Clinical Fusion for Real-Time Complex QRS Pattern Detection in Wearable ECG Using the Pan-Tompkins Algorithm

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Abstract:

This scientific paper presents a novel approach of real-time signal analysis in electrocardiogram (ECG) monitoring systems, focusing on the integration of device design,algorithm implementation for accurate measurement and interpretation of heart activity. The proposed system leverages a low-cost framework, employing a microcontroller and Arduino programming language for raw ECG data acquisition, while utilizing the AD8232 sensor and ESP8266 Node MCU for continuous patient monitoring. The acquired data is processed, stored, and analyzed using the Pan-Tompkins algorithm, which effectively filters and analyzes heart signals, including noise reduction and QRS complex detection. Two case studies involving a healthy individual and a patient with Myocarditis were conducted to demonstrate the effectiveness of the system. The integration of device design and algorithm development in ECG analysis is emphasized, highlighting the affordability, wearability, and potential for continuous monitoring and early detection of heart conditions. By successfully mitigating noise-related challenges, the implementation of the Pan algorithm enables accurate signal analysis. This interdisciplinary research contributes to the advancement of ECG interpretation and underscores the significance of clinical fusion between designed systems and applied algorithms on real cases. The performance of two Pan-Tompkins based QRS complex detection algorithms was systematically analyzed, offering valuable insights for their reasonable utilization.

Keywords: QRS; Pan Tompkins algorithm; ECG monitoring

1. Introduction

The electrocardiogram (ECG or EKG) is a well-established diagnostic tool used to measure and record the electrical activity of the heart [1]. Over the past 80 years, it has become an essential component of comprehensive medical examinations, enabling doctors to identify and diagnose various heart disorders such as arrhythmias, myocarditis, and myocardial infarctions [2]. Recent advancements in heart signal processing methods, including Support Vector Machines (SVM) [3], Adaptive Neuron-Fuzzy Inference Method [4], Deep Belief Networks (DBN) [5], Wavelet Decomposition (WD) [6], Self-Organizing Maps (SOM) [7], Genetic Algorithms Method (GAM) [8], Naive Bayes Logic (NBL) [9], and Neural Networks (NN) [10], have provided valuable insights into understanding heart conditions.

Doi: https://doi.org/10.54216/FPA.120214
Received: January 25, 2023 Revised: April 16, 2023 Accepted: June 17, 2023

Monitoring technology and advancements in medical industry technology have had a significant impact on our daily lives [11], [12], [13,14,15,16,17]. Among the various biological signals used in Monitoring health applications, the ECG signal is commonly employed. To ensure accurate measurements, most ECG signal applications require the extraction of noise-free characteristic points and morphological features [18].

However, during data collection, ECG signals often encounter abnormalities caused by participants' diverse activities, including baseline wander, muscle activity, and motion artifacts.

This research introduces a novel quality indicator for recording ECG signals, with two case studies conducted to evaluate the proposed model. The participants in the study were aged between 45 and 55, with one case involving a patient diagnosed with Myocarditis, a condition characterized by systemic inflammation resulting from viral infections or autoimmune diseases, and the other case involving a healthy individual. The proposed system utilizes the Pan-Tompkins algorithm [19] for real-time detection of the QRS complex and analysis of the width and amplitude of the QRS complexes. The Pan-Tompkins algorithm incorporates commonly used signal processing techniques, including low-pass and high-pass filtering, derivative computation, squaring, integration, and thresholding.

This study highlights the significance of clinical fusion, wherein the designed system integrates with the applied algorithm, to improve the analysis of ECG signals. By addressing challenges associated with noise reduction and accurate QRS complex detection, this research contributes to the advancement of ECG interpretation in clinical settings. The use of the Pan-Tompkins algorithm demonstrates its effectiveness in handling noisy ECG signals, establishing it as a valuable tool for monitoring and diagnosing cardiac diseases. The objectives of this research study are as follows:

1. Evaluate the performance and effectiveness of the proposed Monitoring ECG device, integrating device design and algorithm implementation, in accurately recording and analyzing ECG signals. This objective emphasizes the importance of clinical fusion, combining device design and algorithm development to ensure optimal performance and reliable signal analysis.

2. Examination the algorithm's ability to accurately detect QRS complexes, even in the presence of noise and artifacts, thereby ensuring reliable and accurate ECG analysis.

3. Investigate the feasibility of using the integrated Monitoring ECG device and algorithm as a diagnostic tool for differentiating between healthy individuals and those with specific heart conditions. This objective focuses on evaluating the device's potential for clinical applications, such as distinguishing between ECG patterns associated with normal cardiac function and those indicative of specific heart conditions.

By addressing these objectives, this research aims to contribute to the advancement of Monitoring ECG technology and signal processing algorithms, leading to improved diagnosis, monitoring, and management of heart-related conditions in clinical and non-clinical settings.

