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Article

An Efficient Designing of IIR Filter for ECG Signal Classification Using MATLAB

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Abstract: The electrocardiogram (ECG) is a biological signal that is frequently employed and plays a significant role in cardiac analysis. In analysis of important indicators of the distribution of ECG record of patient. The R wave is crucial for both analyzing abnormalities in cardiac rhythm and determining heart rate variability (HRV). In this article, a brand-new method for classifying and detecting QRS peaks in ECG data based on artificial intelligence is provided. The integration of the ECG signal data is proposed using a reduced order IIR filter design. To construct the reduced order filter, the filter coefficient is optimized using the min-max method. The main focus of this study is on removing baseline uncertainty and power line interferences from the ECG signal. According to the results, the accuracy has increased by about 13.5% in comparison to the fundamental Pan-Tompkins approach and by about 8.1% in comparison to the current IIR-filter-based categorization rules.

Keywords: ECG, Interpretation, Acquisition, HRV, Pan-Tompkins Method, min-max method.

1. Introduction

The World Health Organization has determined that heart arrest is the leading cause of mortality worldwide. Due to this strong emphasis on medicine, preventive, and technology in cardiac health research, investigators have been working to develop the cardiovascular abilities that are typically used in clinics [1,2]. The majority of heart pathology can be understood by looking at the ECG signal. Heart rate and ECG signals are used to evaluate a healthy heart. A cardiac arrhythmia is recognized if we record an ECG from a patient and there is any nonlinearity. Figure 1 depicts an average ECG rhythm. The PQRS-TU wave's length and amplitude provide important information about the severity of the heart disease. In the clinical setting, the ECG signal is subjected to a variety of sounds during acquisition [3]. Outside electromagnetic field incursion, noise, power line interference (PLI), which comprises crucial cardiac foundations, frequency determination, and signal superiority[4,5]. It is advised to solve the issue of contaminated noise removal because it improves accuracy and is crucial for the ECG data. Medical professionals use ECG extensively in the assessment and identification of cardiac health. Cardiologists frequently use ECG as a diagnostic tool to find cardiovascular diseases[6,7,8].The early stages of heart disease are crucial because they can lessen abrupt cardiac failure. Accurate diagnoses require ECG signals of good quality. Electrodes are used to display and record electrical cardiac activity on the body's skin [9].

Normal sinus rhythm (NSR), often known as a regular heartbeat, is present in healthy hearts[10,11,12]. Atrial depolarization is indicated by P-waves. Regular Q waves indicate septal depolarization and are an early descending deflection of the P wave. The ECG's most common waveform for identifying and detecting early ventricular depolarization is the R wave. In R wave fallowed by S wave, which shows the late ventricular depolarization[13,14]. Ventricular repolarization is characterized by the T-wave. The Purkinje fibers that show the most recent ventricular residuals, or U waves, repolarize.

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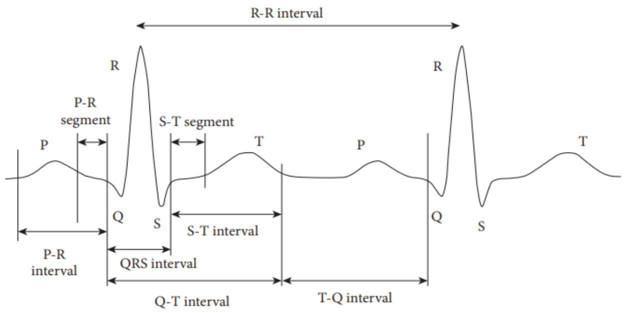


