Research on R-wave localization algorithm based on improved Pan-Thompkins

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ABSTRACT

An improved Pan-Thompkins R-wave localization algorithm is proposed to solve the problem of performance degradation when Pan-Thompkins algorithm is used to locate R-waves in electrocardiogram (ECG) signals of arrhythmia. The algorithm introduces new rules in the threshold adjustment stage to better capture the trend and pattern of the signal; the reverse search mechanism is added in the predefined interval, and the R peak that may be lost is detected by the new rule. In addition, the RR interval check mechanism is added to prevent the T wave from being mistakenly detected as the R wave in the case of complex signal modes. The MIT-BIH arrhythmia dataset and the MIT-BIH noise pressure test dataset are used to test the proposed algorithm with the Pan-Thompkins algorithm and three other commonly used R-wave localization algorithms. The results show that the proposed algorithm has high accuracy and also shows good robustness in the case of arrhythmia.

Keywords: R wave location, pan-Thompkins, RR interval, ECG signal Introduction.

1. INTRODUCTION

Cardiovascular disease is one of the most lethal diseases in the world,accounting for about 32 % of global mortality. The most commonly used diagnostic technique for cardiovascular disease is electrocardiogram (ECG)[1]. ECG is a method for visualizing and recording ECG signals. It provides detailed information on cardiac electrical activity and is used to diagnose heart disease and monitor heart health. ECG signal is composed of P wave, QRS wave, T wave and other waves. By analyzing the waveform characteristics, Abundant medical knowledge and information can be obtained. At present, the majority of computer-driven automatic solutions primarily concentrate on recognizing the QRS wave[2]. In clinical practice, accurate identification of QRS waves is crucial and is the first step in many automated ECG analysis algorithms.

The QRS complex encompasses the Q wave, R wave, and S wave, which usually appear in ECG in turn. Its morphology can be used to identify arrhythmia, such as atrial fibrillation, ventricular fibrillation, etc., which is critical for the timely diagnosis and treatment of arrhythmia. R wave is the highest amplitude wave in QRS complex, and it also stands as the most prominent characteristic of the ECG. It represents the excitation and contraction of ventricular myocardium. In ECG analysis, R wave localization is a necessary step to calculate time interval, heart rate and other indicators and heart beat segmentation [3].Its morphological structure contains a large amount of medical information. Therefore, the position and amplitude of R wave are of great significance for the analysis and diagnosis of ECG[4].

Localization of the R wave represents a crucial avenue of research within the domain of ECG signal processing[5].which has a wide range of application value, especially in the diagnosis of arrhythmia, heart disease monitoring and so on. With the continuous development of technology, R-wave positioning methods are also evolving and optimizing to satisfy the requirements of diverse application contexts. At present, the common algorithms for R-wave localization include Hilbert transform[6], wavelet transform[7], empirical mode decomposition (EMD) [8], and Pan-Thompkin algorithm[9]. Muhammad et al.[10] proposed a dynamic ECG R-wave positioning system, which combines a one-dimensional convolutional network utilizing a verification model to minimize the occurrence of false alarms. The trained model can be used alone to detect R-waves in single-channel ECG data streams, successfully solving the problem of R-wave false detection in ECG signals, but there is still a significant gap in the performance of detecting low-quality ECG signals. Varun Gupta and Monika Mittal[11] introduced a technique that integrates the Burg method with the Hilbert transform of autoregressive modeling. Burg is used for feature extraction, and then the Hilbert transform is utilized to identify missing details, so as to realize R-wave detection. This

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method has high accuracy, but it needs to pay attention to cross-validation, and the algorithm efficiency is low. The method proposed by Salah Hadji[12] detects the R peak from the first three Intrinsic Mode Functions (IMF) components of the converted ECG signal by EMD. This method has high accuracy and low complexity, but it relies too much on the performance of threshold detection, resulting in low stability of the algorithm.

