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Holts Exponential Smoothing Algorithm for Detection of R-Peak in ECG Signals

Akumarthy Viswa¹, Dr M Sailaja², Mrs A. Durga Bhavani³

PG Scholar, Instrumentation and Control Engineering, Department of ECE, UCEK (A), JNTUK, Kakinada, India¹

Professor, Department of ECE, UCEK (A), JNTUK, Kakinada, India²

Assistant Professor, Department of ECE, UCEK (A), JNTUK, Kakinada, India³

ABSTRACT: Electrocardiogram (ECG) is one of the most common biological signals which play a significant role in the diagnosis of heart diseases. One of the most important parts of ECG signal processing is interpretation of QRS complex and obtaining its characteristics. R wave is one of the most important sections of this complex, which has an essential role in diagnosis of heart rhythm irregularities and in determining heart rate variability (HRV). An adaptive threshold R-peak detection algorithm based on Holts exponential smoothing model is proposed in this paper. In this paper, three stages are involved one is preprocessing, peak detection by using the R-peak threshold values that are selected using the proposed smoothing algorithm and finally parametric evaluation. For identifying of R-Peak MIT-BIH Arrhythmia database is used which is publicly available. Parametric values like precision, recall, F1-Score value are evaluated. The F1 score achieved using the proposed model is 99.77%. The experimental results are performed using matlab software tool.

KEYWORDS: Electrocardiogram, Heart Rate Variability, Holts exponential smoothing, MIT-BIH Arrhythmia database

I. INTRODUCTION

The electrocardiogram is the most known diagnostic biomedical signal. It is the graphical representation of the function of the human heart, and can be recorded easily with surface electrodes placed on the limbs and chest. In a clinical environment during acquisition, various types of artifacts get added to the ECG signal. One of the main problems in biomedical signals, like the electrocardiogram, is the separation of the desired signal from noises caused by power line interference, muscle artifacts, baseline wandering and motion artifacts. Since biological signals are low amplitude and low frequency signals, they are easily prone to noise. The predominant artifacts present in the ECG include: Power-line Interference and Baseline Wander. Baseline wandering occurs due to respiration. Poor electrode contact and polarization of the electrodes may also cause low frequency artifacts. Sometimes, the variations in temperature and bias in an instrumentation system may also cause a baseline drift. The main cause for such noise is the electromagnetic interference from the surrounding equipment and poor conductors. The simple electromagnetic shielding of cables and grounding of the chassis of the equipment can reduce the distortions caused by electromagnetic waves. This artifact changes the morphology of the ECG signals, degrades the signal quality, and produces large amplitude signals that can resemble P-Q-R-S-T waveforms.

Consequently, these factors mask small features that are important for clinical monitoring and diagnosis of the heart abnormalities. The solution to this problem is difficult because most biological signals and power line interference are uncorrelated. The annulment of these artifacts in ECG signals is an important factor for better diagnosis. The extraction of high-resolution ECG signals from recordings, which are perturbed by noise, is an important issue. Two problems are considered in this thesis: one is denoising, and the other is the classification of different arrhythmias. The main objective of ECG signal denoising is to separate the desired signal components from the unwanted artifacts, so as to present an ECG that facilitates simple and accurate interpretation. Due to the overlapping between cardiac and non-cardiac components in frequency, especially from 0.01 Hz to 100 Hz, linear filtering (like low-pass or band-pass filter) is insufficient to eliminate such noises, by keeping the desired components unchanged. Real time automated ECG analysis in clinical settings, is of great assistance to clinicians in detecting cardiac arrhythmias, which often arise because of a cardiac disease, and may be life-threatening and require immediate therapy. However, the automated classification of ECG beats is a challenging problem, as the morphological and temporal characteristics of ECG signals show significant variations for different patients, and under different temporal and physical conditions. The focus of

this work is to denoise the ECG signal by developing denoising methods, and to classify different arrhythmia signals by extracting their distinct features.

Biomedical signals are produced by physiological activities in the organism. All living organisms, from gene and protein sequences to neural and cardiac rhythms are capable to produce signals. These signals could be observed or monitored to realize some aspects of a particular physiologic system. In medical assistance, the cardiac signal, ECG, is the more common signal used by doctors to evaluate heart anomalies. The ECG is a representation of heart electrical activity in time, which is highly used to detect heart disorders. According to the most recent statistics, reported by the World Health organization, cardiovascular diseases remaining the main specific cause of mortality in any region of the world [3]. Several studies demonstrate the importance of reducing the time delay to treatment for improving the clinical outcome of the patients in case of acute coronary syndromes [4]. Some of the most common cardiac problems, are myocardial infarction (heart attack), ventricular tachycardia, ventricular fibrillation, or atrial fibrillation, where the early detection of the first symptoms occurrence is crucial, which significantly decreases mortality rate and admission time in a hospital or medical centres [5].