Figure 1: Two cycle regular ECG waveform

2. Relevant Review Work

As communication technology has developed, wireless communication has become one of the most popular ways for people to conveniently exchange ideas and thoughts. An audio noise reduction system is a technique for eliminating noise from audio transmissions. Devices for audio noise reduction use two main strategies. The complementary type, which calls for carefully removing the audio signal before recording it (primarily on tape)[1][2][3][4][5].The relative weight that the filter assigns to data samples is determined by these settings. Typically, to do this, particular frequencies or frequency ranges must be eliminated [6][7][8][9][10][11][12][13]. Contrarily, filters have a wide range of extra aims, particularly in the area of image processing. They don't merely operate in the frequency domain. There is no apparent hierarchy; there are many classification systems, all of which overlap in different ways. Filters come in both linear and nonlinear varieties. System properties include shift invariance, sometimes known as time-variant or time-invariant[14][[15][16][17]. A filter that operates in a spatial domain is said to be space invariant. The filters that handle time- or spatial-domain signals in delayed time[18, 19]. Either the continuous (unsampled) or discrete (sampled) time Discrete-time filters can only be active, whereas continuous-time filters can be both. This study illustrated the effective use of an optimization-based filter for identifying and categorizing ECG peaks. It participates in both passes. In the first pass, a useful lower order IIR filter design method based on transfer function optimization is suggested for detecting QRS peaks. For peak detection performance improvement, the IIR filter and Hilbert transform are used. Three distinct approaches are tested for their filtering effectiveness for baseline wondering.

The majority of people today, between the ages of 40 and 60, experience cardiac-related health problems. An electrocardiogram is the best way to capture heart impulses and identify any abnormalities at an early stage, as demonstrated in Figure 2 (a) Normal ECG and (b) Abnormal ECG. The heart rate variability and QRS complex are used to classify the abnormalities .For the purpose of removing motion distortions from ECG data, numerous authors have put forth various methods. The aforementioned techniques include a number of wavelets transforms (WT), adaptive filters (AF), and empirical mode decomposition (EMD).Blanco-Velasco proposes an ECG enhancement technique to remove baseline drift and noise brought on by high frequency. On the other hand, mode mixing, which yields erroneous intrinsic mode functions, is one of the prevalent problems in empirical mode decomposition.

3. Objectives of Research

Designing an efficient IIR filter for ECG signals to identify heart problems was the main focus of the design, analysis, and implementation of the following subsystems are categorized as the work flow in order to create an effective model for ECG analysis.

- The first theory is furthered by the implementation of modules such arithmetic circuits for filters used in ECG signal classification as well as the construction of parallel prefix circuits with the least amount of depth utilizing FPGA hardware prototype.

- The second theory is that by creating an algorithm that can identify the difficult QRS problem in real-time ECG classification, we may further investigate the effective filter utilized in ECG signal classification.

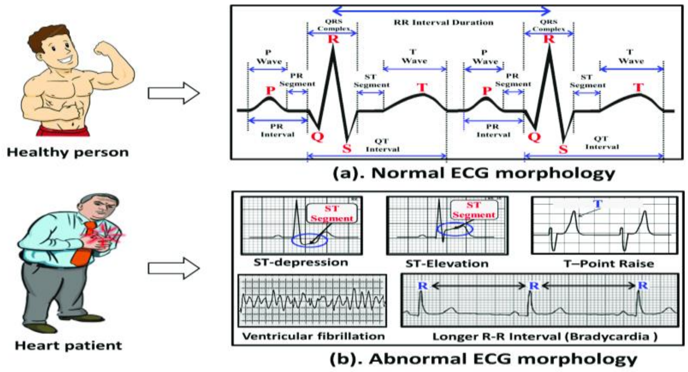


Figure 2: (a) Healthy ECG (b) Diseases ECG

4. Pan- Tompkins Peak Detection Approach

There are numerous strategies created to enhance the effectiveness peak detection and classification efficiency is anticipated to be directly correlated with the effectiveness of the methods used during the preprocessing step. Thus, two current filtering techniques—Pan-Tompkins and a 60 order IIR filter respectively. For the peak identification the technique of Pan and Tompkins is most frequently utilized. However, other variations of the Pan and Tompkins approach were developed to increase the categorization effectiveness of the ECG signal. The updated peak detection algorithm.

5.IIR Filter Design

It is recommended to use the optimization method in order to bring down the expected order of the IIR filter design. A block diagram of the ECG categorization algorithm that has been proposed can be found in Figure 3(a). In the proposed IIR filter, which is a two-stage filter, the pass band filters and stop band filters are laid out in the manner that is depicted in Figure 3(b).

$$\mathbf{Y(n) = X(n) * H1 * H2,} \tag{1}$$

where H1 is the pass band filter's transfer function; an example of a transfer function for 106 MIT-ECG BIH's data is provided as

$$H1=\frac{0.20346\,s^{4}-0.7131\,s^{2}+0.24566}{s^{4}+0.5488\,s^{3}+0.4535\,s^{2}+0.1763\,s+0.1958} \tag{2}$$