At present, the most common R-wave localization method is the technology proposed by Pan and Tompkins, namely the Pan-Thompkins algorithm. This algorithm has low complexity and good detection performance. Due to its relatively simple structure, it is widely used in clinical monitoring and real-time analysis, and has become the basis of many ECG signal processing systems. Nevertheless, in signals that are impure and contaminated with noise, the performance of the Pan-Tompkins algorithm for detecting QRS complexes will be reduced.

This paper examines the restrictions of the Pan-Tompkins algorithm and improves it to optimize the original algorithm's outcome. In order to verify the effectiveness of the enhanced algorithm, the enhanced method is compared with Pan Tompkins algorithm, Hilbert transform method, wavelet transform method and EMD algorithm on two data sets.

2. PAN TOMPKINS ALGORITHM

The Pan-Thompkins algorithm is structured into two phases: preprocessing and decision-making. The flow chart depicting the algorithm is exhibited in Figure 1.

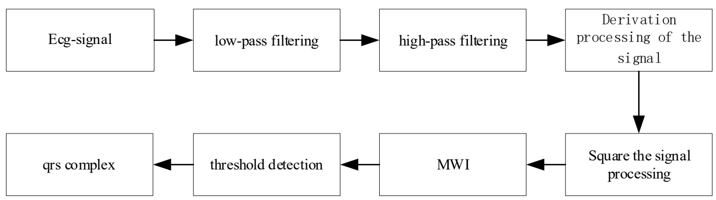


Figure 1. Flow chart of Pan-Thompkins algorithm

The signal is first passed through a digital band-pass filter consisting of a high-pass and a low-pass filter to highlight the required frequency range and reduce noise from other frequencies. The transfer function is as follows:

$$H(z) = (\frac{1}{8T})(-z^{(-2)} - 2z^{(-1)} + 2z + z^2) \tag{1}$$

In the formula, *H(z)* is the frequency domain representation; *t* is the sampling period; *z* is a complex variable.

The filtered signal is derived to obtain a high-frequency signal with a high slope in the QRS complex wave, and the R-wave characteristics are enhanced by square processing of the signal. its calculation formula is as follows :

$$y(nT) = \left(\frac{1}{N}\right)\left[x(nT-(N-1))T + X(nT-(N-2)T) + ... + \mathrm{x(nT)}\right] \tag{2}$$

In the formula, *y (nT)*is the result of MWI ; *nT* is the time of the nth sampling point ; "n" denotes the quantity of samples that fall within the boundaries of the integration window.

Finally, the R wave is identified by double threshold detection technology. The calculation formula is as follows :

$$SPK = 0.125PEAK + 0.875SPK \tag{3}$$

$$NPK = 0.125PEAK + 0.875NPK \tag{4}$$

$$Threshold1 = NPK + 0.25(SPK - NPK) \tag{5}$$

$$Threshold2 = 0.5Threshold1 \tag{6}$$

In the formula, PEAK is the current signal peak ; SPK is the dynamic estimation of the signal peak ; NPK is the dynamic estimation of signal peak and noise peak. Threshold1 depends on the difference between noise estimation and signal estimation, and Threshold2 is half of Threshold1.

3. ALGORITHM IN THIS PAPER

3.1 Definition rules

First, the threshold is initialized by the following equation :

$$Threshold1 = Maxf / 3 \tag{7}$$

$$Threshold2 = 0.5Meanf \tag{8}$$

$$SPK = Threshold1 \tag{9}$$

$$NPK = Threshold2 \tag{10}$$

In the formula, *Maxf* refers to the peak amplitude of the signal during the initial 2-second interval, whereas *Meanf* represents the mean amplitude of the signal within the same duration.

In order to preserve the consistency and compatibility of the original algorithm, two rules (rule − 1 and rule −2) are defined to adjust SPK and NPK to accurately detect R peaks amidst substantial variations in signal patterns. The rule −1 is identical in every respect to the original algorithm. (equations 3 and 4). Rule − 2 is defined as follows:

$$SPK = 0.75PEAK + 0.25SPK \tag{11}$$

$$NPK = 0.75PEAK + 0.25SPK \tag{12}$$

By assigning greater weights to the new observed value *PEAK*, *SPK* and *NPK* can adjust the threshold faster in the case of random noise or large heart rate variability, and thus capture the QRS complex more sensitively.