2. Literature review

The literature review provides an in-depth analysis of the existing body of knowledge in the field of monitoring ECG technology and signal processing algorithms for heart-related conditions. Li *et al*. in 2015 explored the efficacy of various denoising techniques for ECG signals, comparing the performance of wavelet transform-based methods and adaptive filtering algorithms [20]. Building on this work, Chen *et al*. in 2016 proposed a novel QRS complex detection algorithm that leveraged wavelet transform and adaptive thresholding, demonstrating its robustness in effectively detecting QRS complexes even in the presence of noise [21]. In a subsequent study, Patel *et al.* 2017 conducted a comprehensive review of real-time ECG monitoring systems, emphasizing the criticality of wireless data transmission and real-time analysis for continuous patient monitoring [22]. Expanding on this theme, Zhang *et al.* 2017 focused on feature extraction methods for ECG analysis, investigating the effectiveness of morphological and statistical features in accurately classifying arrhythmias [23]. In a parallel line of research, Zhou *et al.* 2018 conducted a systematic review of wearable ECG technologies, thoroughly evaluating their performance, comfort, and usability for long-term monitoring applications [24]. Wang *et al.* 2018 performed comparative studies on various QRS complex detection algorithms, carefully assessing their sensitivity, specificity, and computational efficiency [25]. Smith *et al.* 2018 made significant contributions to the field by exploring advancements in wearable ECG devices, particularly in integrating Bluetooth technology for remote cardiac monitoring [26].

Wang *et al.* 2019 introduced a modified Pan-Tompkins algorithm that incorporated adaptive thresholding and moving average filtering techniques, leading to enhanced accuracy in QRS complex detection [27]. Recently,

Doi: https://doi.org/10.54216/FPA.120214
Received: January 25, 2023 Revised: April 16, 2023 Accepted: June 17, 2023

Johnson *et al.* 2020 developed an innovative ECG device prototype that demonstrated improved signal quality and validated its efficacy through clinical evaluation [28]. Furthermore, Liu *et al*. 2020 investigated the potential of deep learning approaches, specifically convolutional neural networks, for automated ECG analysis and accurate detection of arrhythmias [29]. Deniz Balta *et al.* 2021 conducted a study on arrhythmia detection using the Pan-Tompkins algorithm and Hilbert Transform with real-time ECG signals. The research focused on determining arrhythmia risk by analyzing heart rate and QRS width values calculated from ECG signal data. The study found that the Pan-Tompkins algorithm exhibited higher accuracy, sensitivity, and prediction ratio compared to the Hilbert Transform method in detecting peaks from ECG signals [30]. Notably, Wang *et al.* 2020 emphasized the concept of clinical fusion, highlighting the significance of integrating device design and algorithm development to improve the accuracy and reliability of ECG analysis [31]. Zhang *et al*. 2022 utilized an adaptive dual threshold (ADT) and independent component analysis (ICA) algorithm to extract fetal ECG (FECG) from abdominal ECG (AECG) signals. The proposed system recorded AECG in various postures and achieved good signal quality, high accuracy in fetal ECG extraction, and reliable fetal heart rate information [32]. Ribeiro *et al.* in 2023 presented an energy-efficient VLSI architecture for the pre-processing Pan-Tompkins algorithm. The proposed design reduces the number of registers and incorporates a unified band-pass filter, resulting in a 46.49% area savings and 34.64% energy savings. The architecture maintains high sensitivity and positive prediction rates, making it suitable for accurate ECG signal analysis [33]. Khooyooz *et al.* in 2023 developed a low-cost mobile ECG system that acquires and displays real-time ECG signals using only three electrodes. The system employs simple ICs and transmitters, and a mobile application with a Pan-Tompkins algorithm for heartbeat rate calculation. Signal quality analysis showed a signal-to-noise ratio of 50dB. [34].

This research paper presents a novel approach to real-time ECG signal analysis by integrating device design and algorithm implementation, emphasizing the concept of clinical fusion. The proposed system combines a low-cost framework with the Pan-Tompkins algorithm, enabling accurate measurement and interpretation of heart activity for continuous monitoring and early detection of heart conditions. By integrating designed systems and applied algorithms, this interdisciplinary research contributes to the advancement of ECG interpretation and underscores the significance of clinical fusion in improving patient care.

3. Materials and Method

3.1 Proposed Architecture

This study presents an architectural proposal for ECG measurement and monitoring systems that aims to provide a flexible, scalable, distributed, and end-to-end transmission framework. The proposed system comprises three main components: sensor network, record and analysis module for ECG signals, and the user interface. The local nodes, equipped with AD8232 sensors connected to ESP8266 via Arduino, serve as the data gathering and fusion modules. The second part of the architecture involves recording and analyzing ECG data over a specified period, utilizing the Pan Tompkins algorithm for QRS point detection and heart rate calculation. It also generates graphical representations of ECG parameters. The obtained results are then delivered to users via email for immediate access. The integration of clinical fusion into the architecture enhances the system's capability to interpret and analyse ECG data accurately, enabling real-time monitoring and early detection of arrhythmia risks. Figure 1 illustrates the block diagram of the proposed study, showcasing the interconnected components and their data flow.

