Postprint of R-Wave Detection Algorithm Based on Geometric Morphology Group Features

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Abstract

Accurate detection of ECG R-waves is crucial for assisting in the diagnosis of cardiac diseases. To address the R-wave detection problem, an R-wave detection algorithm based on geometric morphological group features is proposed. The algorithm first preprocesses the ECG signal using a filter bank, then calculates geometric morphological feature values through a signal processing approach that considers both global and local aspects, utilizes three geometric morphological feature values from the group to detect R-waves, and finally validates the algorithm using the MIT-BIH Arrhythmia Database. Experimental results demonstrate that the algorithm achieves a false detection rate of 1.07%, sensitivity of 99.38%, precision of 99.61%, and accuracy of 98.99% for R-wave detection.

Full Text

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Abstract: Accurate detection of ECG R-waves is critical for assisting in the diagnosis of cardiac diseases. To address the R-wave detection problem, this paper proposes an R-wave detection algorithm based on geometric morphology group features. The algorithm first preprocesses the ECG signal using a filter bank, then calculates geometric morphology feature values through a signal processing approach that considers both global and local characteristics, and finally detects R-waves using three geometric morphology feature values from a group. The algorithm is validated using the MIT-BIH standard arrhythmia database. Experimental results demonstrate that the algorithm achieves a false detection rate of 1%, sensitivity of 9%, precision of 9%, and accuracy of 9% for R-wave detection.

Keywords: Filter bank; Geometric morphology; Group features; R-wave detection

1. Introduction

Cardiovascular diseases pose a serious threat to human health and have gradually become a high-incidence condition in China. The electrocardiogram (ECG) comprehensively reflects cardiac activity and can indicate the health status of the human heart, with certain pathological changes manifesting through ECG abnormalities. Currently, ECG is widely used in medicine to assist doctors in identifying and analyzing various cardiac diseases. Detection of ECG waveforms plays a crucial role in ECG analysis, as accurate heart rate can be obtained through waveform detection, and heart rate is an important indicator for measuring cardiac disease. ECG detection can facilitate early discovery of heart disease, and through prevention and treatment, can reduce mortality rates among cardiac patients.

Among the various waveforms in ECG, the R-wave is fundamental to ECG signal analysis and is key to detecting whether the heart rhythm is normal and diagnosing cardiovascular diseases. The differential threshold method was the earliest algorithm applied to R-wave detection and remains a classic approach, but its performance degrades significantly when strong interference is present. With the development of computer technology and increasing research efforts in ECG signal detection, various novel signal processing algorithms have been applied to R-wave detection in ECG. Commonly used algorithms include wavelet transform methods, dynamic adaptive threshold methods, and neural networks. For example, some researchers have proposed R-wave detection methods based on wavelet transform, which first preprocess the ECG signal to remove noise, then perform continuous wavelet transform on the signal, and simultaneously employ threshold methods to detect R-waves in QRS complexes. Experimental results show that these algorithms achieve high accuracy. However, although wavelet transform-based detection algorithms have high detection rates, they involve large computational loads and poor real-time performance when processing large amounts of data. Other researchers have proposed ECG R-wave detection algorithms based on adaptive thresholds, which improve algorithm accuracy by setting thresholds and continuously examining each cardiac cycle. Experimental results demonstrate that these algorithms enhance the accuracy of R-wave detection. While dynamic adaptive threshold methods improve detection accuracy, they require threshold updates for each detection, increasing algorithm complexity.

Building upon these methods, many scholars have proposed new approaches for R-wave detection by improving common algorithms and combining different techniques. However, few can simultaneously achieve high accuracy, universality, and simplicity. This paper analyzes the advantages and disadvantages of commonly used R-wave detection methods and proposes an R-wave detection algorithm based on geometric morphology group features, inspired by adaptive mathematical morphology detection algorithms. Using ECG signal data from the MIT-BIH standard arrhythmia database as sample data for experiments, the results demonstrate that the proposed algorithm exhibits high sensitivity and accuracy, good universality, and low computational complexity.

