. This is considered a crucial first step in automatic ECG analysis and has been the foundation for many subsequent developments in the field (Meyer et al., 2019; Meyer et al., 2006). The algorithm typically involves several stages including band-pass filtering, differentiation, squaring, and moving-window integration, followed by adaptive thresholding for peak detection (Gutierrez-Rivas et al., 2015; Meddah et al., 2019).

Its popularity stems from its relatively simple implementation and good performance under various ECG morphologies and noise conditions. Interestingly, although the Pan-Tompkins algorithm has been widely adopted, researchers have continually sought to improve it. For instance, the Accurate Modified Pan-Tompkins (AMPT) algorithm demonstrates improved computational efficiency by 5-20 times while enhancing correctness (Neri et al., 2023). Other studies have proposed modifications to adapt the algorithm for specific applications, such as fetal ECG analysis (Agostinelli et al., 2017) or implementation on low-cost portable platforms (Gutierrez-Rivas et al., 2015; Ribeiro et al., 2024). In summary, the Pan-Tompkins method remains a benchmark for R-peak detection and serves as a foundation for numerous improvements and adaptations. Its balance of simplicity and effectiveness continues to make it relevant to ECG signal processing, even with the emergence of more advanced techniques.

QRS Compels Peak Detection

The QRS complex detection in ECG signals is crucial for the diagnosis and analysis of cardiac disorders. Various methods have been proposed to address challenges, such as noise interference, baseline drift, and abnormal peak variations (Manikandan & Soman, 2011; Rahul et al., 2020). Common approaches include the following. Wavelet transform-based methods provide efficient time-frequency localization. A four-level bi-orthogonal spline wavelet transform with noise evaluation has shown high accuracy, achieving 99.84% sensitivity and a 99.92% positive prediction value (Lin et al., 2019). Another approach using a synchro-squeezed wavelet transform (SSWT) achieved 99.92% sensitivity and 99.93% positive productivity (Sharma & Sharma, 2016).

Filtering and thresholding techniques, such as median and moving average filters for preprocessing, are followed by peak enhancement and dynamic thresholding. One method achieved 99.70% sensitivity and 99.69% positive predictivity across multiple databases (Rahul et al., 2021). Machine learning (ML) approaches, such as the sliding window-based Max-Min Difference (MMD) algorithm combined with neural network classification, have achieved 99.62% sensitivity and 99.69% positive predictivity for QRS detection (Pandit et al., 2017). Interestingly, some novel approaches have emerged, such as the use of deterministic finite automata with regular grammar, achieving 99.74% sensitivity and 99.86% specificity (Hamdi et al., 2017). Another unique method employs variational mode decomposition, Shannon energy-based nonlinear amplification, and the Hilbert transform, resulting in 99.77% sensitivity and 99.91% positive predictivity (V. V. et al., 2023). In order to summarize it can be stated that while traditional filtering and wavelet-based methods remain popular, newer approaches incorporating machine learning and novel mathematical concepts are showing promise in improving QRS detection accuracy. The choice of the method often depends on the specific application and computational requirements, with some techniques offering a better balance between accuracy and efficiency. Hemant et al. (2021) proposed a new AI-based QRS peak detection and classification method for ECG data, using a reduced-order IIR filter for low-pass smoothing. The method improves the accuracy by 8-13% compared to the basic Pan-Tompkins method. Varun Gupta et al.(2024) have used the fractional wavelet transform (FWT) decomposition and energy distribution for ECG R peak detection. Ali et al. (2024) recently presented an extended survey of various R- Peak detection methods. Over all it can be stated that efficient Peak detection is still an open field of research to improve the accuracy of feature extraction and ECG classification.

4. Proposed ECG processing Block diagram

The identification of QRS peaks is necessary for both disease diagnosis and heart rate variability (HRV) determination .The current suggested method for HRV peak detection is significantly influenced by the chronological recorded analysis; the MIT-BIH verified Arrhythmia ECG measurement dataset is utilised to classify the heart arrhythmias of an aberrant ECG reading.