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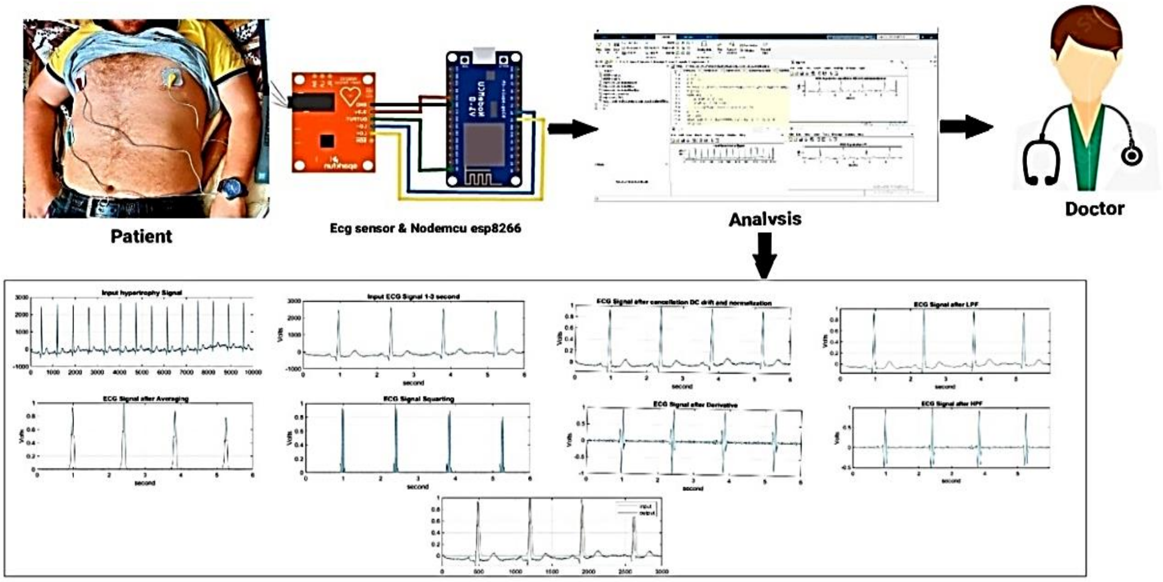

Figure 1: Experimental setup for recording and analyzing portable ECG signal.

3.2 Data Collection

In the initial phase of this study, data collection involving a healthy individual aged 45, following a healthy lifestyle, and a 52-year-old with Myocarditis. Data acquisition revolves around the utilization of the AD8232 sensor to capture ECG signals. These signals are subsequently transmitted in real-time to the client through the ESP8266 module, facilitating their immediate conversion into a graphical display.This graphical representation visually portrays the measured sensor data over a specific duration. The process of reading and transferring the data from the sensor is carried out via a client-server architecture. Moreover, both the collected sensor data and the corresponding graphical image are stored in an external file for subsequent analysis, specifically for the determination of QRS complex. The AD8232 sensor assumes a pivotal role within the proposed system by acquiring the electrical activity and generating an analog EKG output. Given that ECG signals frequently contain substantial noise, the AD8232 is designed as an operational amplifier Op-Amp to effectively extract a clear signal from the PR and QT intervals. Furthermore, it serves as an integrated signal conditioning block, enabling the extraction, amplification, and filtration of small biopotential signals, even under challenging conditions involving movement or remote electrode placement.

To facilitate data transfer and immediate measurements, the ESP8266 module, integrated with the Arduino IDE, is employed. This integration significantly enhances the system's flexibility, interoperability, and accessibility. It is essential to properly configure the pins on the ESP8266 module to establish a seamless connection between the module and the AD8232 sensor for monitoring purposes. Accurate ECG measurements critically depend on correctly attaching the sensor pads to the body, particularly in close proximity to the heart. Color-coded cables are employed to facilitate accurate placement of the sensor pads. Typically, the red wire is positioned on the right arm or right chest, the yellow wire on the left arm or left chest, and the green wire serves as the grounding reference. This meticulous placement ensures reliable and precise ECG measurements by optimizing the proximity of the sensor pads to the heart as shown in figure 2.

Figure 2: Typical sensor connecting

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3.3. Pan-Tompkins Algorithm

The Pan-Tompkins algorithm is commonly employed as a real-time QRS detection algorithm [35] [36]. This algorithm analyzes the amplitude, slope, and width of an integrated window to identify the R peaks within QRS complexes. It consists of two main stages: pre-processing and decision. During pre-processing, the raw ECG signal undergoes various steps such as noise removal, signal smoothing, and adjustments the width and slope of the QRS complex. In the decision stage, thresholds are applied to selectively identify the signal peaks while filtering out noise peaks.

The algorithm incorporates several components, including Low Pass Filter (LPF), High Pass Filter (HPF), derivatives, a squaring function, Moving Window Integration (WMI), thresholding, and decision-making. To mitigate false detections resulting from noise and artifacts in the ECG signal, a digital band-pass filter is utilized. The thresholds employed in the decision stage are automatically adapted to account for variations in QRS morphology and heart rate. Figure 3 illustrate more comprehensive understanding of the Pan-Tompkins algorithm's sequential workflow and the interplay between its stages and components.