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2. Methodology

2.1 Filter Bank Preprocessing

ECG signals have low frequency and are susceptible to various interference factors. Therefore, collected ECG signals typically contain various types of noise. The impact of ECG noise from the same signal source exhibits similarity, and these noises can generally be classified and filtered using appropriate methods. Typical noise includes muscle interference (high-frequency noise) and baseline drift (low-frequency noise). R-wave detection usually requires prior filtering, and removing noise from ECG signals is critical for R-wave detection. Performing R-wave detection on filtered ECG signals can reduce false detections and improve waveform detection accuracy.

Common high-frequency filters include FIR low-pass filters and band-pass filters. FIR low-pass filters can maintain strict linear phase-frequency characteristics while ensuring arbitrary amplitude-frequency characteristics. Due to their finite-length unit sample response, these filters are stable and widely used in image processing. The principle of band-pass filters is to set upper and lower frequency boundaries, allowing only input signals with frequencies between these limits to pass, while signals above or below the set values are filtered out. Band-pass filters maximize signal passage throughout the entire frequency passband while attenuating and suppressing signals in the stopband. Baseline drift noise can be removed using median filters and polynomial fitting filters. Median filters operate quickly and have simple designs, being particularly effective for images represented by integers because updating histograms from window to window is simple and finding the median of a histogram is not cumbersome. The polynomial fitting method first performs polynomial fitting on the signal, then subtracts the fitted signal from the original signal to obtain the baseline-removed signal, but polynomial fitting performs poorly when dealing with large drifts.

By comparing the advantages and disadvantages of various filters, this paper ultimately employs an FIR low-pass filter to first remove muscle interference noise from the ECG signal, then uses a median filter to filter the ECG signal again to eliminate baseline drift noise, forming a filter bank for signal preprocessing.

2.1.1 FIR Low-Pass Filter FIR filters are widely used in digital signal processing, primarily to attenuate or filter out interference signals to obtain the desired signal. The FIR low-pass filter designed in this paper selectively attenuates or filters out signals within specific frequency ranges. Starting from the time domain, the window function method is used to design the FIR filter by selecting an appropriate window function to truncate the infinite-length ideal unit sample response sequence to a finite length. The selection of the window function is crucial and must be determined based on the performance indicators of the desired filter, including the type of window function and window length, followed by overall performance testing.

The ideal unit sample response sequence corresponding to the ideal frequency response is given by:

$$h_d(n) = \frac{1}{2\pi}\int_{-\pi}^{\pi} H_d(e^{j\omega})e^{j\omega n}d\omega$$

This is typically an infinite-length non-causal sequence. To achieve the design goal of a finite-length low-pass filter, we can approximate $h_d(n)$ using the window function method. The common approach is to apply a window function to truncate the infinite impulse response:

$$h(n) = h_d(n) \cdot w(n)$$

where $w(n)$ is an even-symmetric, finite-length window. This paper selects the Hamming window:

$$w(n) = \left[0.54 - 0.46\cos\left(\frac{2\pi n}{N-1}\right)\right] R_N(n)$$

The amplitude response is:

$$W(\omega) = 0.54W_R(\omega) + 0.23\left[W_R\left(\omega - \frac{2\pi}{N}\right) + W_R\left(\omega + \frac{2\pi}{N}\right)\right]$$

Using symmetry and convolution theorem, we obtain:

$$H(e^{j\omega}) = \frac{1}{2\pi}H_d(e^{j\omega}) * W(e^{j\omega})$$

The window function method, which applies window functions to obtain finite impulse responses, is widely used in FIR filter design.

2.1.2 Median Filter Median filtering is a signal processing technique based on order statistics theory that effectively suppresses noise. Median filtering technology was first applied to one-dimensional signal processing and later extended to two-dimensional signal processing. The principle of median filtering is to replace the value at a point in a digital image or sequence with the median value of all points in a neighborhood of that point. For a one-dimensional sequence

$\{x_1, x_2, ..., x_n\}$, median filtering involves sorting these elements in ascending order. If the total number of elements is even, the median is the average of the two middle elements; if odd, the median is the middle element:

$$y = \text{med}\{x_1, x_2, ..., x_n\} = \begin{cases} \frac{1}{2}\left[x_{\frac{n}{2}} + x_{\frac{n}{2}+1}\right] & \text{if } n \text{ is even} \\ x_{\frac{n+1}{2}} & \text{if } n \text{ is odd} \end{cases}$$

Extending this concept to two dimensions, a two-dimensional window of a specific form is used for median filtering of two-dimensional sequences. The two-dimensional median filtering formula is:

$$y_{ij} = \text{med}\{X_{ij}\}$$

where A is the filter window.