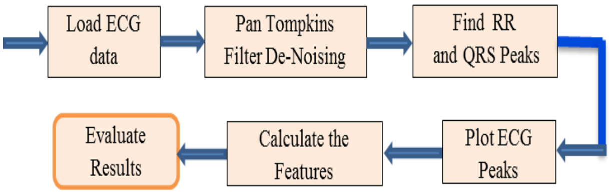


Figure 2 ECG Peak Detection Block Diagram

Figure 2 depicts the block diagram of the fundamental steps in the ECG categorization of NSR data. The Pan Tompkins filter is used for the pre-processing. The absolute squared ECG signal option effectively detects the peaks. . The modified Pan Tompkins based peak detection method is proposed for pre-processing the ECG signals for efficient peaks detection and temporal features determinations for four different ECG patterns as Normal Sinus Rhythm (NSR)

4.1 Proposed Preprocessing Pan Tompkins Method.

Over the R-R intervals, heart rates are monitored in beats per minute. This study's main objective is to demonstrate how using a Pan Tompkins filter design can enhance the ECG classifier performance. The algorithm of the Pan Tompkins method implementation is shown in the Algorithm 1

Algorithm 1: Pan Tompkins Algorithm
1. Load ECG Patterns Data ← $Ecgi_{(t)}$ 2. Reduce the sampling rate ↓ Fs, 3. Followed by applying a 32 order low-pass filter 4 Implement the 32^{nd} order high-pass filter. 5. Execute the four-point derivative-based derivative filter $[\frac{-1}{4}, \frac{1}{4}, \frac{1}{4}, \frac{-1}{4}]$ 6. Implement an Average filter and determine the mean threshold. 7. The ECG signal is then prepared for Peak detection, including RR(t) and R-lo.
End Algorithm

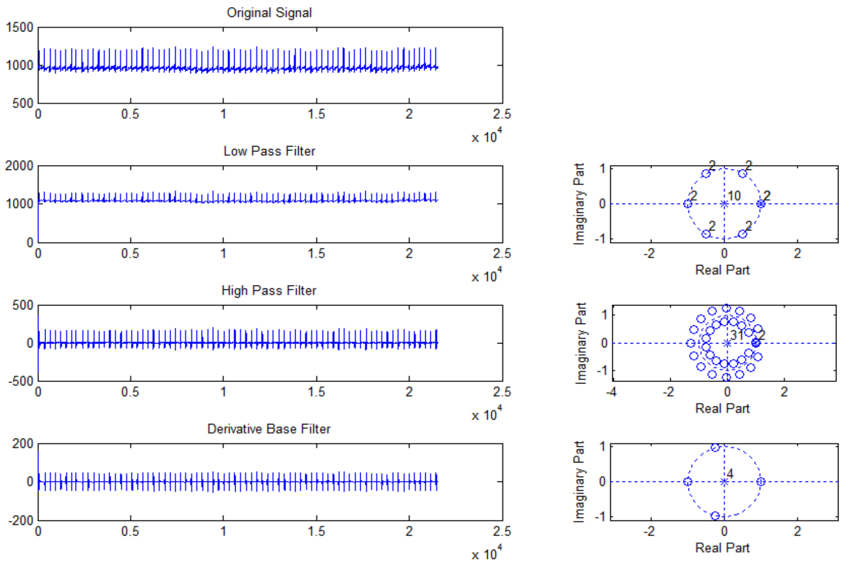
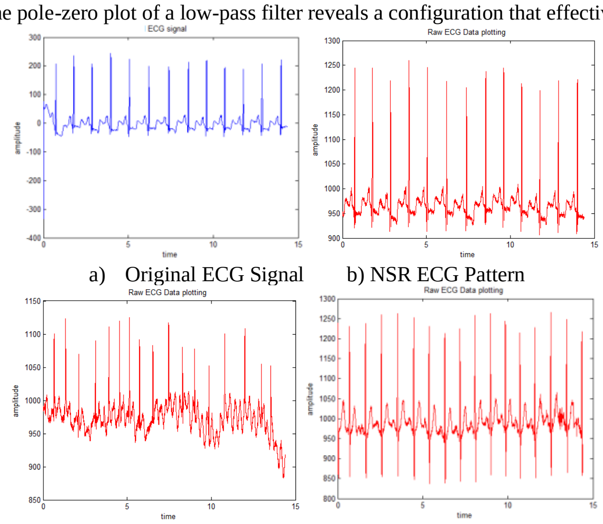


Fig 3 Pre-processing results of the Pan-Tompkins method for NSR peak detection

The pre-processing results of the Pan-Tompkins method for NSR peak detection are illustrated in the Figure 3.