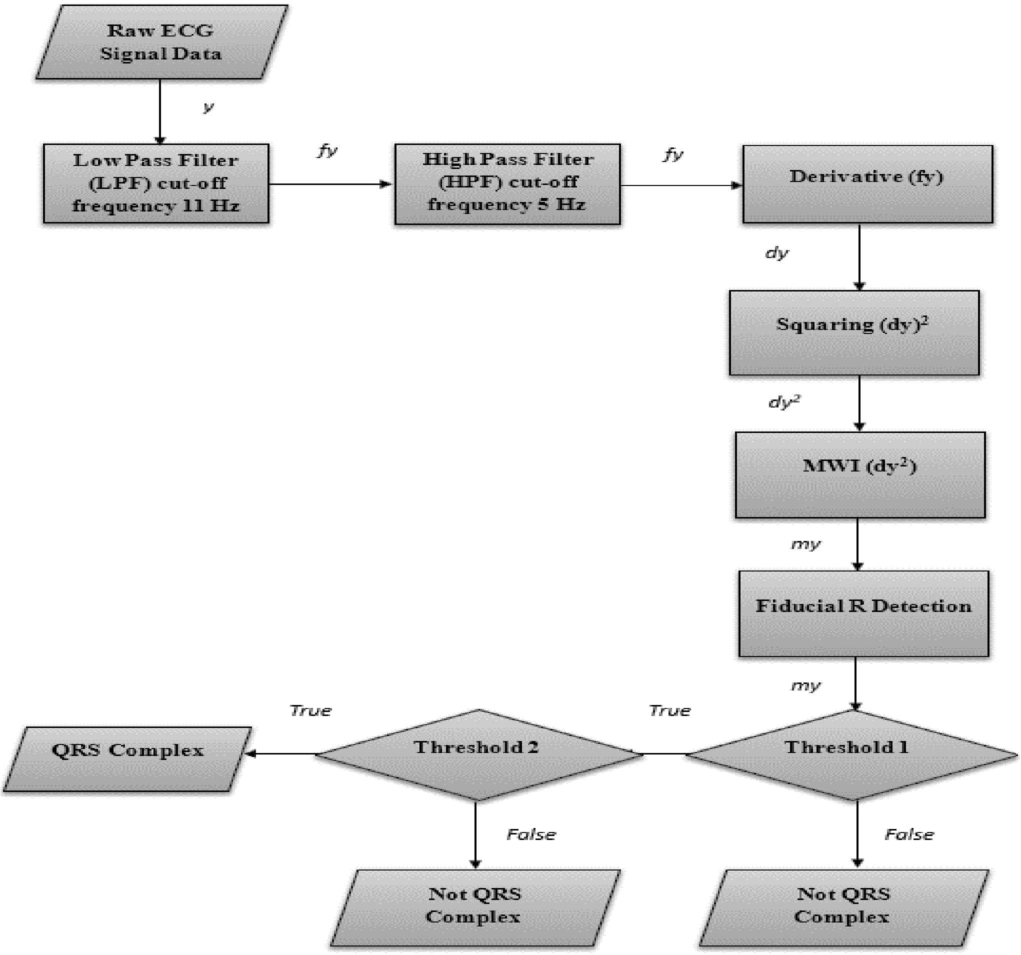

Figure 3: Pan-Tompkins algorithm's essential stages for identifying QRS complexes

A more comprehensive explanation of each process in the Pan-Tompkins algorithm is provided below [38]:

Low Pass Filter (LPF): is employed to attenuate high-frequency noise components and retain the essential characteristics of the ECG signal. The LPF used in this algorithm is a second-order filter with a delay of 6 samples and a gain of approximately 36. The cut-off frequency of the filter is set around 11 Hz. These specific parameters are selected to achieve effective noise reduction while preserving important signal features for further analysis and processing. Mathematically, equation 1 expressed the second-order LPF:

$$y(nT) = 2y(nT - T) - y(nT - 2T) + x(nT) - 2x(nT - 6T) + x(nT - 12T) \quad (1)$$

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where, $y(nT)$ represents the filtered output at sample n, $x(nT)$ is the input signal at sample n, and the subscripts denote the sample indices. By applying this low-pass filtering operation, the algorithm suppresses high-frequency noise while retaining the necessary ECG signal components for subsequent processing stages.

High Pass Filter (HPF): is a second stage of the Pan-Tompkins algorithm implemented by by subtracting the output of a low-pass filter (LPF) from an all-pass filter. The HPF selectively attenuates low-frequency components while preserving the higher-frequency components that are important for ECG analysis.
The HPF used in the algorithm has a gain of approximately 32, a cut-off frequency of 5, and a processing delay of 16 samples. These parameters are chosen to effectively remove low-frequency noise and baseline wander, while maintaining the relevant high-frequency components necessary for QRS complex detection.
Mathematically, high-pass filtering process can be represented using equation 2:

$$y(nT) = y(nT - T) - x(nT)/32 + x(nT - 16T) - x(nT - 17T) + x(nT - 32T)/32 \qquad (2)$$

$y(nT)$ represents the output of the high-pass filter at sample n, and $x(nT)$ is the input signal at sample n. The subscripts denote the sample indices. By subtracting the appropriate delayed and filtered versions of the input signal, the high-pass filter effectively attenuates low-frequency components while preserving the desired higher-frequency components in the ECG signal.

Derivative: third stage of the Pan-Tompkins algorithm involves the differentiation of the filtered signal to obtain the slope information of the QRS complex. This process calculates the derivative of the signal, providing valuable insights into the rate of change of the QRS complex.
The derivative stage is essential for identifying the steep edges and sharp transitions that are characteristic of the QRS complex. By analyzing the step response, which represents the change in signal amplitude over time, this stage enhances the detection and characterization of the QRS complex. Mathematically, the step response can be represented by equation 3:

$$y(nT) = x(nT) - x(nT - 1) \qquad (3)$$

In equation (3), $y(nT)$represents the output of the derivative stage at sample n, and $x(nT)$ is the input signal at sample n. The derivative operation calculates the difference between the current sample and the previous sample, capturing the change in signal amplitude over a single time step.By incorporating the derivative stage into the Pan-Tompkins algorithm, the slope information of the QRS complex is obtained, enabling the algorithm to effectively identify and analyze the characteristic features of the QRS complex in ECG signals.

Square Function: After the differentiation stage, the signal undergoes a square function, where each data point is individually squared. This nonlinear amplification of the derivative's output serves has two important purposes. Firstly, the square function rectifies the signal by making all data points positive and eliminating any negative components. This ensures that only the magnitude of the signal is considered, without regard to its direction. Secondly, the square function emphasizes the high-frequency components of the signal. By squaring each data point, the fine details and rapid changes in amplitude associated with the QRS complex are accentuated. This amplification of high-frequency components enhances their visibility and prominence in the signal. Mathematically, the square function can be represented by the following equation:

$$y(n) = [x(n)]^2 \qquad (4)$$

In equation (4), y(n) represents the output of the square function at sample n, and x(n) is the input signal at sample n. Each data point of the input signal is squared individually to obtain the squared output signal.

