Mobile ECG QRS detection algorithm and implementation

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Abstract

The ECG signal contains a lot of interference in the mobile ECG monitoring system. Reasonable selection of signal filtering and QRS wave detection method are the key to ECG signal analysis. According to the characteristics of ECG signals, the design of low-pass filtering and the improved median filter that can filter the interference has been conducted in the paper. Meanwhile, addressing to the limitation generated by selecting and fixing the median threshold using the traditional differential slope method, the paper has proposed the adaptive dynamic threshold and used quadratic difference algorithm to process signal in order to obtain R wave, and then locate Q and S wave based on R wave location. In addition, combining the characteristics of the QRS wave group, judgments on the missing and over detection are conducted, so that the algorithm is robust and has good fault-tolerant ability. The experimental results show that, this algorithm can not only satisfies the need of the real-time QRS wave detection, but is also more suitable for the transmission and processing of ECG signals in mobile ECG monitoring.

Keywords: mobile ECG signal, QRS detection, algorithm

1 Introduction

Mobile ECG monitoring device can quickly detect the real-time dynamic ECG signal to provide emergency ambulance, disease surveillance, medical advice and guidance services for users. Its application prospect is thus very promising [1].

Taking into account that the mobile ECG detection method shall be easily used by the users, the detection of the lead ECG signal is conducted by pressing the metal conductor with both thumbs. The Dynamic ECG signals obtained by this method contain a large amount of 50HZ interference, baseline drift, EMG interference and motion artifacts, as well as noise interference [2]. Various noises degrade the accuracy of diagnosis, and thus suitable methods must be used to conduct the filtering prior to the calculation of the heart rate data [3].

In this paper, the original data is received by the mobile phone from the Bluetooth transmission module. Raw data is then filtered by FIR low pass filter. Low frequency interferences, such as baseline drift, are removed through improved median filter. The smoothed data is finally returned. The said process is shown in Figure 1.

Since the mobile ECG monitoring equipment requires the real-time processing and transmission of ECG information [4], it is very important to design an accurate and fast heart rate detection algorithm.

At present, there are various ECG detection algorithms, such as difference vector analysis method [5], template matching method [6], wavelet transform method [7, 8] and neural network method [9, 10], etc. The differential threshold method has a simple algorithm which is fast in the processing speed and easy to be implemented in engineering [11, 12]. The template matching method is simple in principle, but it is very sensitive to high frequency noise and baseline drift [13, 14]. Wavelet transform method has excellent characteristics of time frequency localization, as well as high detection accuracy, but the amount of calculation is huge, which is not suitable for real-time processing [15, 16]. The neural network method can achieve a very good effect of discrimination, but its training time is long, and its real-time performance is poor [17, 18].

The said methods have both advantages and disadvantages. Addressing to the limitations caused by selecting and fixing the threshold in the traditional difference method, an adaptive dynamic threshold is set in this paper according to the signal characteristics. First, the initial data is intercepted and its first order difference is calculated, from which the initial threshold and amplitude threshold are obtained. Then, dynamic threshold adjustment is made by self-learning method. Finally, R wave is located according to the threshold. Q, R, S wave is then accurately localized based on QRS waveform characteristics.

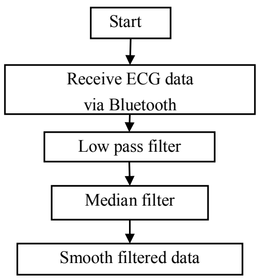

FIGURE 1 The flow diagram of signal filtering

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2 Filtering algorithm

2.1 LOW-PASS FILTER DESIGN

There are two ways to design low-pass filter design: one is IIR - infinite impulse response filter, and the other is FIR - finite impulse response filter. The difference lies in: IIR filter can get very high selectivity with the lower order, and it uses less memory, less calculations, and therefore it is not only economic but high in efficiency. However, high efficiency costs nonlinearity of the phase; hat is the better the selectivity, the more serious the nonlinearity is. In contrast, FIR filter can obtain a strictly linear phase. However, a higher order is required to get a certain selectivity, which asks for more memory and longer operation. As well, the signal delay is relatively large. In view of the fact that the mobile ECG signal has a strict requirement on the linear phase, and its stability in operation must be good, and noise power of the output signal caused by calculation error shall be small, as well as its nature of real-time shall be strong and operation speed shall be high [19], in this paper the window function method is adopted to design the filter [20].