Figure 3 illustrates the step-by-step process of the Pan-Tompkins algorithm for identifying QRS complexes in electrocardiogram (ECG) signals. This method employs various filtering techniques to isolate QRS complexes that are indicative of heart contraction. The original unprocessed ECG signal is displayed in the upper left panel. This raw waveform contained multiple frequency components and exhibited considerable noise. The Pan-Tompkins approach utilizes three distinct filters: low, high-pass, and derivative-based filters. Each filter targets a specific frequency range relevant to the QRS complex. High-frequency noise is reduced by the low-pass filter, whereas the high-pass filter eliminates low-frequency elements such as baseline drift. The derivative filter accentuates the rapid transition characteristics of the QRS complex. Column b) of Figure 3 depicts the frequency response of these filters using pole-zero diagrams. Diagrams illustrate the positions of the poles and zeros of the filters in a complex plane. The arrangement of these poles and zeros determines the response of the filter to different frequencies. The specific pole-zero plots for each filter demonstrates the selective attenuation or amplification of certain frequencies. The distribution of poles and zeros in each wave aligns with the filter function, as evidenced by filtered signals shown in the left panels. For instance, the pole-zero plot of a low-pass filter reveals a configuration that effectively suppresses higher frequencies.



a) Original ECG Signal b) NSR ECG Pattern

c) AFL ECG Pattern d) APB ECG Pattern

Fig. 4 Different type of ECG Arrhythmia patterns used for the peak detection

The different ECG patterns used for the study in this research are presented as example in Figure 4. These patterns are Normal Sinus Rhythm (NSR), Atrial Flutter (AFL), and the atrial premature beats (APBs), It can be seen that significant variation in time features of the AFL and APB ECG patterns.

5 Limitations of PQRST Peak Detection

Owing to several restrictions, peak detection in ECG signals is a challenging task, particularly for PQRST complexes. Some of these include low-amplitude waves, inconsistent rhythms, complex computations, threshold choice; sampling frequency limitations, starting point drift, inter lead variability, morphological variability, noise sensitivity, and sensitivity to electrode placement, individual characteristic adaptation, and time-varying signal characteristics. It is vital to create efficient algorithms that can manage these difficulties, because these factors may result in missed true peaks or false detections. Furthermore, to overcome these constraints and increase the accuracy and robustness of PQRST peak detection, it is necessary to combine several strategies, adaptive algorithms, and signal preprocessing techniques.

The calculation of heart rate variability (HRV) and diagnosis of illnesses primarily depend on the identification of PQRST peaks. The proposed method for detecting HRV peaks was significantly influenced by the sequential analysis. Using the MIT-BIH-certified Arrhythmia ECG measurement database, abnormal ECG readings were classified into various types of cardiac arrhythmia. The HRV plays a crucial role in electrocardiogram (ECG) classification and cardiac diagnosis.

It provides valuable information regarding the function of the autonomic nervous system, facilitates the identification of arrhythmias, contributes to risk stratification, assesses stress and recovery, serves as an early warning mechanism, distinguishes between normal and abnormal conditions, monitors treatment efficacy, enables personalized medical approaches, offers a noninvasive assessment method, and enhances the accuracy of cardiac condition classification. The proposed approach utilizes sequential analysis for HRV peak detection, which may improve the accuracy and reliability of ECG classification, particularly when applied to an MIT-BIH Arrhythmia database.-BIH certified Arrhythmia ECG measurements database.

The major difficulty for PQRST Peaks are for the AFL and APB ECG patterns as in such case no rhythmic pattern is ideally followed and thus PQRST peak detection fails. such as in the case of Figure 5.