3.2 Reverse search mechanism

If no QRS complex is found within the predefined time (166 % of the average current RR time interval), a reverse search operation is performed to detect whether there is a missing QRS complex within that duration. The calculation formula is as follows:

$$RR \cdot AVERAGE = 0.125\left(RR_{n-7} + RR_{n-6} + \cdots + RR_n\right) \tag{13}$$

$$RR \cdot MISSED \cdot LIMIT = 166\% \cdot RR \cdot AVERAGE \tag{14}$$

where, $RR\ AVERAGE$ is the average of the recent eight consecutive RR intervals; RR_n is the nearest RR interval; $RR\ MISSED\ LIMIT$ for the predefined time.

Add a set of thresholds (Threshold3) to calculate when searching for missing R peaks, and the calculation formula is:

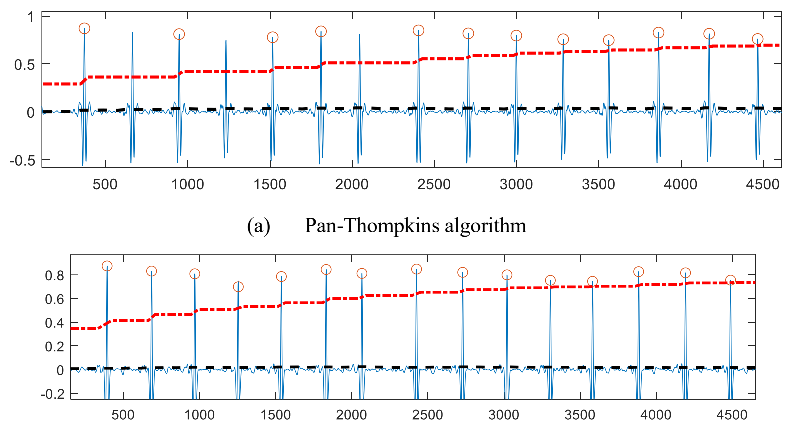
$$Threshold3 = 0.5 \cdot Threshold2 + 0.5 \cdot Meansb \tag{15}$$

In the formula, $Meansb$ is a window with the first three QRS complexes and the last three peaks.

The starting position of the window is set to 360 ms after the nearest R wave, and the ending position is set to the current QRS complex position. The maximum point is found in the search window. If the peak value within the window exceeds Threshold3, it is categorized as an R wave. When the QRS complex is detected by utilizing Threshold3, SPK and NPK are adjusted according to the rule − 2 (equations 11 and 12).

3.3 RR interval check

Usually, the amplitude of the T wave is small, and after the QRS complex. If the heart rate changes, the current RR interval falls below half of the mean RR interval. The Pan Tompkins algorithm occasionally misdetects the T wave as the R wave, resulting in a decrease in the accuracy of the R wave localization. Therefore, the RR interval inspection mechanism is added on the basis of the original algorithm. After the R wave is detected, the time interval between adjacent R waves is measured and analyzed.



(a) Pan-Thompkins algorithm

(b) proposed algorithm

Figure 2. R-wave localization after defining rules

In general, the slope of QRS wave and T wave is significantly different. QRS wave has a steeper slope, while T wave is the opposite. The current peak slope m1 and the average slope m of the first 70 ms window where the R peak was recently detected were calculated respectively. The formula is as follows:

$$m_1 = \frac{V_{peak} - V_{adjacent}}{\Delta_t} \tag{16}$$

$$m = \frac{\sum_{i=2}^{N}\left(V_i - V_{i-1}\right)}{\sum_{i=2}^{N}\left(t_i - t_{i-1}\right)} \tag{17}$$

In the formula, V_{peak} is the signal value at the current peak ; $V_{adjacent}$ is the signal value of adjacent time points ; N represents the quantity of sampling points in the 70 ms window ; V_i is the amplitude of the i^{th} sampling point ; t_i is the time of the i th sampling point.

If $m1 < m$ * 60 %, it is classified as T wave, otherwise classified as QRS wave. Finally, we use rule-1 (equations 3 and 4) to adjust the threshold.