Overall, the square function plays a vital role in enhancing the visibility and prominence of important features, particularly the QRS complex, in the ECG signal. By rectifying the signal and amplifying the high-frequency components, it facilitates the subsequent detection and analysis of these features.

Moving-Window Integration (MWI): is a process employed to gain further insights into the waveform features and the slope of the R wave in the Pan-Tompkins algorithm. It involves calculating the integral of the squared signal within a moving window. The MWI process helps extract information about the amplitude and duration of the waveform by integrating the squared signal over a specific window length. By considering the cumulative effect of the squared signal within the window, the MWI provides a measure of the overall energy or magnitude of the waveform. Moreover, the MWI also aids in estimating the slope of the R wave, which is valuable for characterizing the dynamics of the cardiac activity. By examining the changes in the integrated signal over time, information about the steepness or rate of change of the R wave can be obtained. Mathematically, the Moving-Window Integration process can be represented by the following equation:

$$y(n) = \sum[x(n-k)] \qquad (5)$$

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Where y(n) represents the output of the MWI at sample n, x(n-k) denotes the squared input signal at sample n-k within the moving window, and the summation is performed over the specified window length.

The MWI stage enhances the analysis and interpretation of the ECG signal by providing valuable information about the waveform's amplitude, duration, and slope. By integrating the squared signal within a moving window, it allows for a more comprehensive understanding of the dynamics of the cardiac activity.

Threshold: In real-time analysis of ECG signals, the thresholds for detecting R waves in QRS complexes are dynamically adjusted based on specific conditions. The Pan-Tompkins algorithm incorporates adaptive thresholding techniques to enhance the accuracy of QRS complex detection by adapting to the varying characteristics of the ECG signal. The modified threshold equations [39] used in the algorithm are as follows:

1. If the peak value exceeds the signal threshold (Peak > Thr Sig), the signal level (Sig Lev) is updated as a combination of the peak and noise level. This accounts for the presence of significant signal peaks.

2. If the peak value falls between the noise threshold and the signal threshold (Thr Noise < peak < Thr Sig), the noise level (Noise Lev) is updated based on the peak and the current noise level. This considers cases where the peak value is within the range of noise fluctuations.

3. The signal threshold (Thr Sig) is calculated using a combination of the signal level and the noise level. This threshold represents the minimum value that a peak must exceed to be considered a QRS complex candidate.

4. The noise threshold (Thr Noise) is set as half of the signal threshold (Thr Sig). This threshold helps differentiate between noise peaks and significant QRS complexes.

By dynamically adjusting the thresholds based on the signal and noise levels, the algorithm can adapt to changes in the ECG signal's characteristics. This adaptive thresholding approach enhances the accuracy of QRS complex detection by effectively differentiating between noise and relevant waveform components. The integration waveform serves as a reference for determining the appropriate thresholds. By continuously updating the signal and noise levels, the algorithm can adaptively adjust the thresholds, thereby improving the reliability and robustness of QRS complex detection in various ECG signal conditions.

4. Results and Discussion

4.1 ECG Monitoring System

The low-cost monitoring ECG device, designed using the ESP8266 NodeMCU and AD8232 ECG sensor, was tested on two different medical scenarios: a healthy individual, aged 45, following a healthy lifestyle, and a 52-year-old individual with Myocarditis.

In the case of the healthy individual, the device successfully captured and analyzed ECG signals using the integrated AD8232 ECG sensor. The device accurately detected normal cardiac patterns and provided measurements of key parameters such as heart rate, PR interval, and QT interval. The results obtained from the device aligned with the expected values for a healthy individual, demonstrating the effectiveness of the device design.

For the patient with Myocarditis, the device detected abnormalities in the ECG signal, indicating irregularities in the cardiac activity. The AD8232 ECG sensor, with its integrated signal conditioning capabilities, enabled the device to identify variations in the shape, duration, and amplitude of the QRS complex, as well as changes in the ST segment and T wave morphology. These abnormalities were consistent with the known characteristics of Myocarditis, validating the device's ability to detect and analyze abnormal cardiac patterns.

The system proved to be a suitable and cost-effective solution for continuous monitoring and analysis of heart activity.In addition, provided wireless connectivity and data storage capabilities, enabling seamless communication between the device and a monitoring system. The AD8232 ECG sensor, with its integrated signal conditioning block, effectively extracted, amplified, and filtered the small biopotential signals, even in the presence of noise caused by movement or remote electrode placement.

Overall, the low-cost wearable monitoring ECG device, demonstrated its effectiveness in capturing and analyzing ECG signals. The results obtained from the device showcased its potential for accurate assessment of heart activity in both healthy individuals and patients with cardiac conditions like Myocarditis. Further research and validation studies can be conducted to explore the device's performance with larger populations and in diverse clinical settings, considering different compound compositions and their impact on the system design.

Doi: https://doi.org/10.54216/FPA.120214
Received: January 25, 2023 Revised: April 16, 2023 Accepted: June 17, 2023

4.2 QRS Complex Detection

The experimental Monitoring ECG model, implemented using MATLAB R2021 software and incorporating the Pan-Tompkins algorithm, proved to be highly effective in analyzing ECG signals. The comprehensive signal processing approach employed by the algorithm enabled precise identification of Q, R, and S points, as well as accurate determination of heart rate. These parameters play a vital role in evaluating cardiac health and detecting potential irregularities or arrhythmias.