The optimization method is suggested to reduce the expected IIR filter design's order.

$$H2=\frac{0.3201\,s^{16}+4.517\,s^{15}+30.45\,s^{15}+130\,s^{13}+393.2\,s^{12}+892.9\,s^{11}+1574\,s^{10}+2196\,s^{9}+2452\,s^{8}+2196s^{7}+1574\,s^{6}+892.9s^{5}+393.2\,s^{4}+130s^{3}+30.45\,s^{2}+4.517\,s+0.3201}{s^{16}+12.12s^{15}+70.25s^{14}+258.1\,s^{13}+672.2\,s^{12}+1316s^{11}+2004s^{10}+2419s^{9}+2340s^{8}+1819\,s^{7}+113s^{6}+559.4s^{5}+214.8\,s^{4}+62\,s^{3}+12.7\,s^{2}+1.649\,s+0.102} \tag{3}$$

Equations (1), (2), and depict the transfer function for the IIR filter, the pass band filter, and the stop band filter, respectively (3).

A. Optimization Methods

The methods of ECG processing that are used most frequently are discussed below.

B. The low-pass differentiation approach (LPD)

The total band-pass filter significantly reduces the effects of all sorts of unwanted inte ferences and frequency noise. This algorithm chooses the necessary QRS complexes based on a set of thresholds. Modifying the threshold according to the magnitude of the peak. The thresholds for this algorithm are determined by a human component. The operator's thresh-old-setting expertise may be the main source of error in this Pan and Tompkins method.

C. Hilbert Transform (HT)

In the Hilbert transform, it is the 90o phase angle shift of each component of the signal h(t). The Hilbert transform of h(t), using h(t) as its signal representation, can be inscribed as,

$$\bar{\square} = \frac{1}{\pi}\int_{-\infty}^{\infty}\frac{\square(p)}{t-p}\,dp \qquad (4)$$

The HT approach was employed by researchers in [13, 25–28] as an implementation for the recognition of ECG QRS.

D. Optimum Reduced Order IIR Filter Design

The basic IIR filter requires 16 orders, as can be seen from the equations above. In this study, MINMAX optimization is proposed as a way to reduce the order of the transfer function. Figure 3 shows that image detection and classification methods in sequence.

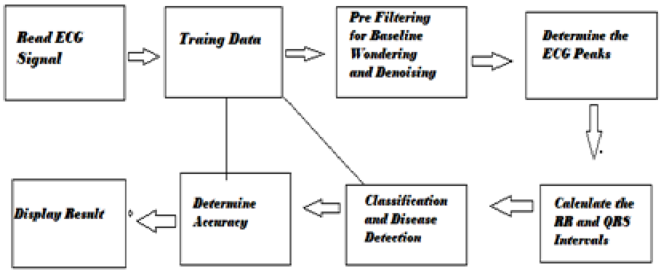


Figure 3(a): Image detection and classification methods

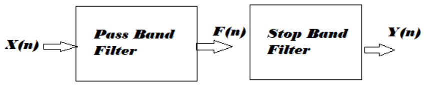


Figure 3(b): Basic IIR filter design procedure in two stages

$$\min_{x1 \in X} \max_{x2 \in X} f(x1, x2) \qquad (5)$$

where, X Rdx1, Y Rdx2 are convex sets, f is a differentiable objective function, and x1 and x2 are optimization variables. Transfer function coefficients are optimized in a sequential manner, as demonstrated in the sequential Min-Max optimization technique.

1. To assess a particular instance a samples are suggested.
2. Suggest designing an optimization approach for the denoising of herring assistance signal using a minimized order IIR filter.
3. Two different filters must consider the proposed IIR filter before denoising.

6. IIR Filter Design Algorithm

The following lists each step taken in the suggested algorithm:

i. The ECG data containing occurrences of arrhythmia has 48 channels.
ii. Define ECG characteristics.
iii. Establish the standard QRS interval (0.098 sec.) and sampling frequency Fs (500 Hz), i.e., the QRS (t)
iv. A 60 order IIR high pass filter is used to perform baseline wondering.
v. Create the best 150 Hz IIR low pass filter possible. Design an upper and lower cutoff frequency FL and FH for a pass band Butterworth filter (5.1). Create a stop band (5.2). FL1 and FH1 are the lower and higher cutoff frequencies for the Butterworth IIR filter.
vi. With a 100 coefficient IIR stop band filter, eliminate interference from power lines.
vii. Determine the average of the regular and irregular heart rates.