4. EXPERIMENTAL PROCESS AND RESULT ANALYSIS

4.1 Data sets and evaluation indicators

In this paper, MIT-BIH arrhythmia data set and MIT-BIH atrial fibrillation data set are selected. The MIT-BIH arrhythmia dataset contains a variety of arrhythmia samples extracted from ECG records of 24 different patients. The MIT-BIH atrial fibrillation dataset contains 25 sets of atrial fibrillation data, most of which are paroxysmal atrial fibrillation. These data are manually labeled to complete different rhythm types, such as atrial fibrillation, atrial flutter, junctional rhythm and normal rhythm.

F-score, Precision, Sensitivity and the time t of processing a 1min ECG signal were selected to evaluate the training effect of the model. The formula for the specific computation is outlined as follows:

$$Precision = \frac{TP}{TP + FP} \tag{18}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{19}$$

$$F-score=\frac{2\times Precision\times Sensitivity}{Precision+Sensitivity} \tag{20}$$

In the formula, *TP* is true positive; *FP* was false positive; *FN* was false negative.

4.2 The comparison experiment between the proposed algorithm and the pan tompkins algorithm

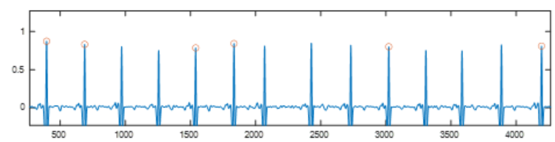
In order to verify the potency of the algorithm discussed in this work, a random noise is appended to the No.100 data in the MIT-BIH arrhythmia data set, and the Pan-Thompkins algorithm and the algorithm in this paper are used to locate the R wave. The results are shown in Figure 2.

It can be seen from the analysis and comparison that the Pan-Thompkins algorithm fails to accurately detect some R waves when the noise is large or the signal changes rapidly. It can be seen from Formula (3) (4) that PEAK only accounts for 12.5 % of the weight, while the previous NPK and SPK account for 87.5 % of the weight, which makes the threshold update too dependent on historical information, and the response speed to the current signal characteristics is slow, and the threshold cannot follow the signal changes in time. The algorithm in this paper adjusts the weight by rule-2, which can adapt to signal changes more flexibly.

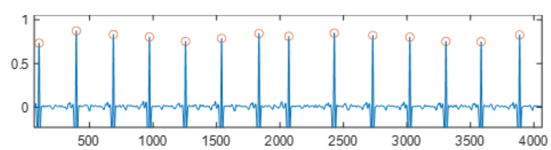
The validity of the reverse search window was tested using the 208 (ventricular premature beat) data in the MIT-BIH arrhythmia data set. The illustrations are displayed in Figure 3.

It can be seen from Formula (5) (6) that the threshold is too dependent on SPK and NPK, and it is adjusted in a linear way, which will lead to the detection of the algorithm is not sensitive enough when the signal mode changes. The introduction of Meansb window in this algorithm takes into account the overall statistical information. The new threshold Threshold3 solves the problem of sensitivity reduction caused by over-reliance on historical information by weighted average of Threshold2 and Meansb.

It can be seen from the analysis and comparison that the new threshold Threshold3 solves problem of sensitivity reduction.



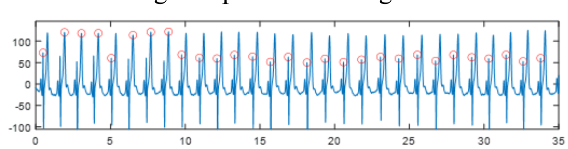
(a) Pan-Thompkins algorithm



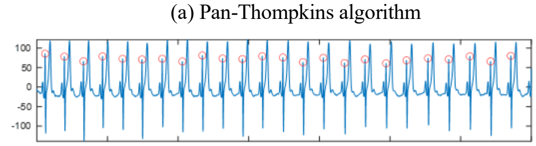
(b) proposed algorithm

Figure 3. R-wave location after adding reverse search

The No.109 (right bundle branch block) data in the MIT-BIH arrhythmia data set was used to test the effectiveness of the RR interval inspection mechanism. The findings are presented in Figure 4.