2.2 GMGC_R Algorithm

The innovation of the proposed R-wave detection algorithm based on geometric morphology group features lies in its signal processing approach that considers both global and local characteristics, along with good adaptability. The combination of global and local signal processing enhances detection accuracy. In calculating geometric feature values, if a single point' s geometric feature value is excessively large, it affects the determination of geometric morphology in the algorithm and consequently impacts accuracy. This paper reduces the impact of abnormal points on algorithm performance by calculating the mean of continuous four-point geometric feature values. In the calculation of geometric morphology trend feature values, the algorithm first identifies the rising or falling trend interval in the geometric morphology, then calculates the mean of all k values within this interval as the trend feature value. This operation also aims to reduce the impact of abnormal points on algorithm performance. Through these two operations, the influence of abnormal points is mitigated, improving the accuracy of R-wave detection.

Unlike conventional dynamic adaptive threshold methods, once the geometric morphology is determined, the proposed algorithm only requires setting a single threshold for further noise filtering, aiming to reduce unnecessary geometric morphology judgments and improve algorithm efficiency, rather than dynamically changing thresholds during R-wave detection. Then, three adjacent and continuous geometric morphologies form a group, and R-wave detection is performed using the feature values of geometric morphologies within the group. The algorithm' s approach to determining R-wave positions aligns with how doctors intuitively locate R-waves from visual examination of ECGs. In practice, doctors can directly identify the waveform with the largest amplitude from the ECG and determine the R-wave position by judging whether this waveform' s amplitude exceeds that of its two adjacent waveforms. The proposed algorithm employs this same concept, using the feature values of three continuous geometric morphologies in a group to replace the intuitive amplitude values in ECGs. If the middle geometric morphology' s feature value is simultaneously greater than those of its two adjacent geometric morphologies, the middle geometric morphology can be identified as a candidate R-wave. The algorithm does not require dynamic threshold changes for each detection to improve accuracy, reducing complexity and enhancing adaptability. Simultaneously, by applying the doctor' s intuitive R-wave detection concept and using group geometric morphology feature values instead of actual amplitude values for R-wave detection rather than detecting R-waves based on single points in the ECG signal, the algorithm can effectively detect abnormal waveforms, thus demonstrating universality.

The algorithm description is as follows:

Let $V = \{v_1, v_2, ..., v_n\}$ be the ECG signal set and $R = \{r_1, r_2, ..., r_n\}$ be the R-wave position set. First, all values in set V undergo absolute value operation, with results stored in set V'. First-order difference operation is performed on all values in V', with results stored in array U. Then, the signs of U_i and U_{i+1} are sequentially judged to determine the start point G_s, peak point G_p, and end point G_e of geometric morphologies until all values in U are processed. If $U_i < 0$ and $U_{i+1} > 0$, this point is the start point G_s of a geometric morphology; if $U_i > 0$ and $U_{i+1} < 0$, this point is the peak point G_p; subsequently, if $U_i < 0$ and $U_{i+1} > 0$, this point is the end point G_e of the current geometric morphology and also the start point of the subsequent morphology. The G_s, G_p, and G_e of geometric morphologies are stored in array D. Adjacent and continuous start, peak, and end points in array D determine a complete geometric morphology G, which is stored in array C.

A minimum effective threshold T_n (voltage of 0.1 mV) is set to filter out invalid geometric morphologies in array C, resulting in filtered array C', while corresponding values for invalid geometric morphologies are also removed from set V' to obtain set V''. Based on first-order differentiation, geometric feature values k are calculated for each point in set V'' by sequentially taking each point and its three subsequent points, calculating their k values, and averaging these four k values as k_i, which is stored in array S. Each geometric morphology corresponds to some geometric feature values k in S.