Let the expected approximation response function of filter frequency be $H\left(e^{j\omega}\right)$, $h_d\left(n\right)$ be the corresponding unit impulse response, $H\left(z\right)$ be a system function. Then we can have the following equation:

$$H\left(e^{j\omega}\right)=\sum_{n=0}^{N-1}h_d(n)e^{-j\omega\omega}, \quad (1)$$

$$h_d\left(n\right)=\frac{1}{2\pi}\int_{-\pi}^{\pi}H\left(e^{jw}\right)e^{jwn}d\omega, \quad (2)$$

$$H\left(z\right)=\sum_{n=0}^{N-1}h(n)z^{-n}. \quad (3)$$

Generally speaking, $h_d\left(n\right)$ is infinitely long, and thus it needs an approximation of $H\left(e^{j\omega}\right)$. When the window function design method is adopted, the ideal filter unit sampling response and window function can be used to conduct the filter design:

$$h(n)=h_d(n)w(n), \quad (4)$$

where $\omega\left(n\right)$ is a window with a finite length, with a value of 0 outside the interval of $0 \le n \le N$, and it is symmetric with the middle point:

$$\omega\left(n\right)=\omega\left(N-1-n\right). \quad (5)$$

The frequency response can be obtained by the convolution theorem:

$$H\left(e^{j\omega}\right)=\frac{1}{2\pi}\int_{-\pi}^{\pi}H_d(e^{j\theta})W\left(e^{j(\omega-\theta)}\right)d\theta. \quad (6)$$

The degree of approximation of the frequency response of the filter designed using the window function method to the ideal response is determined by two factors: $\omega\left(e^{i\omega}\right)$ the width of the main lobe, and $\omega\left(e^{i\omega}\right)$ the amplitude of the side lobe.

In order to satisfy the requirement of stopband attenuation index, and at the same time to ensure the effective denoising while making the calculation time be the shortest, the low-pass filter of 34 orders and cutoff frequency of 35Hz is selected in this paper to remove the interference noise. The amplitude frequency characteristics is shown in Figure 2, and its denoising effect is shown in Figure 3.

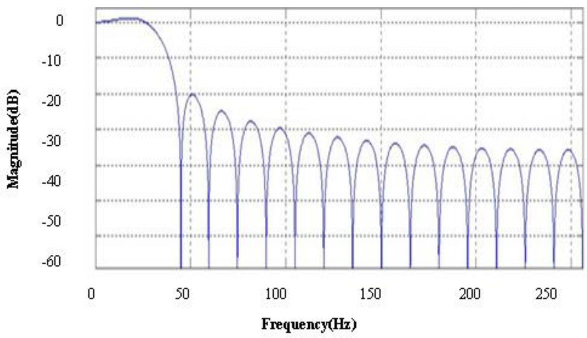

FIGURE 2 The low-pass filter characteristics

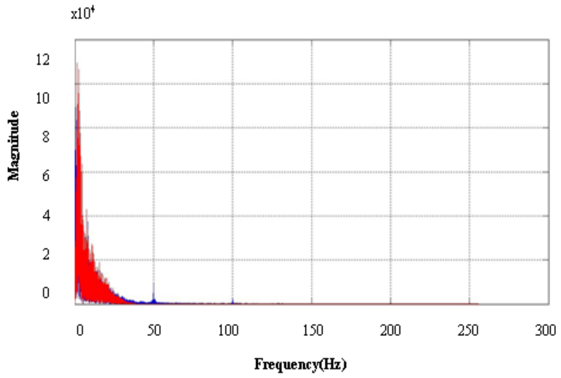

FIGURE 3 Low-pass filtering effect diagram

The red part is filtered spectrum, and the blue one is the original signal spectrum in Figure 3, from which we can see that the design of the low-pass filter can well remove the 50HZ frequency interference and quadratic harmonic of 100HZ frequency.