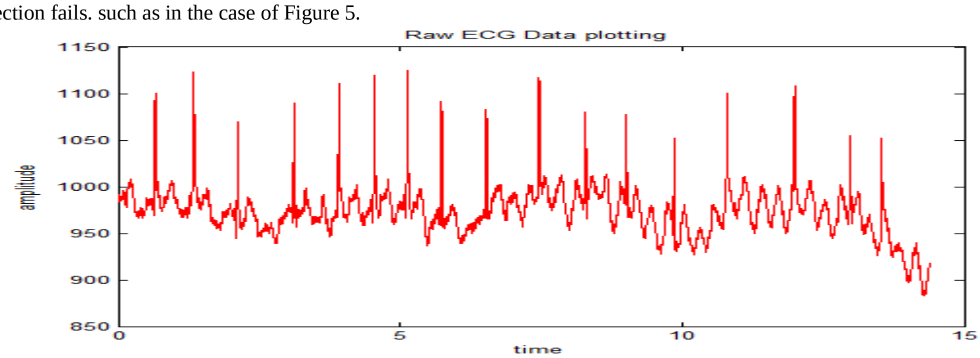


Figure 5 case of AFL ECG where PQRST peak detection fails.

Thus in this paper it is proposed to adopt the R peak detection to determine the time domain features. The flow chart of the proposed method is given in the Figure 6.

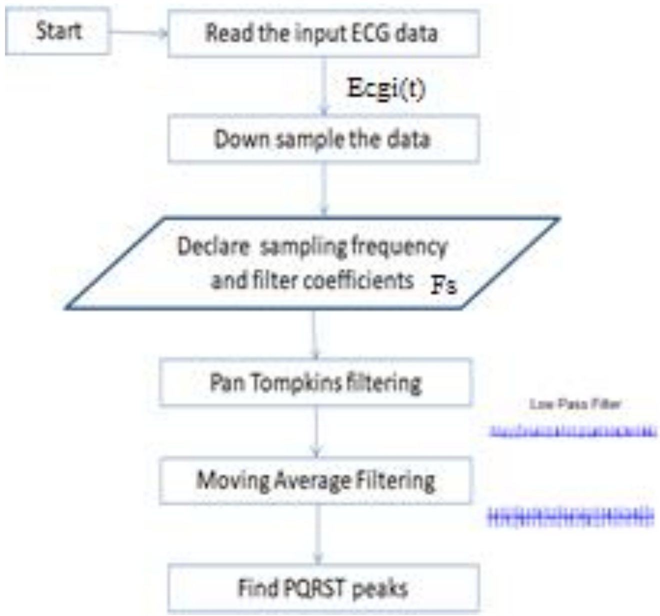
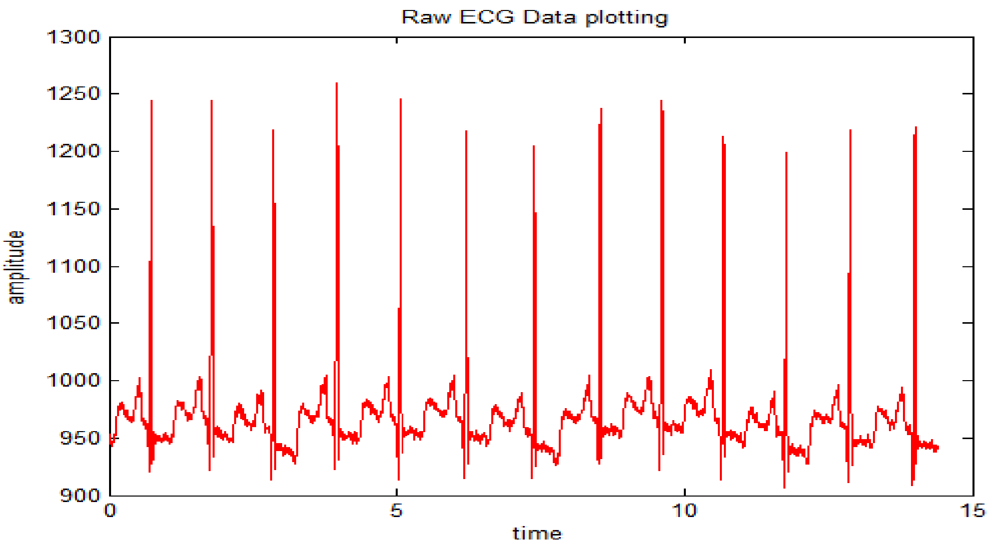
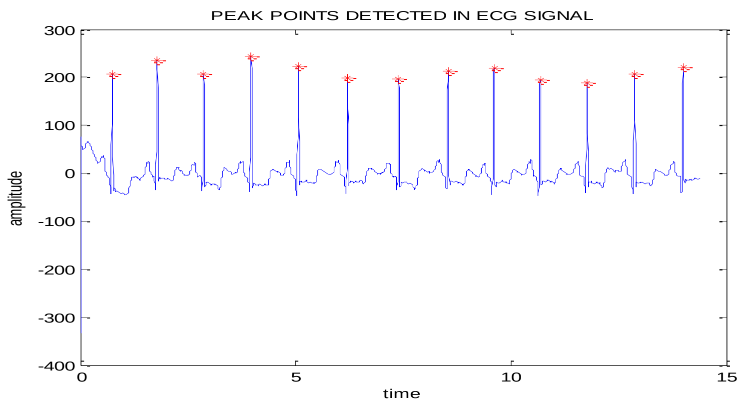