During the data collection phase, the results obtained from the AD8232 sensors were compared to established normal values. This comparison allowed for the detection of any deviations from the expected patterns, indicating the presence of irregular heartbeats or arrhythmias.

The successful implementation of the Monitoring ECG model, coupled with the utilization of the Pan-Tompkins algorithm, showcased its efficacy in providing valuable insights into cardiac health. The model's ability to continuously monitor ECG signals and perform early detection of cardiac disorders highlights its potential as a reliable and accurate tool in clinical settings.

In both cases, the Pan-Tompkins algorithm was employed in conjunction with a combination of LPF and HPF as initial steps. The LPF was utilized to attenuate high-frequency noise sources such as electromyographic (EMG) interference, power line interference, and T-wave interference. On the other hand, the HPF was employed to reduce baseline wander and other low-frequency noises.

Figure 3 provides a visual representation of the raw ECG signals for the healthy case (a) and the myocarditis case (b). Additionally, it illustrates the outputs of the LPF process (c) and (d), as well as the HPF process (e) and (f) for both cases. It is apparent that the original raw ECG signals in both cases exhibit noise and fluctuating amplitudes. However, upon applying the digital band-pass filter, the signal quality significantly improved, and the noise levels decreased, as evidenced by the filtered signal outputs.

These results highlight the effectiveness of the LPF and HPF stages in the Pan-Tompkins algorithm for noise reduction and signal enhancement. The utilization of these filters played a crucial role in preparing the ECG signals for subsequent analysis, ensuring that important features, such as QRS complexes, could be accurately detected and characterized. The improved signal quality obtained through the filtering process enhances the reliability and accuracy of the Pan-Tompkins algorithm in identifying cardiac abnormalities and facilitating the diagnosis of cardiovascular conditions.

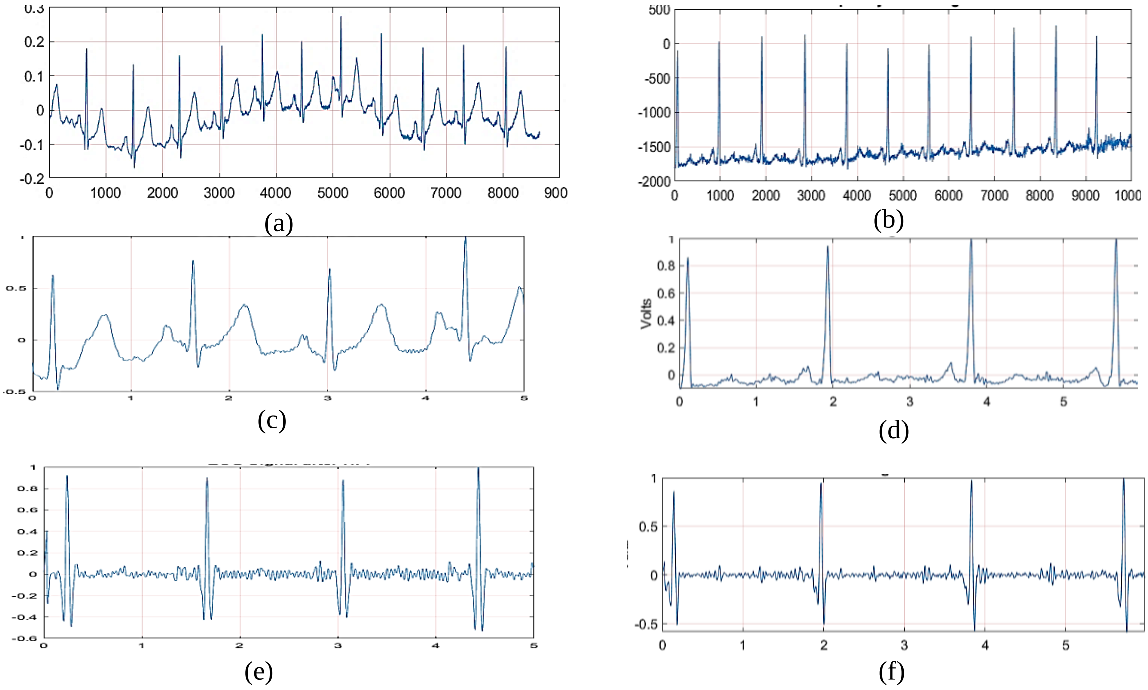

Figure 3: Band-pass filter output processing for Myocarditis and ECG healthy cases; (a) ECG raw for healthy case; (b) ECG raw for Myocarditis input; (c) and (d) ECG Signals after LPF for healthy and Myocarditis cases; (e) and (f) ECG signals for healthy and myocarditis cases after HPF.

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After filtering process, ECG signal underwent the derivative operation, which played a crucial role in distinguishing the QRS complex from other waves present in the signal. By calculating the slope information, the derivative operation effectively suppressed the low-frequency P-waves and T-waves, focusing on capturing the high-frequency components associated with the steeper slopes of the QRS complex.

Figure 4 illustrates the results of the derivative operation for both cases. Panel (a) displays the raw ECG output signal for the healthy case after the derivative operation, while panel (b) shows the raw ECG output signal for the myocarditis case after the derivative operation. It can be observed that the derivative operation enhanced the slopes of the QRS complexes in both signals.