The heartbeat is determined as Beats Per Minute (BPM). Fundamental segments are P, QRS, and T waves. P wave is utilized to speaks to the changes within the cells of the atria. The QRS is utilized to speaks to the changes in the cells of the ventricles and the T wave is to speak to the changes in the potentiality of the ventricles. U is said to be the successor of one of the fundamental segments termed as T wave. O is the source point. The standard representation of ECG signal is shown in figure 1.

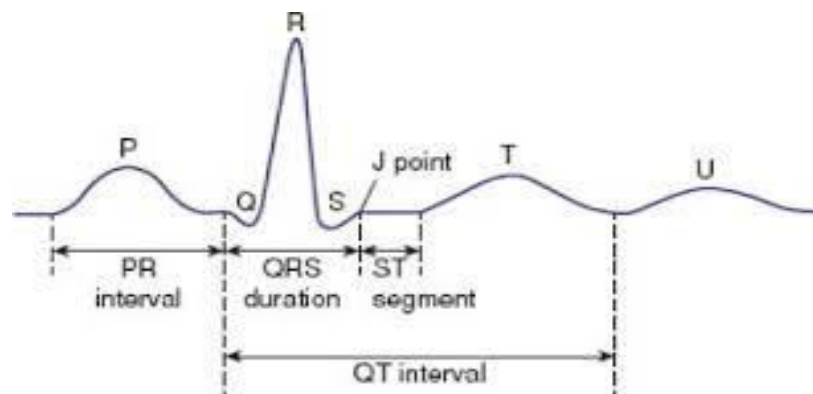


Figure1. Representation of standard ECG signal

The detection of R peak is one of the crucial elements to find several heart diseases. In this paper the detection of R peak is done using Holts Exponential Smoothing Algorithm. In section 2, the previous existing models in detection of R peak is discussed. The proposed model of the work is discussed in section 3. In section 4, the results achieved are been discussed and finally concluded in section 5.

II. RELATED WORK

It is challenging to create automated and broadly applicable algorithms because of the substantial morphological variance in ECG data. This challenge helps to explain why academics are always working on ECG signal processing. ECG detection algorithms are becoming as successful and dependable as skilled cardiologists, with the goal of increasing classification accuracy. Automatic R-peak recognition is a classic ECG signal processing challenge that has been thoroughly studied by researchers. Pan-Tompkins [6] presented the popular real-time R-peak detection technique. After a learning time, this traditional algorithm may process and provide the detection result for every sample. In contrast to more contemporary algorithms, the Pan-Tompkins method has a modest level of detection accuracy and a high level of complexity [7-8].

The majority of R-peak identification methods, however, have the drawback of potentially having a greater computing complexity and requiring unrealistic assumptions, such as the requirement for global statistical knowledge of the complete input signal [9-11]. Two-parameter parabolic fitting has been effectively employed by researchers to identify

ECG signal R points [12]. However, because these techniques rely on computationally demanding procedures like wavelet filtering, isoelectric line localisation, and high-order band-pass filters, they are not appropriate for wearable technology. Furthermore, a thorough comprehension of the entire ECG signal is required.

The R-peak detection step locates the R-wave, and the neural network approach [16–18] and threshold method [13–15] are often employed techniques. The threshold method's benefits include its ease of calculation and the threshold's multilayer and adaptable capabilities. Adaptive signal thresholds and adaptive noise thresholds are used by the very traditional PT technique in the field of ECG QRS wave recognition to identify R-peaks [19], which performs exceptionally well on ECG samples with a high signal-to-noise ratio. Finding an appropriate threshold to separate the noise peak from the R-peak from the signal amplitude level is challenging, though, because the PT algorithm's noise threshold is poorly established and does not accurately represent the noise's size.

Although the author in [20] greatly decreased the false and missed detection rates by localising the R peaks using dual thresholding of time and amplitude in conjunction with statistical false peak elimination, this method is still inapplicable to ECG signals with low signal-to-noise ratios because the threshold definition does not adequately account for the noise magnitude. This study proposes an adaptive threshold R-peak detection solution for the challenging R-peak detection issue, based on Holts exponential smoothing model.