Figure 6 Proposed Flow chart Pan Tompkins approach



a) Original ECG Signal NSR



b) R Peaks Detection

Figure 7 Peak detection results validation using R Peaks

Figure 7 illustrates the process of identifying R-peaks in an electrocardiogram (ECG) signal The waveform depicted in Figure 7 (a) represents the unprocessed ECG signal, exhibiting characteristic peaks and troughs that reflect the electrical activity of the heart. The signal amplitude oscillated around the baseline, indicating normal heartbeat variations.

Figure 7 (b) shows the results of the R-peak detection. R-peaks, which are the highest points in the QRS complex of an ECG, indicate ventricular depolarization. These peaks are highlighted by red markers overlaid on the processed version of the original ECG signal.

The blue line depicts a filtered or modified form of the initial ECG signal, which enhances the visibility of the R-peaks. This outcome demonstrates the capability of the peak-detection algorithm to accurately identify R-peaks within a complex ECG signal. The algorithm successfully located the most significant peaks, which were crucial for the precise analysis of the heart rate and rhythm. The wave in Figure 8 have presented the variation in heart rates per ECG beat

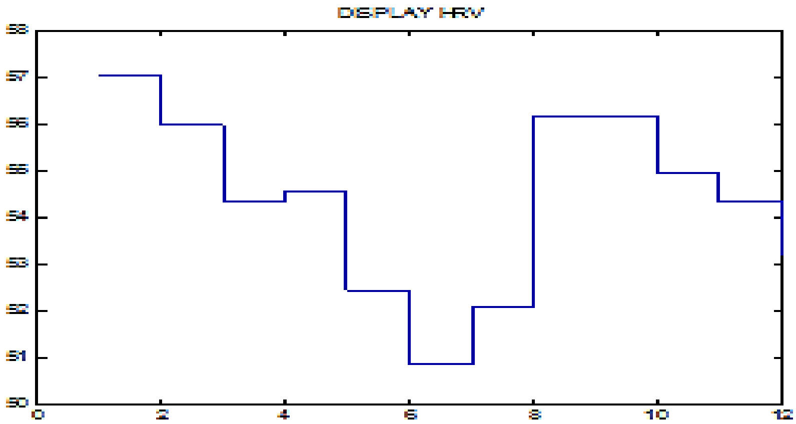


Figure 8 the validated HRV Values per ECG pulse.