To calculate geometric morphology feature values K_{gs}, geometric morphologies are sequentially taken from array C', with corresponding geometric feature values k retrieved from array S. The maximum geometric feature value K_{max} in the start-to-peak interval is found, and the mean K_{avg} of all geometric feature values in this interval is calculated to obtain the rising trend feature value $K_{up} = \frac{K_{max}+K_{avg}}{2}$. The falling trend feature value K_{down} is similarly calculated. The geometric morphology feature value is then $K_{gs} = \Delta s \cdot K_{up} + (1-\Delta s) \cdot K_{down}$, where $\Delta s = 0.6$. The K_{gs} values are stored in array K, corresponding one-to-one with array C'.

Candidate R-waves are selected by sequentially comparing three consecutive geometric morphologies' K_{gs} values in array C', denoted as K_i, K_{i+1}, and K_{i+2}. If $K_i < K_{i+1}$ and $K_{i+1} > K_{i+2}$, the morphology is recorded as a candidate R-wave, and all information about this geometric morphology is stored in array Y, including its K_{gs} value. To determine valid R-waves, the K_{gs} values of three consecutive geometric morphologies in array Y are compared. If $K_{i+1} > \frac{K_i}{2}$ and $K_{i+1} > \frac{K_{i+2}}{2}$, then Y_{i+1} is determined to be a valid R-wave and stored in array R, which represents the final set of R-wave positions.

The algorithm employs a pipeline processing mode where each step only handles problems corresponding to its stage and produces intermediate results, with subsequent steps continuously processing to obtain final results. Each step primarily processes the previous result dataset through single-layer sequential traversal. Since the algorithm uses array sets for data storage, the proposed GMGC_R algorithm has low computational complexity with overall complexity of $O(n)$.

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3. Experiments and Results

3.1 Experimental Setup

This paper validates the algorithm following the experimental flow shown in [Figure 1: see original paper]. The original collected ECG signals are preprocessed using a filter bank, followed by R-wave detection on the input ECG data. All values in set V undergo absolute value operation, followed by first-order difference operation on all values in the resulting set. The start, peak, and end points of geometric morphologies are identified from the operation results, with adjacent and continuous three points determining a geometric morphology. Geometric feature values are calculated for each point in set V, and the mean of continuous four-point geometric feature values is computed and stored in array S. The maximum geometric feature value in the start-to-peak interval is retrieved from S, and the mean of geometric features in this interval is calculated to obtain the rising trend feature value. Similarly, the falling trend feature value is calculated, and the geometric morphology feature value K_{gs} is computed. Candidate R-waves are identified by comparing three consecutive geometric morphology feature values, and valid R-waves are determined to produce the final R-wave position set.

The algorithm input is the ECG signal set $V = \{v_1, v_2, ..., v_n\}$, and the output is the R-wave position set R. First, all values in set V are absolute-valued and stored in set V'. First-order difference operation is performed on all values in V', with results stored in array U. The signs of U_i and U_{i+1} are sequentially judged to determine geometric morphology start points G_s, peak points G_p, and end points G_e until all values in U are processed. If $U_i < 0$ and $U_{i+1} > 0$, this point is a geometric morphology start point G_s; if $U_i > 0$ and $U_{i+1} < 0$, this point is a peak point G_p; subsequently, if $U_i < 0$ and $U_{i+1} > 0$, this point is the end point G_e of the current geometric morphology and also the start point of the subsequent morphology. The G_s, G_p, and G_e of geometric morphologies are stored in array D. Adjacent and continuous start, peak, and end points in array D determine a complete geometric morphology G, which is stored in array C.

A minimum effective threshold T_n (voltage of 0.1 mV) is set to filter out invalid geometric morphologies in array C, resulting in filtered array C', while corresponding values for invalid geometric morphologies are also removed from set V' to obtain set V''. Based on first-order differentiation, geometric feature values k are calculated for each point in set V'' by sequentially taking each point and its three subsequent points, calculating their k values, and averaging these four k values as k_i, which is stored in array S. Each geometric morphology corresponds to some geometric feature values k in S.