2.2 MEDIAM FILTER DESIGN

In addition to the filtering of the high frequency interference, a filter must be designed to remove the baseline drift, and the DC component.

Since the band mobile ECG baseline drift is less than 2HZ, if the filter cutoff frequency is too low, it cannot properly eliminate the baseline drift, but if the cutoff frequency is chosen too high, it would make the S-T segment definition waveform distort, as shown in Figure 4.

In Figure 4, the Q wave passing a high pass filter weakens downward, and the S wave rises up and T wave also weakens very significantly. Spectral contrast diagram before and after the filtering by the high-pass filter is shown in Figure 5, where the red part is filtered signal spectrum, and the blue part is the original signal spectrum. The spectrum chart shows that the filtering effect lower than 10Hz band is very poor. If the 0-2HZ band is to be filtered, higher order high pass filter would be needed, but the resulting high time-consumption is not suitable for mobile ECG detection. Hence, we turn to adopt the improved median filtering method.

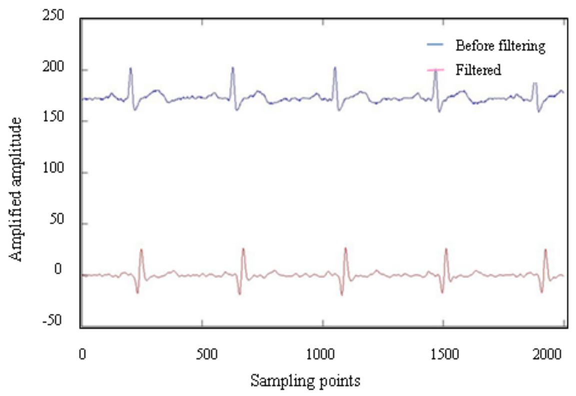

FIGURE 4 The filtered comparison chart in high-pass filter

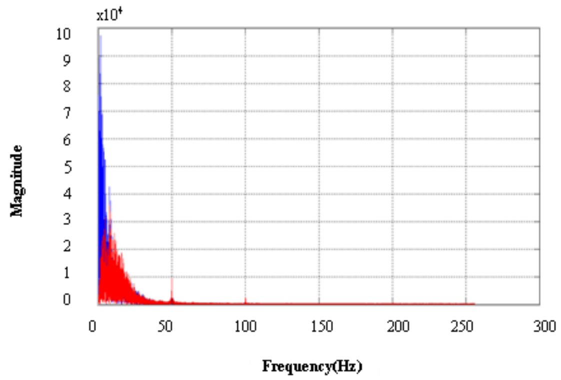

FIGURE 5 High-pass filter effect spectrum diagram

The traditional median filtering method is based on a value of $X(i)$ as the center and the odd point nearby as the window. The points of odd numbers are sorted, and then the median is taken as the new value of $X(i)$, and so on. The window length is generally in odd numbers like 5 or 7.

The improved median filtering method is: the window is taken at the centre point whose length is marked by an odd number larger than or equal to 127 The data of window lengths shall be sorted to obtain the median,, and then the new median is subtracted from the original median point, thus removing the DC component. It is also quite inhibiting against baseline drift.

The specific algorithm is as follows:

$X(i)$ is data of No. i sampling point of the original signal. Through the $X(i)$, values from the $X(i\text{-}63)$ to $X(i\text{+}63)$ are sorted to take the median value, *mid*. Then $Y(i)$ is take as $X(i)$ - mid (i.e. $X(i)$ minus *mid*), where $Y(i)$ is No. i sampling signal after the median filtering.