III. METHODOLOGY

The electrocardiogram (ECG) signal is one of the most essential and well-known biological signals used for diagnosing people's health. One of the most crucial steps in the analysis of the ECG signal is the detection of the QRS complex. Because of its large amplitude and structural structure, QRS detection—particularly the R wave in the cardiac signal—is simpler than other parts of the ECG signal. An effective and non-invasive method for diagnosing heart functions is the electrocardiogram (ECG), which can offer long-term cardiac data. The most crucial aspect of automated ECG diagnostic applications is the accurate and dependable categorisation of ECG beats. The steps of process flow of the work are shown in figure1.

A. Dataset Used

One of the most significant and well-known biological signals used to diagnose people's health is the electrocardiogram (ECG) signal. One of the most crucial steps in the analysis of the ECG signal is the detection of the QRS complex. Because of its large amplitude and structural structure, QRS detection—in particular, the R wave in the cardiac signal—is simpler than other parts of the ECG signal. An effective and non-invasive method for diagnosing heart functions is the electrocardiogram (ECG), which can offer long-term cardiac data. The most crucial aspect of automated ECG diagnostic applications is the accurate and dependable categorisation of ECG beats. The Arrhythmia Database, which contains 48 half-hour recordings of two-channel ambulatory ECG signals, is one example. Annotated ECG samples with an 11-bit resolution and a 360 Hz sampling rate over a 10-mV range are included in the database.

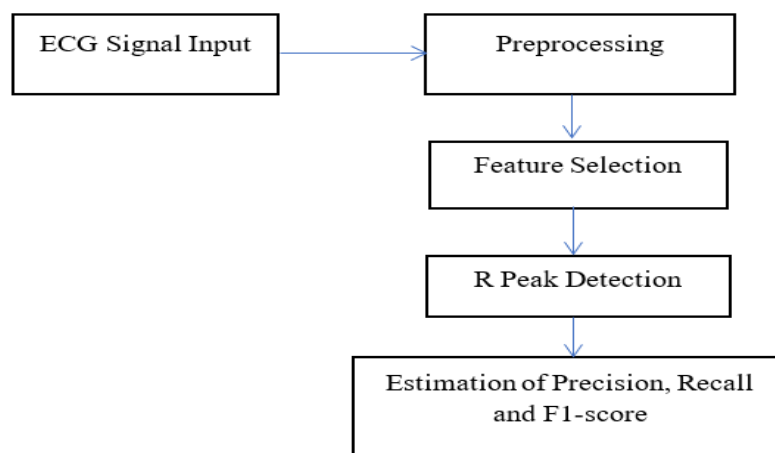


Figure2. Block Diagram of Proposed Model

B. Pre-Processing

Enhancing the signal-to-noise ratio and emphasising the R-peak morphological features are the goals of the preprocessing phase. Bandpass filtering and frame splitting are used in this step. We picked a duration of three seconds to guarantee that each frame contains at least one QRS complex wave because the typical ECG paper measures a minimum heart rate of thirty beats per minute, or two seconds for a heartbeat. ECG data are frequently tainted by noise from a variety of sources, including muscle noise, baseline wander, and powerline interference. The noise is removed using a Butterworth bandpass filter with an 8th order cutoff frequency of 10 Hz and 25 Hz.

C. Feature Selection

Even after pre-processing, there will still be a significant amount of noise interference in the wearable single-lead ECG data, which significantly impairs R-peak recognition. We initially observe the noise in order to prevent the interference. The region following the previous R-peak of 0.1 s and preceding the subsequent R-peak of 0.1 s is designated as the noise area. In this region, the ECG signals are regarded as noise. In order to prevent the impact of noise peaks, we can set the R-peak detection threshold higher than the highest noise value after observing the noise and determining the degree of noise interference at the signal amplitude level. Figure 2 shows an illustration of the noise area.