The 30 ECG data, which have a wide variety of ECG data, were chosen for the current investigation out of the 48 channels that humans have available. Figure 5 displays the input ECG data. At a rate of 360 samples per second, the following ECG data are captured. The ECG information is displayed in Figures 6(a)-6 (f). The ECG data shows the most erratic variations in these channels. Therefore, it is important to show how well the peak detection method works against them. These channels were chosen for another reason: several ECG peak detection techniques already in use, such the ones in [29], also take them into account.

A. Min-Max Optimization Enabled Filter Design

This research suggests a fundamental change to the ECG signal processing procedure in order to develop an optimal reduced order IIR filter. In order to achieve smoothing, the proposed lower order IIR filter design is used in place of the traditional FIR low-pass filters. The sequential results for the proposed IIR filter using optimization strategies for filtering the ECG signal are shown in the last row in Figure 11makes it evident that the projected technique significantly smoothes out the artifacts while also maintaining the characteristics of the QRS peaks.

B. Results of Optimized Filter ECG Design

Figure 5 provides a outcome comparison for the suggested IIR filter design. Three filters are given after results with stop band as an IIR filter. The proposed filter design, it can be seen, increases the magnitude of The following data are included in this collection: 100, 101, 102, 103, 104, 105, 100, 101, 102, 103, 104, 105, 106, 107, 108, 109, 111, 113, 114, 200, 201, 202, 203, 207, 208, 209, 210, 212, 213, 214, 215, 217, 219, 221, 222, and 228.

As there is, the original ECG signal's characteristics are preserved as well. With the improved filtering representation for the 3500 and 2000 initial samples, which is clearly displayed in Figure 9, further analysis is much clearer. The results for the ECG 110m signal were shown in the figure 9(a). Figure 9(b)zoomed)'s view of the filtering makes the baseline filtering effects for 2000 samples very obvious to see. Figures 10 and 11 shows the number of samples taken into consideration for the experiment on the x-axis.

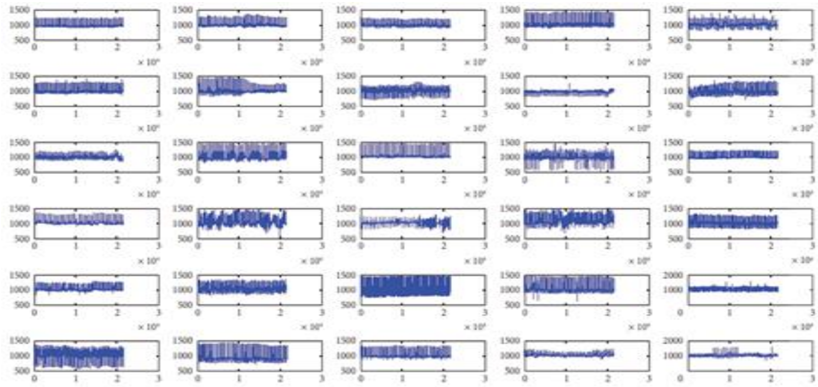


Figure 5: Enter data from the 5.556-second ECG arrhythmia database of 35 people recorded for more than 25 minutes at the MIT-BIH/ Physio Net, used in the current investigation.

C. Simulation Results of QRS Peak Detection in MATLAB

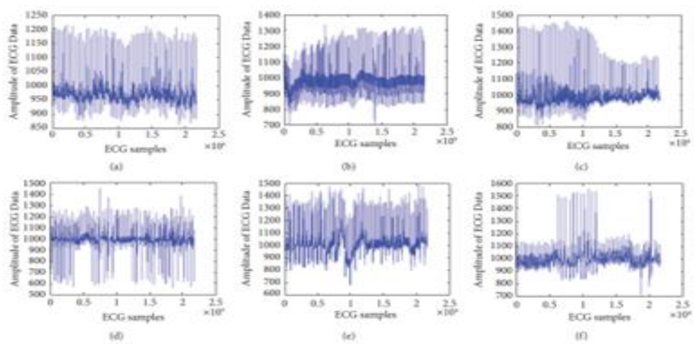


Figure 6: For perceptual result representation, six distinct ECG data with various feature difficulties are taken into account: (a) 102, (b) 106, (c) 109, (d) 200, (e) 208, and (f) 228.