Spectrum comparison chart before and after the median filtering is as shown in Figure 6.

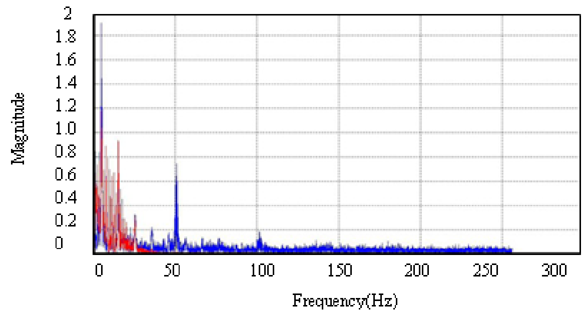

FIGURE 6 Median filter effect spectrum diagram

The filtering results of low-pass filter and median filter as shown in Figure 7.

As the figures show, the improved median filtering method can effectively eliminate the DC component, and the location of the baseline in Figure 7 effectively returns to zero. The algorithm is simple, and less time-consuming, which is suitable for low frequency filtering of the mobile ECG signal.

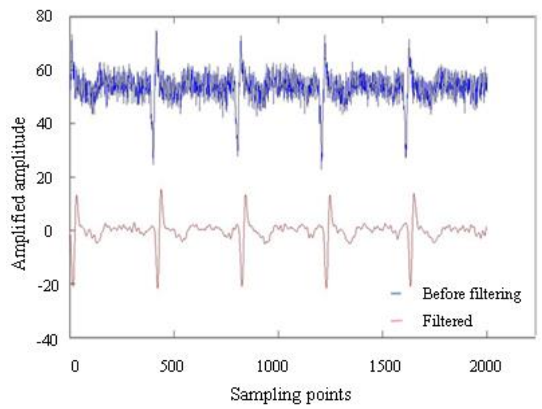

FIGURE 7 The filter effect results

2.3 SIGNAL SMOOTHING

The average smoothing filter is suitable for filtering the signals that have random noise, and the smoothing effect is obvious. However, if the window length selected is too large, the peak clipping phenomenon would be serious, because the average obtained in the apex of R wave and the surrounding points can reduce R wave characteristics. On the other hand, if the window length is too small, it will greatly reduce the smoothing effect. In order to improve the method of average smoothing filter, the average of several points around a point is taken as the new value of this point:

$$Y(i)=\big(Y(i-3)+Y(i-2)+Y(i-1)+Y(i)+\\ Y(i+1)+Y(i+2)+Y(i+3)\big), \tag{7}$$

where the window length is determined according to the 7 sampling points.

3 QRS wave group detecting

3.1 DETECTION ALGORITHM

The key point to use the differential threshold method is to determine a reasonable detection threshold, but the R wave form and amplitude will vary due to detection of different objects. Therefore, it is difficult to find a unified detection threshold that is suitable for various objects to be detected. In order to solve this problem, this paper adopts the self-learning algorithm to build the detection threshold.

Set the divergent ECG signal as $x(n)$, the length of the signal is L. An improved differential algorithm is adopted to detect the QRS wave group:

$$y(n)=x(n+2)+x(n+1)-x(n-1)-x(n-2), \tag{8}$$

where, $n = 2, 3, ..., L - 2$.

Take the first order difference of $X(n)$:

$$d(n)=x(n+1)-x(n), \tag{9}$$

where, $n = 1, 2, L–1$

It is known from Equation (8) that, obtaining the signal $y(n)$ from the five point difference will prominently display the characteristics of R wave. The judgment on the R wave is made by using the self-learning difference threshold conditions against $y(n)$. Combining the above with self-adaptive threshold set would preliminarily locate the R wave.