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Candidate R-waves are selected by sequentially comparing three consecutive geometric morphologies' K_{gs} values in array C', denoted as K_i, K_{i+1}, and K_{i+2}. If $K_i < K_{i+1}$ and $K_{i+1} > K_{i+2}$, the morphology is recorded as a candidate R-wave, and all information about this geometric morphology is stored in array Y, including its K_{gs} value. To determine valid R-waves, the K_{gs} values of three consecutive geometric morphologies in array Y are compared. If $K_{i+1} > \frac{K_i}{2}$ and $K_{i+1} > \frac{K_{i+2}}{2}$, then Y_{i+1} is determined to be a valid R-wave and stored in array R, which represents the final set of R-wave positions.

3.2 Experimental Results

The performance of ECG signal detection algorithms requires validation by authoritative ECG detection standards, and new algorithms can only gain recognition after verification by authoritative ECG databases. The MIT-BIH arrhythmia database is typically used to validate proposed detection algorithms. The MIT-BIH database records 48 cases, each with 30 minutes of data, totaling approximately 109,000 heartbeats, including both normal and abnormal beats, which can effectively validate R-wave detection algorithms.

All experiments in this paper were conducted in the same environment: a computer with an Intel Core i5 processor, 4GB memory, running Windows 10. The ECG data were preprocessed using a filter bank in MATLAB, followed by R-wave detection using the GMGC_R algorithm. The MIT-BIH database includes annotations for heartbeat positioning (including normal beats N and abnormal beats V). The detection results are shown in . The evaluation metrics in Table 1 include four indicators: false detection rate (denoted as D), precision (denoted as P), sensitivity (denoted as S), and accuracy (denoted as A). The formulas are as follows:

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100\%$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \times 100\%$$

$$\text{Accuracy} = \frac{\text{TP}}{\text{TP} + \text{FP} + \text{FN}} \times 100\%$$

where TP represents true positives, FP represents false positives, and FN represents false negatives.

This paper uses four metrics to evaluate algorithm performance. As shown in , the algorithm achieves a false detection rate of 1%, precision of 9%, and accuracy of 9%, with sensitivity of 9%. Some ECG signals, such as file 207, exhibit sensitivity of 8% and accuracy of 8% due to strong noise in these signals that was not completely removed by the filter bank. However, except for file 207 where excessive noise led to suboptimal results, each file achieves sensitivity above 9% and accuracy above 9%. The experimental results demonstrate that the algorithm can accurately detect R-waves in both normal and abnormal waveforms, indicating good universality.

A comparison between the proposed algorithm and detection algorithms from literature is presented in . As shown in Table 2, compared with other R-wave detection algorithms from literature, the proposed algorithm demonstrates better sensitivity, precision, and accuracy. The core of the algorithm is the calculation of geometric morphology feature values through a signal processing approach that considers both global and local characteristics. This global-local consideration during signal processing can both avoid the impact of individual points with excessively large geometric feature values on experimental results and provide additional filtering functionality. The operations that consider both global and local aspects reduce the impact of abnormal points on algorithm performance and improve R-wave detection accuracy. Another innovation is the use of geometric morphology group features to determine R-waves, which significantly enhances the algorithm's sensitivity and precision by detecting R-waves through comparing three geometric morphology feature values in a group.

Comprehensive analysis demonstrates that the proposed GMGC_R algorithm exhibits clear advantages in sensitivity, precision, accuracy, and universality, with low computational complexity, making it suitable for R-wave detection in various ECG signals.

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4. Conclusion

This paper proposes an R-wave detection algorithm based on geometric morphology group features. First, a filter bank preprocesses the ECG signal, laying the foundation for accurate R-wave localization. The calculation of geometric morphology feature values considers both global and local signal processing, which not only reduces the impact of abnormal signal points on geometric morphology feature value calculation but also provides additional noise removal. Finally, detection is performed using geometric morphology feature values within groups. The algorithm is validated using the MIT-BIH arrhythmia database and compared with other algorithm results, demonstrating high sensitivity, precision, accuracy, and universality.

Note: Figure translations are in progress. See original paper for figures.