D. ECG Image Classification

Three distinct ECG classification rules were offered in our article. In Algorithms 3, 4, and 5, respectively, the guidelines for the HRV-based ECG classifications of regular or irregular

ECGs are enumerated. When the method fails to locate a precise beat, a false negative (Fn) is produced. Fns are taken out of the corresponding annotation case in the MIT-BIH record. An inaccurate beat outcome is referred to as a false positive (Fp), whereas a true positive (Tp) is the precise beat that was recognized using the approach that has been suggested. Additionally, true negative (Tn) is accurate and does not include detected beats.

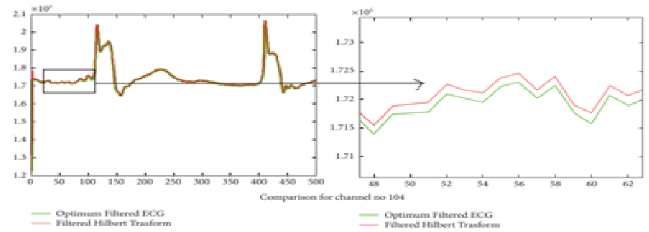


Figure 7 : Hilbert transform for channel number 105.

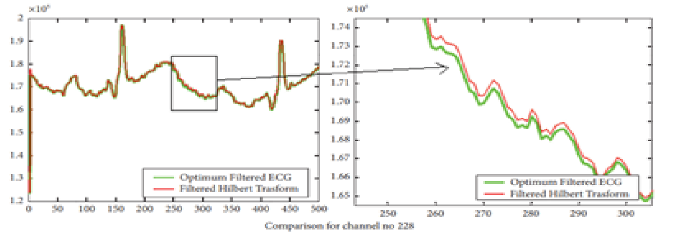


Figure 8: The channel number 228's R peak detection efficiency

E. Time Domain HRV Parameter Analysis

The proposed ECG classification and peak detection approach includes the examination of time domain statistical HRV characteristics. Using the same RR intervals that were used to analyze the ECG signal, several parameters in the time domain are determined. The following definitions apply to the parameters this study employed for analysis. Table 1 displays the statistical results of the measured parameters for the six input ECG signals using the suggested peak detection method. According to Table 1, SDNN is produced at its highest level for 228 m channels and its lowest level for 106 m ECG channels. The maximum evaluation of the parameter RMSSD is for the following math problems: 102m.mat, 106m.mat 102m ECG channel, with 106m ECG channel as the minimum.

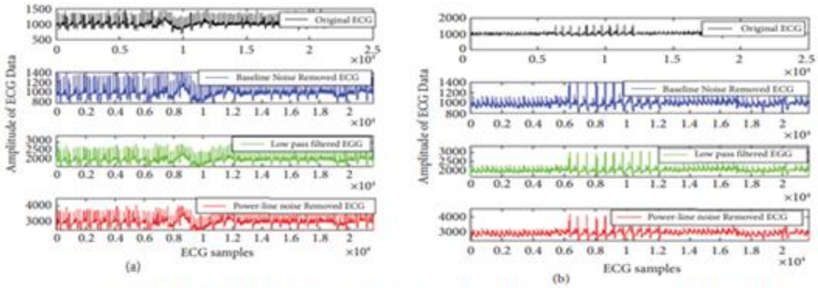
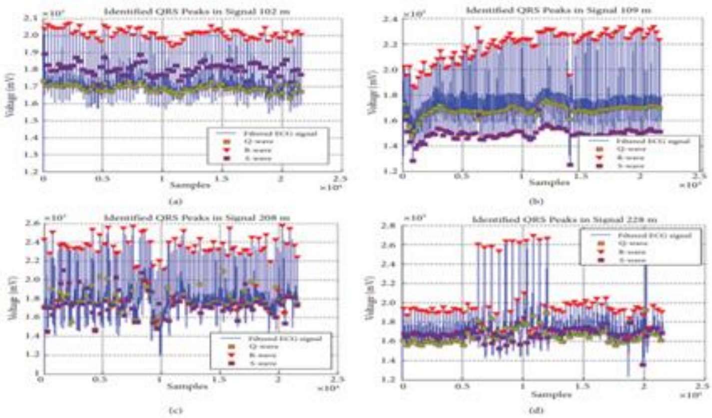


Figure 9: For the 3500 samples, ECG signal pre-processing is plotted for the (a) 101th ECG data and (b) 106th ECG data.