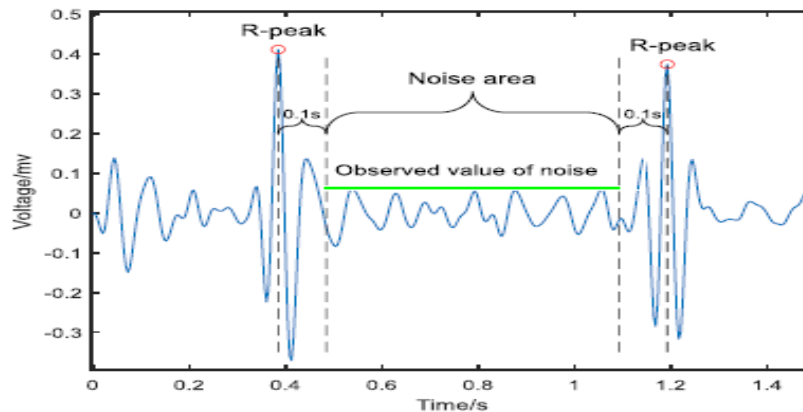


Figure 3. Noise area of ECG signal

Thresholding of R-Peak:

The R-peak threshold should be situated between the maximum noise peak amplitude and the R-peak amplitude to differentiate between noise peaks and R-peaks at the signal amplitude level. The amplitude of the R-peak and the magnitude of the noise observed in the preceding moment can be used to determine the R-peak threshold that is appropriate for detecting each R-peak. This threshold is defined as the observed value of the R-peak threshold using the following equation (1).

$$R_{th_{observed}} = N_{y_{observed}} + K(RP_y - N_{y_{observed}}) \tag{1}$$

where $N_{y_{observed}}$ denotes the observed value of the noise, RP_y denotes the R-peak amplitude, $R_{th_{observed}}$ denotes the observed value of the R-peak threshold, and K denotes the interval coefficient between the R-peak amplitude and the observed value of the noise, which is taken as 0.5 in order to balance the influence of both. The observed value of the current R-peak threshold indicates the most suitable threshold size for the current R-peak detection.

Holts exponential smoothing (HES) algorithm

Due to the interference of dynamic strong noise, the R-peak detection algorithm based on fixed empirical thresholds cannot adapt to a variety of complex situations, so some thresholds and parameters need to be updated. However, the thresholds are updated mainly based on the R-peaks detected in the past and some observed quantities, so the threshold updating method is very important for the ability to x the observation errors and the response speed to the changes of the observed quantities. The Holts exponential smoothing model is chosen as the adaptive threshold update method in this paper. Holt's exponential smoothing (HES) is a time series forecasting method that extends simple exponential

smoothing to capture trends in the data. It involves two equations: one for the level and one for the trend. Holt's method is particularly useful for data with a linear trend.

- The keys components of HES are:

a. Level (l_t)-

The smoothed value of the series at time t. The (l_t) is given as eq (2);

$$l_t = \alpha(y_t) + (1 - \alpha)(l_{t-1} + b_{t-1}) \tag{2}$$

Here, y_t is the actual value of time; α is the smoothing parameter for the level $0 < \alpha < 1$; l_{t-1} is the level at time t-1; b_{t-1} is the trend at time t-1;

b. Trend (b_t)-

The estimated trend (slope) at time t and is given by eq (3),

$$b_t = \beta(l_t - l_{t-1}) + (1 - \beta)b_{t-1} \tag{3}$$

Where β is the smoothing parameter for the level $0 < \beta < 1$; $l_t - l_{t-1}$ is the difference between the current and previous level.

Compute the time interval between the consecutive R peaks for smoothing of threshold level.

D. R- Peak Detection

Finding the R-peaks as precisely as feasible is the aim of the peak detection stage.

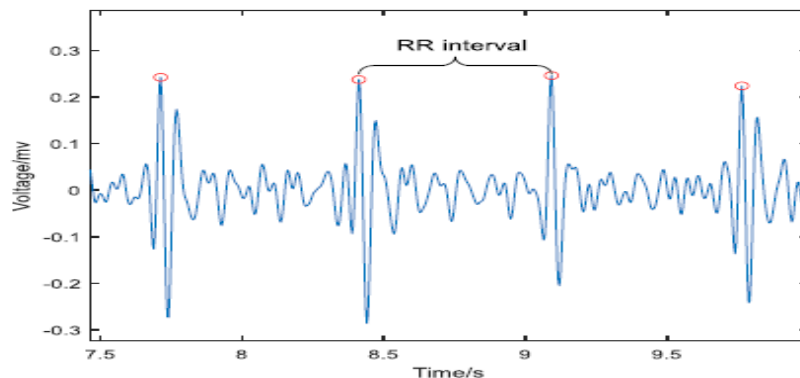


Figure 4. RR interval in ECG Signal

The R-peak threshold is updated in this work, and the noise and RR interval are predicted using the Holts exponential smoothing model. To eventually achieve robust identification of R peaks under dynamic strong noise interference, the design is implemented at the signal amplitude level and RR interval time level. This is based on the current amplitude variation of R peaks and noise, as well as the slow change of RR interval.