Equation (9) shows that $d(n)$ signal is obtained by conducting the first-order differential of the $y(n)$ signal. Corresponding relationship between the singular points of $y(n)$ in the $d(n)$ is established, and thus effectively confirm the R wave. The differential of zero crossing as well as the initial average amplitude thresholds left and right of R wave are calculated to accurately position the ECG QRS wave group.

In the actual detection, when a human body first contacts the electrode, an unstable phenomenon may occur. Through the pilot test, it is determined that the initial 6 seconds is the unstable period. In this paper, the ECG signal sampling frequency is 512HZ. Considering the data processing speed and data buffering problem, real-time computing takes the data collected within 2 seconds as the dynamic cycle. Figure 8 is the heart rate calculation flow chart, where DDmax and DDmin, AAmax are the initial maximum, minimum and maximum threshold, TH is the initial amplitude drop.

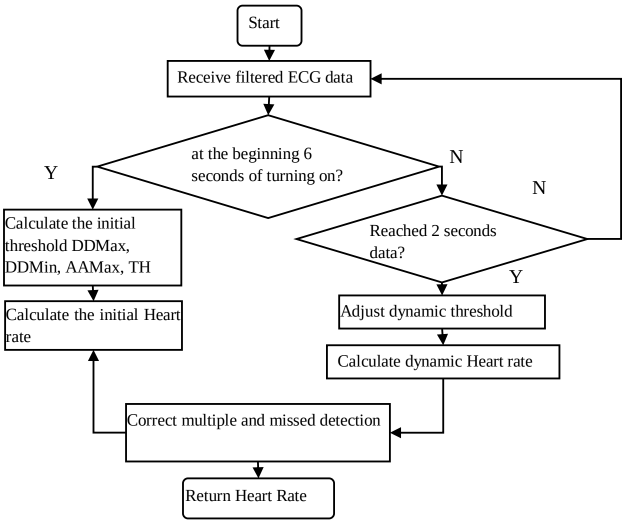

FIGURE 8 Heart rate calculation flowchart

3.2 ALGORITHM DESCRIPTION

3.2.1 Calculate the various initial thresholds

In this paper, X_i, the data in the initial 6 seconds of filtered $x(n)$, is divided into 3 sections, with the unit cycle taken as 2 seconds. Differential operation is conducted according to Equation (8) on each section to obtain the maximum difference value $D\max i$ and the minimum negative difference value $D\min i$ of its ECG data, as well as the maximum and minimum amplitude of the Xi signal. The arithmetic mean of Dmax i, Dmin i, Amax i and amplitude difference (Amax i - Amin i) is taken to obtain the initial thresholds of DDmax, DDmin, AAmax and initial amplitude drop threshold TH. These thresholds can be expressed as the following equation:

$$\left.\begin{aligned}
DD\max &= D\max/TH = 1/TH\left\{\frac{1}{3}\sum_{i=1}^{3} D\max i\right\}\\
DD\min &= D\min/TH = 1/TH\left\{\frac{1}{3}\sum_{i=1}^{3} D\min i\right\}\\
AA\max &= A\max/TH = 1/TH\left\{\frac{1}{3}\sum_{i=1}^{3} A\max i\right\}\\
TH &= (A\max - A\min)/TH = 1/TH\left\{\frac{1}{3}\sum_{i=1}^{3}(A\max i - A\min i)\right\}
\end{aligned}\right\}, \tag{10}$$

where $D\max i = \max\left(Y\left[k\right]\right)$, $D\min i = \min\left(Y\left[k\right]\right)$, $A\max i = \max\left(X\left[k\right]\right)$,

$Y\left[k\right] = X\left[k\right] + X\left[k-1\right] - X\left[k-3\right] - X\left[k-4\right]$.

The threshold of each unit cycle is jointly determined by the initial threshold, the maximum difference, the minimum difference and the maximum amplitude of the current section, *TH* is the parameter of the threshold. It can be adjusted according to the ECG R wave amplitude, and its value shall be an exponent with 2 as the base number.