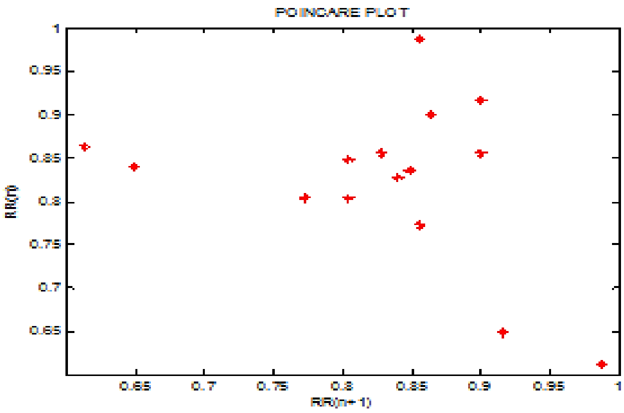


Figure 9 Poincare plot for representing the HRV index

Figure 9 presents a Poincare plot, a visual tool frequently employed in heart rate variability (HRV) analysis. This graph illustrates the correlation between consecutive RR intervals, which measure the time elapsed between heartbeats. Each red marker on the plot denotes an individual data point, depicting one RR interval in relation to the subsequent one.

The horizontal axis represents RR(n+1), indicating the RR interval at a specific moment, while the vertical axis shows RR(n), representing the immediately preceding RR interval. The distribution and configuration of these data points offer insights into how the autonomic nervous system regulates heart rate. A more dispersed and oval-shaped pattern typically suggests higher HRV, which is often associated with improved cardiovascular health and adaptability. In contrast, a more condensed and circular arrangement may indicate lower HRV.

6. Conclusions

This research focuses on using the peak detection method to extract features for classifying heart disease patterns from electrocardiographic (ECG) data. The proposed approach utilizes the Pan-Tompkins algorithm for pre-processing. : It is observed that the derivative filter emphasizes QRS complex's rapid transition. ECG signals and efficiently detecting peaks and temporal features for four different ECG patterns Normal Sinus Rhythm (NSR), Atrial Flutter (AFL), and Atrial Premature Beats (APB). The algorithm employs low-pass, high-pass, and derivative-based filters to isolate QRS complexes. However, peak detection in ECG signals is challenging due to various limitations.

The proposed method focuses on R-peak detection to determine time-domain features, as PQRST peak detection fails in cases like AFL and APB ECG patterns where no rhythmic pattern is ideally followed. The research validates the peak detection results using R-peaks, presents the variation in heart rates per ECG beat, and uses a Poincaré plot to represent the heart rate variability (HRV) index, providing insights into the autonomic nervous system's regulation of heart rate.

A more dispersed and oval-shaped pattern typically suggests higher HRV

It is also concluded that wavelet based filter are capable of efficiently detect the R peaks of ECG signals. Also efficient tuning of threshold is require to meet.

In future the peak detection based feature extraction and classification methods may be designed.