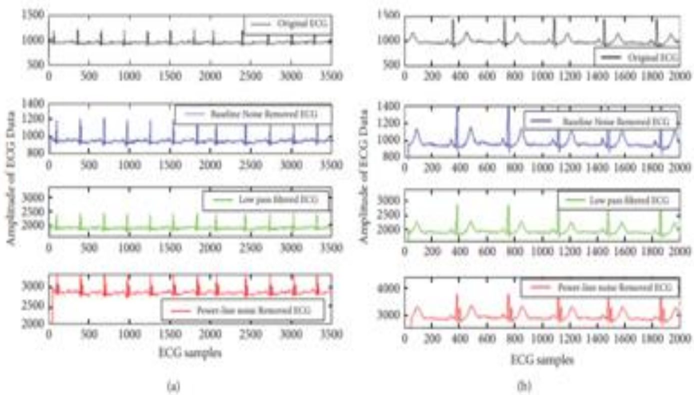


Figure 10: A signal provides a effects of ECG signal artifact reduction.

Figure 11: Results of the suggested optimum IIR filter technique for QRS peak identification for four ECG signals

Maximum and lowest heart rate evaluations are done for 106m ECG channels, respectively. The most effective method for keeping track of the dynamic shift in self-care under anesthesia may be Poincare plotting. The point on the plot is represented by the value of each subsequent pair of RR intervals.

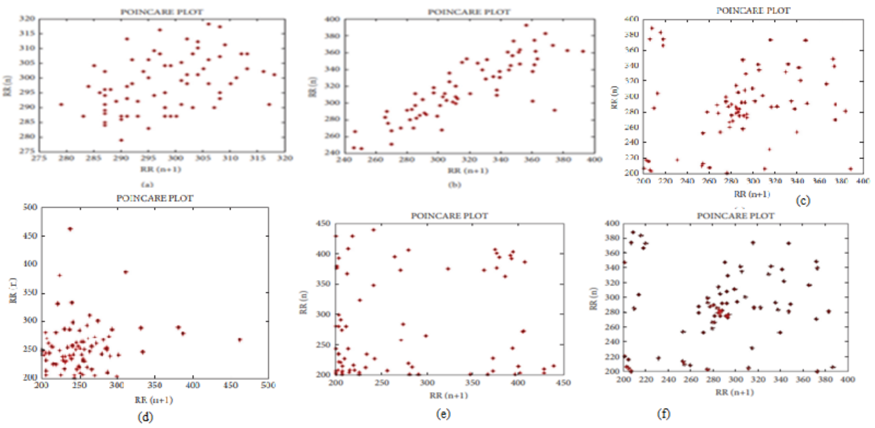


Figure 12: Results of HRV analysis

Table 2: Comparative analysis for Statistics parameters of Existing Method with Proposed Method

Ref. No.	Accuracy	QRS peak detection	RR interval	HRV Analysis
[2]	85%	No	No detected	No
[4]	85.6%	No	No detected	No
[6]	88%	No	No detected	YES
[8]	89%	No	No detected	No
[14]	90%	YES	detected	YES
[20]	91%	YES	detected	NO
[26]	92.67%	YES	detected	YES
This work	**96.87%**	**YES**	**detected**	**YES**

6. Conclusion

QRS peak detection helps detect diseases and heart rate variability (HRV). The temporal history affects HRV detection. This study proposed a new ECG data classification and QRS peak detection method. The min-max method optimises reduced-order filter coefficients. This study proposes a fuzzy-based ECG classification rule to improve performance. The projected ideal filter increases amplitude and maintains ECG characteristics, improving detection. The classification rule increases true positives and decreases false negatives. This study reported ECG analysis Poincare plot results. The projected filter with optimization method outperforms because it achieves 100% precession and improves accuracy by 13.5% over the basic Pan-Tompkins approach and 8.1% over the current IIR-filter-based classification rules. We hope to find more ECG signal peaks using our analysis method. Identifying ECG peaks can be used for many CVD detection applications.

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Conflicts of Interest: The authors declare no conflict of interest.

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