Peak Detection Based on R-peak Threshold

First, the R-peak threshold is used to find the highest point in the ECG signal in this frame. The RR interval threshold is then set to 0.2 seconds. Then, the sizes of the found local peaks are compared to the R-peak threshold in order of when they were found. We consider an R-peak any local peak point that is bigger than the R-peak threshold. Once an R-peak is found, this R-peak magnitude and noise magnitude are used to make the R-peak cutoff right.

Abnormal State Backtracking Judgement

This feature is used to fill in the missing R peaks and get rid of the wrong R peaks. The RR interval changes slowly. First, the previous RR interval is used to predict the next moment's RR interval. Then, the detected RR interval value is compared with the predicted RR interval value to see if the current RR interval is abnormal. If it is, it is looked at to see if the abnormality is caused by the wrong R peak or the missed R peak. Finally, the missed R peak is filled and the wrong R peak is deleted.

Step 1: Use Holt's exponential smoothing model to predict the RR interval.

Step 2: Decide if the RR gap is odd.

Abnormal R Peak Detection

It is thought that the current detection R peak may be wrong when the difference between the current RR interval and the expected RR interval value is more than 0.4 times the forecast RR interval value. If the current RR interval is longer, it means that the abnormal RR interval may have been caused by R-peak missed detection. If the expected RR interval value is longer, it means that the abnormal RR interval may have been caused by R-peak misdetection. Then, the sizes of the next four RR intervals are tracked and recorded at the same time, along with the sizes of the four RR intervals that came before them. This is done so that more before-and-after correlation data can be used to accurately find the R-peak abnormalities based on how smoothly the RR interval changes.

Filling of Undetected R-peaks

Once it is known that the missed R-peak is what caused the RR interval oddity, the process of filling in the R-peaks is initiated. The process is to find the nearest peak point between the current R-peak and the previous R-peak that has an amplitude greater than the expected noise amplitude. Then, the biggest amplitude peak point is chosen as the missed R-peak, without considering any other possibilities.

IV. RESULTS AND DISCUSSION

The environment considered for implementation of work is suitable for processing of ECG signals. System with intel i7 processor, 16GB RAM, 1TB harddisk and matlab software tool with version 2024 is been utilized to observed the performance of proposed model. The results obtained are shown in following section. The ECG signals are obtained from the database. The input ECG signal is shown in figure 3.

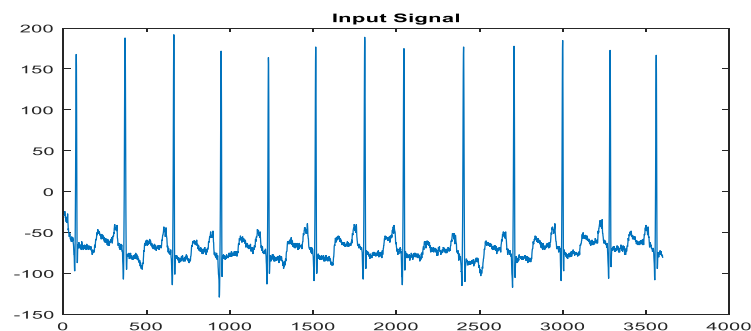


Figure 5. Input ECG Signal

After preprocessing of the input signal. The output obtained is shown in figure 4 which is a preprocessed ECG signal.

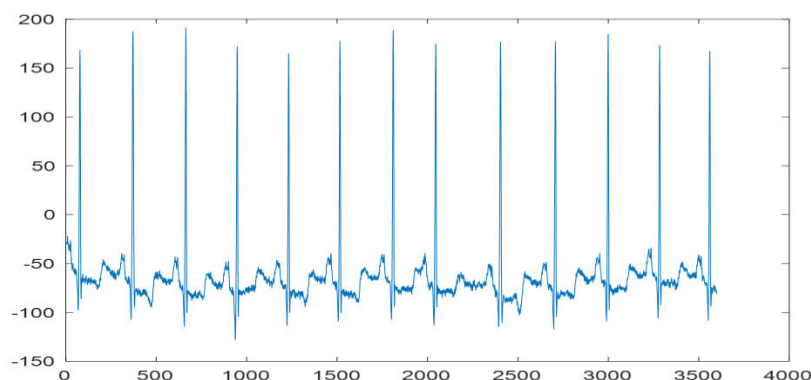


Figure6. Pre-processed ECG signal

The R peaks in the ECG signals are been localized for further processing. By fixing the thresholds limits and apply holts exponential algorithm the R peaks are been identified properly. The Identified and localized R peak is shown in figure 5.