3.2.2 Dynamic threshold adjustment

After the R wave is detected in the 6 seconds data using the initial threshold, the detection threshold is modified using the sliding average method. This paper takes every 2s as the dynamic threshold adjustment range. The newest threshold is jointly determined by the current segment threshold and the initial threshold. The update form of new threshold is:

$$\left.\begin{aligned} DD\max &= DD\max \cdot 2/3 + D\max\left[i\right]/3 \\ DD\min &= DD\min \cdot 2/3 + D\min\left[i\right]/3 \\ AA\max &= AA\max \cdot 2/3 + A\max\left[i\right]/3 \end{aligned}\right\}. \qquad (11)$$

In the dynamic range, if the measured R wave amplitude *A*max[*i*] increases, the new threshold of the *AA*max new will increase. The threshold is dynamically adjusted, so the stability of the system is enhanced.

3.3 QSR WAVE DETECTION

3.3.1 R wave detection

After the detection threshold is obtained, the R wave detection shall be conducted on the signal of $y(n)$. When the current difference value and the difference value of the next point is larger than the positive difference threshold *DD*max, and the current amplitude is larger than the amplitude threshold value *AA*max, this point shall be used as a starting point for the 160ms window. If there is a point that has difference value less than the negative difference threshold DDmin, the maximum peak point within the window shall be found as the peak of the R wave. Then the threshold in each sub cycle shall be adjusted according to the Equations (10) and (11), and the initial R wave is detected again with the new threshold. According to the "refractory period" principle in medical field [21], it is believed that the R wave won't appear again within 200ms, so we can skip the refractory period to conduct the detection. The R wave detection process is illustrated in Figure 9.

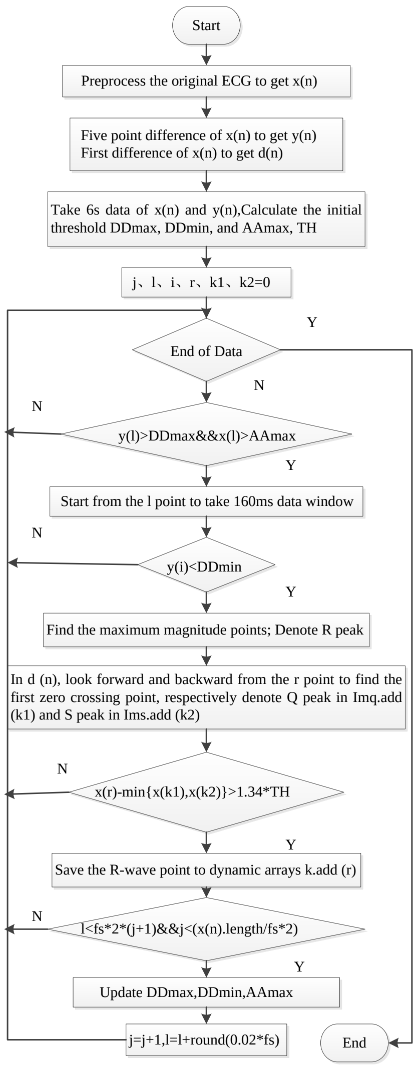

FIGURE 9 The R wave detection process

3.3.2 Q and S wave detection

After the detection of R wave is conducted, use a peak value of R wave point as the centre, forward and backward search the *Q* and *S* points.

In this paper, the first-order differential $d(n)$ is used to detect the initial position detection of *Q*, *S* wave. The relation between the R wave and its corresponding *Q*, *S* wave position is: if the R wave value is the down zero (its value is negative) corresponding to the QRS wave group in the $d(n)$. The *Q* wave shall appear in the first upward zero (its value is positive) before the R wave location; the *S* wave is the first upward zero (its value is positive) after the R wave position.