(a) Pan-Thompkins algorithm



(b) proposed algorithm

Figure 4. R wave localization after increasing the RR interval check mechanism

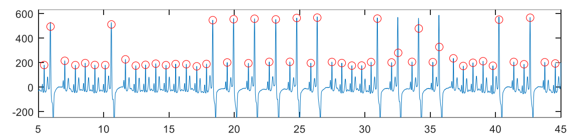
Apparent from the analysis and comparison that the T wave and R wave are similar in some abnormal heart rhythms, and the Pan-Thompkins algorithm cannot adapt to the complex changes of the signal. After increasing the RR interval check, by calculating the relationship between the current RR interval and the average value and using the slope information, the algorithm throughout this document has good stability on the ECG signal with high T wave which is easy to cause false detection.

4.3 The comparison experiment between the algorithm in this paper and the commonly used algorithm

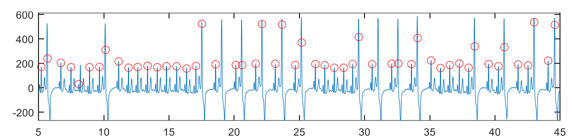
First, the No.119 data in the MIT-BIH arrhythmia data set is utilized in testing scenarios. As shown in Figure 5, the experimental results of the proposed algorithm and three common R-wave localization algorithms are shown.

Evident from Figure 5, substantial alterations occur in ECG signals, the first three algorithms have different degrees of missed detection and false detection in R-wave positioning, while the computational method described in this study has a good R-wave detection effect in the face of unstable heart rhythm.

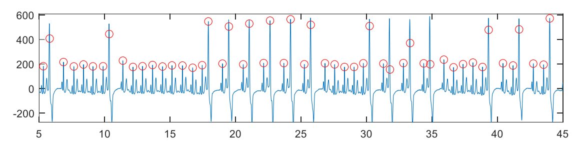
Then, the 08455 data in the MIT-BIH atrial fibrillation database is used for testing. As shown in Figure 6, the empirical outcomes achieved by the proposed algorithmic approach and three common R-wave localization algorithms are shown.



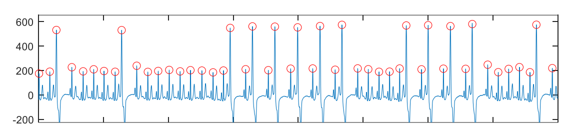
(a) Pan-Thompkins algorithm



(b) proposed algorithm

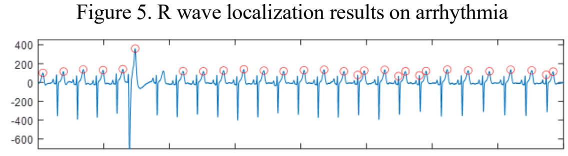


(c) EMD algorithm

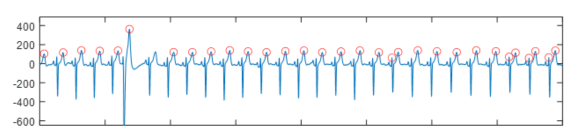


(d) proposed algorithm dataset

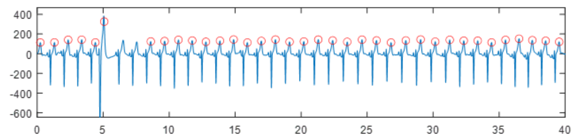
Figure 5. R wave localization results on arrhythmia



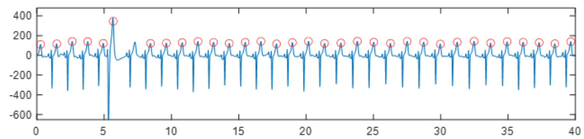
(a) Pan-Thompkins algorithm



(b) proposed algorithm



(c) EMD algorithm



(d) proposed algorithm

Figure 6. R wave localization results on atrial fibrillation

By observing Figure 6, it can be found that the accuracy of R-wave localization on atrial fibrillation ECG signals is generally not high by comparing the first three algorithms. The algorithmic approach outlined in this work largely overcomes the challenges of other algorithms in complex signal environments, and R-wave localization performs better.