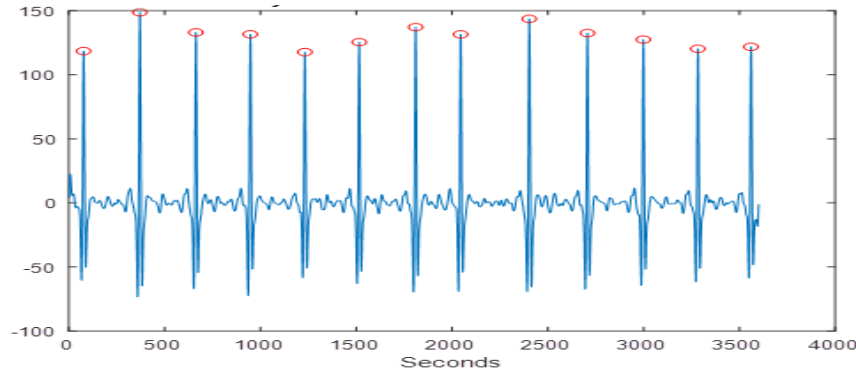


Figure 7. R-Peaks Localized

Different forecast methods are used to change the thresholds, and algorithmic measurement metrics on a self-built dataset are used to judge how well each method works. Compared to other time-series predicting methods, the Holts exponential model works better. When you change the smoothing factors in the Brown exponential smoothing model, you can find a balance between how quickly you can respond to changes in the measured quantities and how well you can smooth out observation errors. Also, the smoothing factors that work best for this forecast case are found by minimising the relative sum of squared errors between the predicted and observed values. This gets rid of the problems that come with human empirical selection, like big mistakes that are hard to fix. The parameters evaluated after processing of ECG signal using Holts Exponential Algorithm are precision, Recall and F1-Score. These parameters evaluated are compared with existing Brown exponential smoothing algorithm.

Precision (also called positive predictive value) is the fraction of relevant instances among the retrieved instances. Written as a formula in eq (4):

$$Pr = \frac{tp}{tp+fn} \tag{4}$$

Recall (also known as sensitivity) is the fraction of relevant instances that were retrieved. Written as a formula in eq (5):

$$Re = \frac{tp}{tp+fp} \tag{5}$$

F1 Score is a measure that combines precision and recall is the harmonic mean of precision and recall, the traditional F-measure or balanced F-score and is given in eq (6),

$$F1 - Score = 2 \cdot \frac{precision \cdot recall}{precision + recall} \tag{6}$$

The results achieved are shown in table 1. The results show proposed model achieved good results in terms of existing model.

Table1. Evaluation of metrics

Parameter/Technique	Brown Exponential Smoothing Model	Proposed Holts Exponential Model
Precision (%)	99.58	99.74
Recall (%)	99.66	99.80
F1-Score (%)	99.62	99.77

V. CONCLUSION

There is a problem with finding the R-peak in ECG signals when there is strong noise interference. This work suggests an adaptive R-peak detection method based on Holt's exponential smoothing model to fix the problem. First, three features are chosen based on the shape and pattern of R peaks in portable single-lead ECG signals. The R peaks are then found at the signal intensity level and time level to effectively tell the difference between R peaks and noise peaks. Then, the threshold values were changed based on how the chosen features changed over time. This was done using Holt's exponential smoothing model, which responds quickly to changes in the observed quantities and can smooth out observation mistakes. Lastly, the judgement method is made even more accurate by going backwards to get rid of the wrongly discovered R-peaks and fill in the ones that were missed. We tested the algorithm on the MIT-BIH dataset and found that the suggested R-peak detection algorithm gets 99.74% in precision, 99.80% in recall, and 99.77% in F1 score. You can find some problems with your ECG by using the method used to find the R peak. To help doctors make better diagnoses, the same method can be used on other medical signs like EEG, EMG, and so on. Using optimisation methods to raise the rate of accuracy can make the R peak recognition used in this paper even better.

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