Because of the time - delay relation, the R wave position corresponds to the extreme position, k.get(i) in the $y(n)$, and corresponds to the k.get(i)+3 position in the $d(n)$. Similarly we can calculate the *Q* and *S* wave. The algorithm is as follows:

1) In the $d(n)$, starting from k.get(i)-3, from back to front, search the first upward zero crossing point; mark its location as $Imq(i)$.

2) In the $d(n)$, starting from k.get(i)+3, from front to back, search first upward zero; mark its location as $Ims(i)$.

3) Search the $Imq(i)$ and $Ims(i)$ in the $X(n)$; identify them as the positions of the Q and S wave, and calculate its amplitude.

4) Calculate the values of $Imq(i)$-3, $Imq(i)$-2, $Imq(i)$ corresponding to that in the $X(n)$, the minimum amplitude is Q wave position of $X(n)$ signal.

5) Calculate the values of $Imq(i)$-3, $Imq(i)$-2, $Imq(i)$ corresponding to that in the $X(n)$, the minimum amplitude is the S wave position of the ECG signal.

3.3.3 Processing the over detection and missing detection

In order to improve the detection accuracy, before the detection is completed, each RR interval (heartbeat interval) is judged. If the current RR interval is less than 0.6*RR, it is believed that there may be over-detections that need further treatment. If it is greater than 0.6*RR, and the sum of two adjacent RR clearances is less than 1.5*RR, the existence of over-detection would be confirmed. If over-detection is the case, the amplitude shall be re-adjusted, and the R wave is detected with the algorithm again to revise the detections. The process of fixing over-detection is shown in Figure 10.

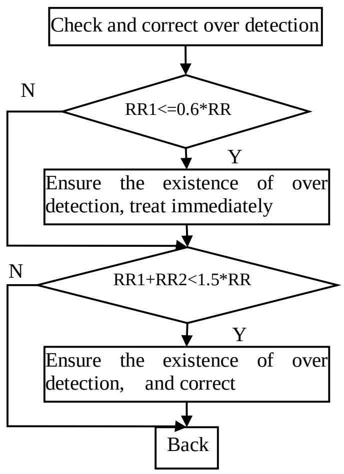

FIGURE 10 Over-detection process

In addition to over-detection, there may also be missing detection. The missing detection judging method is as follows: check whether the RR interval is greater than 1.6*RR or not. If the interval is between 1.6*RR and 2.6*RR, it shows that there is likely to be missed detections. Further, if there exists a data in the interval of 0.7*RR to 1.2*RR and with amplitude of 0.5HR (Heart Rate) to 1.5HR interval [22], it can be judged that an R wave is missed in the detection, and the missing R wave would be filled it into the R wave sequence automatically. If the said conditions are not met, it shall be determined whether the R wave is inverted or not. The process of fixing R wave missing-detection is shown in Figure 11. If none of the above cases occurs, it is believed that there is no over-detection or missing detection of the R wave, and then the detection of the next R wave can be conducted.