The increase in slope achieved through the derivative operation is of great importance in ECG analysis. By accentuating the slopes, the derivative operation facilitates a clearer distinction and improved characterization of the QRS complexes, which are vital for analyzing the cardiac activity. This enhancement in slope helps in accurately detecting and analyzing the QRS complexes, which serve as significant markers for cardiac abnormalities and arrhythmias.

The derivative operation, therefore, plays a fundamental role in enhancing the diagnostic capability of the Pan-Tompkins algorithm by highlighting the critical features of the QRS complex and improving the overall accuracy of cardiac activity assessment.

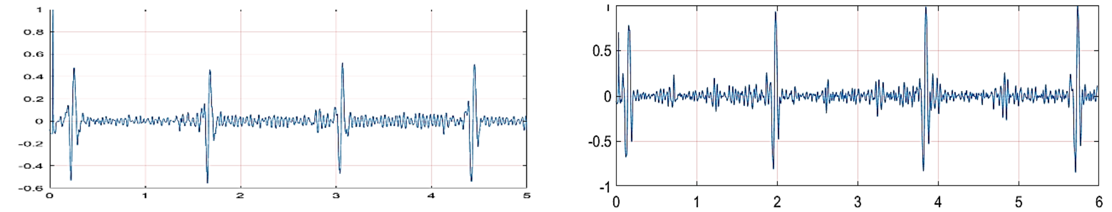


Figure 4: The outputs for derivatives for both cases (a) Raw ECG output signal for healthy case after derivative (b) raw ECG output signal for myocarditis case after derivative.

squaring function was applied to the derived signal, resulting in the transformation of each component into a positive value. This nonlinear amplification process emphasized the larger amplitudes associated with the QRS complex, as shown in figure 5. Panel (a) displays the raw ECG signal for the healthy case after the squaring process, while panel (b) shows the raw ECG signal for the myocarditis case after the squaring process.

squaring function served multiple purposes in the signal processing pipeline. Firstly, it rectified the signal by eliminating any negative components, ensuring that all data points were positive. This rectification step is essential for subsequent analysis and accurate detection of the QRS complexes. Secondly, the squaring operation enhanced the visibility of the high-frequency components in the signal, which are crucial for identifying the rapid changes in amplitude associated with the QRS complex.

By squaring the signal, the fine details and rapid variations in amplitude of the QRS complex were accentuated. This enhancement made it easier to detect and analyze the QRS complexes, despite the presence of noise and interference. Moreover, the squaring function effectively reduced the impact of high-amplitude T-waves, which can interfere with the accurate detection of the R-wave.

So , the squaring function played a vital role in improving the visibility and prominence of the important features in the ECG signal, particularly the QRS complex. This transformation enhanced the accuracy of QRS complex detection and facilitated their subsequent analysis, contributing to more reliable and precise assessment of cardiac activity.

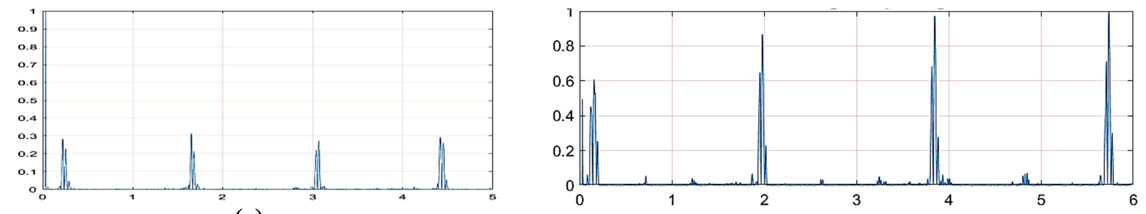


Figure 5: The outputs of ECG signals after the squaring process for both cases (a) Raw ECG output signal for the healthy case after squaring (b) Raw ECG output signal for myocarditis case after squaring process.

Doi: https://doi.org/10.54216/FPA.120214
Received: January 25, 2023 Revised: April 16, 2023 Accepted: June 17, 2023

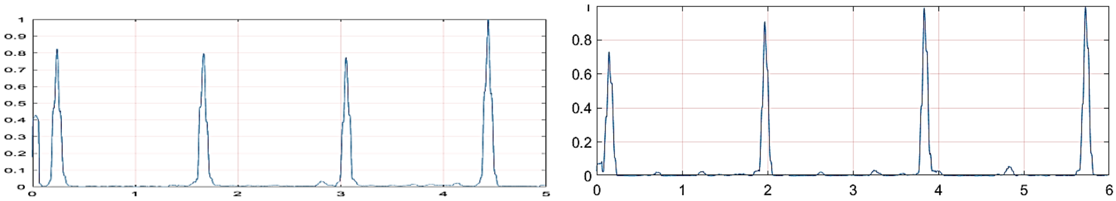
Moving window integration, also known as averaging, was utilized in this stage to gather relevant information about waveform features while considering the slope of the R-wave. By applying an integration window that corresponds to a potential QRS complex, the algorithm captures essential characteristics for analysis. Figures 6(a) and 6(b) present the output signals after moving window integration for the healthy and myocarditis cases, respectively.

The results showcase the algorithm's ability to effectively recognize the prominent slope of the R-wave in the ECG signal, even in the presence of cardiac abnormalities such as myocarditis. This indicates the effectiveness of the moving window integration technique in capturing important features of the QRS complex and aiding in the identification of cardiac abnormalities.