REFERENCES

1. Bae, T. W., & Kwon, K. K. (2021). ECG PQRST complex detector and heart rate variability analysis using temporal characteristics of fiducial points. Biomedical Signal Processing and Control, 66, 102291. https://doi.org/10.1016/j.bspc.2020.102291
2. Ge, Z., Cheng, H., Tong, Z., Wang, N., Alhudhaif, A., Alenezi, F., Wang, H., Zhou, B., & Wang, Z. (2023). ECG-MAKE: An ECG signal delineation approach based on medical attribute knowledge extraction. Information Sciences, 637, 118978., https://doi.org/10.1016/j.ins.2023.118978
3. Meddah, K., Kedir Talha, M., Bahoura, M., & Zairi, H. (2019). FPGA-based system for heart rate monitoring. IET Circuits, Devices & Systems, 13(6), 771–782. https://doi.org/10.1049/iet-cds.2018.5204
4. Meyer, C., Harris, M., & Gavela, J. F. (2006). "Combining Algorithms in Automatic Detection of QRS Complexes in ECG Signals. IEEE Transactions on Information Technology in Biomedicine, 10(3), 468–475. https://doi.org/10.1109/titb.2006.875662
5. Gutierrez-Rivas, R., Hernandez, A., Marnane, W. P., & Garcia, J. J. (2015). Novel Real-Time Low-Complexity QRS Complex Detector Based on Adaptive Thresholding. IEEE Sensors Journal, 15(10), 6036–6043. https://doi.org/10.1109/jsen.2015.2450773
6. Neri, L., Jaipalli, S., Borghi, C., Geminiani, G. A., Oberdier, M. T., Suzuki, M., Tumarkin, E., Halperin, H. R., & Augello, A. (2023). 'Algorithm for Mobile Platform-Based Real-Time QRS Detection. Sensors, 23(3), 1625. https://doi.org/10.3390/s23031625
7. Agostinelli, A., Di Nardo, F., Moretti, E., Fioretti, S., Burattini, L., Sbrollini, A., & Marcantoni, I. (2017). Noninvasive Fetal Electrocardiography Part I: Pan-Tompkins' Algorithm Adaptation to Fetal R-peak Identification. The Open Biomedical Engineering Journal, 11(1), 17–24. https://doi.org/10.2174/1874120701711010017
8. Ribeiro, L., Almeida, S., Da Costa, P., Da Costa, E., Paim, G., & Bampi, S. (2024). VLSI Architecture for Energy-Efficient and Accurate Pre-Processing Pan-Tompkins Design. IEEE Transactions on Circuits and Systems II: Express Briefs, 71(11), 4768–4772. https://doi.org/10.1109/tcsii.2023.3241124
9. Manikandan, M. S., & Soman, K. P. (2011). A novel method for detecting R-peaks in electrocardiogram (ECG) signal. Biomedical Signal Processing and Control, 7(2), 118–128. https://doi.org/10.1016/j.bspc.2011.03.004
10. Rahul, J., Sora, M., & Sharma, L. D. (2020). Exploratory data analysis based efficient QRS-complex detection technique with minimal computational load. Physical and Engineering Sciences in Medicine, 43(3), 1049–1067. https://doi.org/10.1007/s13246-020-00906-y
11. Hamdi, S., Ben Abdallah, A., & Bedoui, M. H. (2017). Real time QRS complex detection using DFA and regular grammar. BioMedical Engineering OnLine, 16(1). https://doi.org/10.1186/s12938-017-0322-2
12. Lin, C.-C., Yeh, C.-Y., Chang, H.-Y., & Huang, Y.-H. (2019). A Novel Wavelet-Based Algorithm for Detection of QRS Complex. *Applied Sciences*, *9*(10), 2142. https://doi.org/10.3390/app9102142
13. Pandit, D., Zhang, L., Liu, C., Chattopadhyay, S., Aslam, N., & Lim, C. P. (2017). A lightweight QRS detector for single lead ECG signals using a max-min difference algorithm. *Computer Methods and Programs in Biomedicine*, *144*, 61–75. https://doi.org/10.1016/j.cmpb.2017.02.028
14. Rahul, J., Sora, M., & Sharma, L. D. (2021). Dynamic thresholding based efficient QRS complex detection with low computational overhead. *Biomedical Signal Processing and Control*, *67*, 102519. https://doi.org/10.1016/j.bspc.2021.102519
15. Sharma, T., & Sharma, K. K. (2016). QRS Complex Detection in ECG Signals Using the Synchrosqueezed Wavelet Transform. *IETE Journal of Research*, *62*(6), 885–892. https://doi.org/10.1080/03772063.2016.1221744
16. V V., Peyrodie, L., & Cao, H. (2023). Variational Mode Decomposition-Based Simultaneous R Peak Detection and Noise Suppression for Automatic ECG Analysis. *IEEE Sensors Journal*, *23*(8), 8703–8713. https://doi.org/10.1109/jsen.2023.3257332
17. Hemant Amhia, A. K. Wadhwani, "Designing an Optimum and Reduced Order Filter for Efficient ECG QRS Peak Detection and Classification of Arrhythmia Data", Journal of Healthcare Engineering 2021, https://doi.org/10.1155/2021/6542290
18. Varun Gupta, Nitin Kumar Saxena, Abhas Kanungo, Parvin Kumar, Sourav Diwania "An Efficient R-Peak Detection in Electro-Cardio-Gram Signal Using Intelligent Signal Processing Techniques", Wireless Personal Communications Issue 2. 2024,
19. Ali STA, Kim S, Kim Y-J. Towards Reliable ECG Analysis: Addressing Validation Gaps in the Electrocardiographic R-Peak Detection. Applied Sciences. 2024; 14(21):10078. https://doi.org/10.3390/app142110078