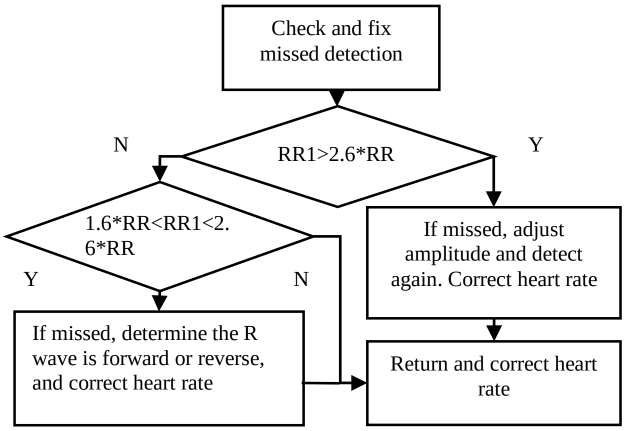

FIGURE 11 The process of R wave detection missed

4 Results

4.1 ALGORITHM VERIFICATION

The multiple groups of the ECG data from the MIT-BIH are adopted to validate the algorithm. After comparing the algorithm test results with the R wave and QRS wave group position provided by the MIT-BIH library [23], it shows that the method can accurately locate the position of the R wave. Tests show that the algorithm can have a detection rate above 99% of normal ECG R waveforms, but the detection rate for the disease ECG waveform (QRS deformation, high P wave and T wave etc.) is over 96%. The average accuracy rate can exceed 97.8%. The following table lists the experimental results respectively. In Table 1, A means atrial premature beat; / means delayed take-off; L means left bundle branch is blocked; a means abnormal atrial premature beat; V means premature ventricular contraction; F means ventricular fusion beat; N means normal; R means right bundle branch is blocked.

TABLE 1 MIT-BIH database library QT signal detection results

MIT-BIH Data record number	Signal Characteristics	False detection rate	Missed detection rate	Accuracy
100	A	0	0	100%
107	/	0	0	100%
108	V	1	3	96%
111	L	0	0	100%
119	VV	0	0	100%
122	N	0	0	100%
201	a	1	0	100%
208	FV	1	1	99%
212	R	0	0	100%
221	V	0	0	100%
234	N	0	0	100%

4.2 HEART RATE DETECTION

The algorithm is adopted to implement the mobile ECG real-time sampling. The mobile ECG detector consists of an integrated precision operational amplifier, a 12 bit digital to analogue converter, a high performance processor and Bluetooth module. It can realize the detection of ECG signals from the fingertips of both hands in the environment of strong background noise and high output impedance. Under the different experimental conditions, the authors have conducted the real-time ECG detection on 12 normal people. The data are as shown in Table 2.

TABLE 2 Mobile ECG monitoring clinical effects

Mobile ECG monitor file name	Visual QRS wave group number	Over detection number	Missed detection number	Error detection rate	Accuracy
201306261321	1992	4	1	2	99.65%
201306261407	1878	1	5	2	99.37%
201306281533	1893	0	2	1	99.84%
201306281607	1589	0	1	2	99.81%
201307011007	1678	3	2	3	99.53%
201307011110	1788	1	2	2	99.72%
201307051310	1684	0	0	3	99.83%
201307051443	1774	3	1	1	99.72%
201307101002	1678	0	1	3	99.77%
201307101120	1567	0	0	0	100%
201401071114	1956	3	0	1	99.58%
201401071207	1556	2	3	1	99.61%
201401071312	1782	1	4	0	99.71%
201401071618	1685	2	3	1	99.64%
201401081110	1856	1	3	2	99.67%
201401081211	1825	2	1	0	99.83%
201401081321	1736	0	0	0	100%
201401081505	1592	2	1	3	99.62%
201401081612	1683	0	1	0	99.94%

The experimental results in Table 2 show that the overall accuracy of the algorithm is above 99%. Experiments show that, in cases of the strong interference, the EMG interference or the conductive body being contacted, the algorithm can accurately calculate the QRS wave. Its detection accuracy is high; its operation speed is fast, and its memory consumption is small, which is suitable for mobile ECG signal processing and application.

5 Conclusion

This paper puts forward the improved detection method based on the difference threshold detection, and has solved the problem of the limitation caused by selecting and fixing the threshold in the traditional differential threshold method. The algorithm is simple, fast in operation, accurate and easy to realize. It can extract and identify the main characteristic parameters of the ECG signals, and lay a solid foundation for the further recognition and diagnosis. The algorithm is tested in the Android intelligent mobile phone, and the test results are satisfactory.

In addition, the system only realizes the lead measuring. The algorithm can be generalized to multiple lead detections, and thus the complete and further detection of the ECG signals can be conducted based on the characteristics of the *P* wave and *T* wave, so as to realize the analysis on the characteristics of more heart diseases.

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