The evaluation indicators on the MIT-BIH arrhythmia dataset and the MIT-BIH atrial fibrillation dataset are depicted in Table 1 and Table 2 as delineated.

Table 1. MIT-BIH Arrhythmia Dataset

	FP(%)	***FN(%)***	***Pre(%)***	***Se(%)***	***F-score (%)***	***t(s)***
Hilbert transform method	1.21	1.74	96.43	96.73	96.57	2.34
Wavelet transform method	1.13	1.69	97.12	97.56	97.34	2.89
EMD algorithm	0.94	1.22	98.87	98.91	98.89	2.61
proposed algorithm	0	0.23	99.13	99.16	99.14	1.24
Improved Pan-Thompkins algorithm	0	0	99.59	99.18	99.53	1.98

Table 2. MIT-BIH arrhythmia dataset

	FP(%)	***FN(%)***	***Pre(%)***	***Se(%)***	***F-score (%)***	***t(s)***
Hilbert transform method	1.08	1.56	96.98	96.95	96.96	2.32
Wavelet transform method	1.02	1.49	97.26	97.64	97.44	2.65
EMD algorithm	0.95	1.18	98.95	98.96	98.95	2.14
proposed algorithm	0.79	0.67	99.23	99.38	99.30	1.28
Improved Pan-Thompkins algorithm	0.18	0	99.61	99.42	99.49	1.89

Analysis of Table 1 and Table 2 shows that the methodology presented in this work greatly improves the missed detection and false detection of other algorithms in the face of unstable heart rate, and the accuracy and sensitivity are improved. In general, the Pan-Tompkins algorithm can robustly detect R waves in ECG signals, but the performance of some atypical ECG signals will decrease. Combined with the data in Table 1 and Table 2, the Pan-Tompkins algorithm serves as a benchmark, with the algorithm introduced in this paper achieving an accuracy boost of 0.46% and 0.38% on the two datasets, respectively.

Due to the high requirements of the Hilbert transform method for ECG signals, the signal needs to have a certain periodicity and stability. In the case of poor signal quality or more interference, it will lead to inaccurate detection. The accuracy of the algorithm in this paper is 3.16 % and 2.63 % superior to the Hilbert transform method when applied to both datasets. The performance of the wavelet transform method is affected by the scale parameters, and the appropriate scale needs to be selected. The algorithm has high computational complexity and is sensitive to noise and signal interference, resulting in false detection and missed detection. Relative to the wavelet transform method, methodology presented in this work demonstrates an increase in accuracy by 2.47% and 2.35% on the respective datasets. The EMD algorithm needs to continuously construct IMFs, which will lead to high computational complexity. When the signal is transformed or interfered, the algorithm may cause overlap or aliasing between the extracted IMFs, thus reducing the positioning performance. The accuracy of the algorithm in this paper is 0.72 % and 0.66 % higher than that of the EMD algorithm on the two data sets.

Because the algorithm in this paper adds new rules in threshold adjustment and other aspects, and adds reverse search window and RR interval checking mechanism, the complexity of the algorithm will be slightly increased. It can be seen from Table 1 and Table 2 that the time of processing signals in this algorithm is 0.74 s and 0.61 s longer than that of Pan-Thompkins algorithm, but combined with other data and the obtained results, the methodology presented in this work has more advantages.

5. CONCLUSION

An enhanced R-wave localization algorithm, derived from the Pan-Tompkins method, is proposed in this paper. Define rules to adjust the threshold, use the newly defined rules in the presence of interference and noise in the signal, add new thresholds and windows in the predefined interval for reverse search, and finally add RR interval check to calculate the slope to detect the authenticity of R-wave detection. outcomes demonstrate the effectiveness of the enhanced algorithm proposed in this paper has achieved a significant improvement in the accuracy of R-wave localization, successfully overcome the limitations of other algorithms in complex signal environments, and provide a more reliable and efficient solution for automatic analysis of ECG signals.

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