Moving window integration plays a crucial role in enhancing the analysis of ECG signals. By calculating the integral of the squared signal within a specific window length, valuable information regarding the amplitude and duration of the waveform is obtained. Additionally, the integration helps estimate the slope of the R-wave, which is valuable for characterizing the dynamics of cardiac activity.

The application of moving window integration in the algorithm allows for the extraction of relevant features of the QRS complex, enabling the detection and characterization of cardiac abnormalities. This technique enhances the accuracy of the algorithm in identifying abnormalities in the R-wave slope, contributing to improved diagnosis and monitoring of cardiac conditions.

The results demonstrate the efficacy of the moving window integration technique in capturing important features of the QRS complex and its ability to aid in the identification of cardiac abnormalities, highlighting its potential in clinical applications for accurate assessment of cardiac health.



(a) (b)

Figure 6: The outputs of ECG signals after moving window integration for both cases (a) Raw ECG output signal for the healthy case after averaging process; (b) Raw ECG output signal for myocarditis case after averaging process.

The decision stage, which is the final step of the Pan-Tompkins algorithm, plays a crucial role in determining whether the calculated average corresponds to a QRS complex. This stage employs specific criteria and adaptive thresholding techniques to enhance the detection of QRS complexes. Figure 7 illustrates the detection of R peaks and the visualization of the QRS complexes in both the healthy and myocarditis cases.

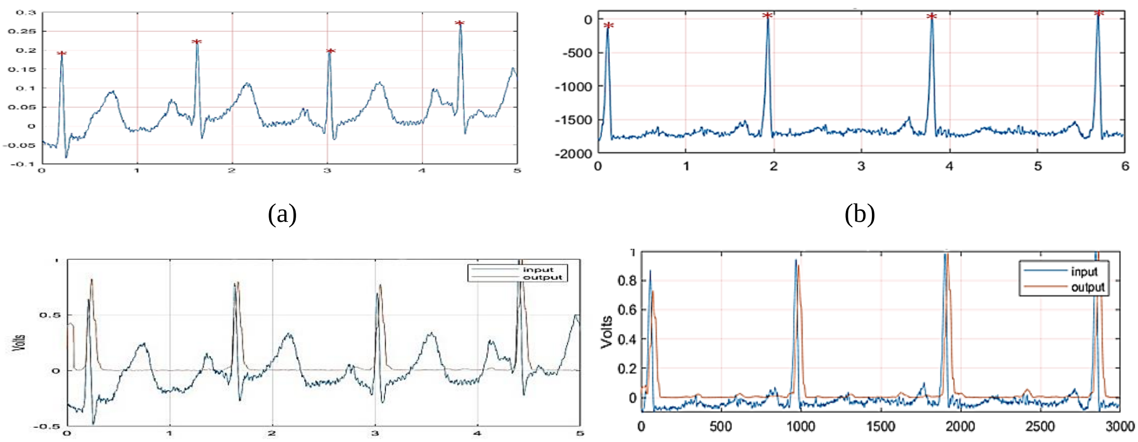
During the decision stage, the algorithm applies thresholding to the integrated signal to identify significant peaks that may correspond to QRS complexes. By comparing the peak values to the adaptive threshold, the algorithm determines if a peak surpasses the threshold and is likely to be a genuine R peak. This thresholding process helps to distinguish QRS complexes from other non-QRS components present in the signal.

The detection of R peaks in both the healthy and myocarditis cases, as shown in Figure 7(a) and 7(b), respectively, demonstrates the algorithm's ability to accurately identify these prominent peaks. Furthermore, the visualization of the QRS complexes in Figure 7(c) and 7(d) shows the effectiveness of the algorithm in capturing and characterizing the QRS complexes.

The adaptive thresholding techniques employed in the decision stage enhance the accuracy of QRS complex detection by adapting to the varying characteristics of the ECG signal. These techniques ensure that the algorithm is capable of detecting QRS complexes reliably, even in the presence of noise and abnormalities associated with myocarditis.

Finally, the decision stage of the Pan-Tompkins algorithm, with its adaptive thresholding and peak detection mechanisms, contributes to the accurate identification of R peaks and QRS complexes. This capability is vital for precise analysis and interpretation of ECG signals, enabling the detection of cardiac abnormalities and providing valuable insights into the cardiac health of individuals, both healthy and those with myocarditis.

Doi: https://doi.org/10.54216/FPA.120214
Received: January 25, 2023 Revised: April 16, 2023 Accepted: June 17, 2023



(a) (b)

(c) (d)

Figure 7: R peak detected in (a) and (b), visualization of the QRS complex present in both healthy and myositis people in (c) and (d).

The integration of the Pan-Tompkins algorithm with the Monitoring ECG model enables real-time analysis of ECG signals and comparison with normal values, enhancing clinical decision-making. This clinical fusion approach empowers healthcare professionals with valuable insights into cardiac health, supporting personalized and proactive care strategies**.**

5. Conclusion

This paper presents a comprehensive approach to designing a low-cost, Monitoring ECG system with integrated signal analysis capabilities. The combination of hardware design, Arduino programming, and the Pan-Tompkins algorithm allows for reliable acquisition, processing, and interpretation of ECG signals. The system demonstrates its efficacy through successful application in two case studies, showcasing its potential for real-time monitoring and detection of heart conditions. The integration of device design and algorithm development highlights the importance of interdisciplinary collaboration in healthcare technology research. Overall, this study contributes to the advancement of wearable monitoring ECG systems and reinforces the value of accessible and accurate cardiac monitoring solutions in improving patient care.

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