Design of dynamic ECG diagnosis system based on multi-resolution

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Abstract. This article proposes a multi-resolution wavelet peak detection method for R wave localization to realize dynamic ECG diagnosis including RR interval, heart rate counting, bradycardia and bradycardia. Detection of R wave involves lots of cardiovascular diseases diagnosis, and plays an important role in ECG signal detection. Wavelet transform can describe the time-frequency characteristics of signals, allowing different resolutions to represent the time characteristics of signals; therefore, it is an appropriate tool for analyzing ECG signals. This method has been verified by MIT-BIH database’s R-wave records. The sensitivity of R wave method is 99.92%, and the positive predictive rate is 99.93%, and the dynamic ECG diagnostic system performs well.

1. Introduction

QRS waves are important part of ECG and the comprehensive manifestations of multi-myocardial cells, among them, the accurate location of R-wave is the key to waveform recognition.

Location of R-wave has been studied for a long time. [1-4], it mainly includes empirical mode decomposition, mathematical morphology, filtering, nonparametric model and wavelet transform [5-9]. The parameter white noise ratio coefficients and average times of empirical mode decomposition depend on empirical settings, which results in low accuracy of processing results and adaptability to unknown signals; Through morphological operations, QRS waves can be eliminated, so that the starting and ending points of P and T waves can be determined. The shape and size of morphological elements directly affect the effect of waveform recognition; The filtering method is simple, but its effect depends largely on itself stability and signal-to-noise ratio. The above-mentioned methods have different scope of application, and each has its own advantages and disadvantages. Signal de-noising and R waves localization based on wavelet transform are helpful to further analysis of ECG waveform [10,11].

We present here a multi-resolution wavelet peak detection method for R wave localization. Based on LabVIEW platform, a dynamic ECG diagnostic system is implemented for RR interval, heart rate counting, bradycardia and bradycardia. Wavelet transform describes signals’ time-frequency, allowing different resolutions to represent the time characteristics of signals; therefore, it is an appropriate tool for analyzing ECG signals. including the different characteristics of frequency (QRS compound wave, P-wave, T-wave). In addition, noise and artifacts affecting of signals can also be removed.

This article concludes: Section 2 introduces the content of multi-resolution wavelet peak detection. Then, the R-wave detection results are explained. Section 3 compares with the other algorithm and gives the verification results of MIT-BIH database and. In the end, the conclusion is given in Section 4.
2. Multi-resolution Wavelet Peak Detection
This article proposes multi-resolution wavelet peak detection method to detect R waves. The theory is introduced in the following.

2.1. Peak/valley recognition
Wavelet analysis uses approximate and detail coefficients to represent signals (as shown in Fig.1). Zero-crossing points in detail coefficients correspond to peak and trough values of signals.

![Figure 1. Zero-crossing points of peak and trough](image)

Here we use the biorthogonal 3.1 wavelet to perform R waves detection, which is most similar with ECG signal.

2.2. Multi-resolution analysis
Multiresolution analysis is helpful to identify signal peaks and troughs, which makes waves location more accurate and stable than peak detection based on threshold or curve fitting.

Signal usually contains low-frequency part and high-frequency part. Low-frequency part changes slowly with time, which requires lower time resolution and higher frequency resolution. High-frequency component changes rapidly with time, which requires higher time resolution. Lower frequency resolution is used for accurate time location. Therefore, multi-resolution analysis can identify the long-time trend and short-time change of signals, in which low-resolution information can effectively locate the features of interest, such as peak value; high-resolution observation can thin overall features and provide more specifics (as shown in Fig.2).
Figure 2. Multi-resolution thinning process of wavelet peak detection

The approximate coefficients (A1, A2, A3, A4, A5) and detail coefficients (D1, D2, D3, D4, D5) of the original signal are obtained by five-layer non-decimation wavelet transform (UWT), which can be expressed as follows:

\[
\text{Signal} = D1 + A1 \\
= D1 + D2 + A1 \\
= \ldots \\
= D1 + D2 + D3 + D4 + D5 + A1
\] (1)

For non-decimated wavelet transform signal, the zero-crossing point of D5 is checked first, corresponding to the peak of A4, and then the zero-crossing point of D4 is checked. Because of the high frequency component or noise, there may be more zero-crossing points in D4 than in D5. Therefore, the zero-crossing points closest to D5 associated with the peak of A3 will be selected, and the refining process will be repeated until the best scale of D1.

2.3. Wavelet transform level
Appropriate wavelet decomposition layers can better determine the peak and valley of the input signal and ensure that the peak and valley location and amplitude are the desired results. Small decomposition layers are suitable for processing noiseless data. Larger decomposition layers can reduce noise or discard unimportant peaks. In this article, level of UWT is 4.

3. R-wave detection
Here comparisons of algorithms are made, and verified by results of MIT-BIH database

3.1. Comparing methods
Compare multi-resolution wavelet peak detection and curve-fitting-based peak detection to locate the peak of ECG signals (as shown in Fig.3).
When the bandwidth of curve fitting is small, there will be false detection and wrong location of non-peak; when the bandwidth of curve fitting increases, there will be missed detection and some real peaks cannot be identified. Multi-resolution wavelet peak detection has advantages over curve fitting based peak detection.

3.2. R-Wave performance

Data sets are signals from MIT-BIH database [12], but the signal usually contains lots of useless information. As waves do not change in the entire signal, it is useless to research each wave. Therefore, the part defining ECG will be analyzed. The method’s capability will be tested by some difficult cases. These cases are Normal Sinus Rhythm Database (nsrdb), Atrial Fibrillation Database (afdb), CU Ventricular Tachyarrhythmia Database (cudb) and BIDMC Congestive Heart Failure Database (chfdb).

In this paper, classical evaluation standard : sensitivity Se and positive predictive rate + P (accuracy) were used to analyze the experimental results.

\[
Se = \frac{TP}{FN + TP} \times 100\% \quad (2)
\]

\[
+P = \frac{TP}{FP + TP} \times 100\% \quad (3)
\]

In the formula, TP represents true positive, which presents R peaks consistent with the actual labeling results, FN represents false negative, which presents missed R peaks, and FP represents false positive, which presents false R peaks.

| Database  | R waves | TP   | FP  | FN  | Se   | +P   |
|-----------|---------|------|-----|-----|------|------|
| nsrdb     | 64387   | 64339| 42  | 48  | 99.92| 99.93|
| afdb      | 63910   | 63801| 135 | 109 | 99.83| 99.79|
| cudb      | 54709   | 54621| 57  | 88  | 99.84| 99.90|
| chfdb     | 52838   | 52689| 109 | 159 | 99.72| 99.79|

The detection results by our multi-resolution wavelet peak detection method of R waves location are shown in Table 1. The algorithm has not learning cycle and achieves good detection performance on four research databases. For nsrdb, SE = 99.92% and + P = 99.93%, although on chfdb, our algorithm presents SE = 99.72% and + P = 99.79%.

3.3. Dynamic ECG diagnostic system

Based on multi-resolution wavelet peak detection method for R waves localization (as shown in Fig.4), a dynamic ECG diagnostic system is implemented for RR interval, heart rate counting, bradycardia and bradycardia on LabVIEW platform (as shown in Fig.5).
As shown in Fig. 5. The R peaks are marked with green fork number. The RR interval is the distance from the starting position of the R-wave to next R-wave. Sampling frequency is presented with $f_s$:

$$RR\text{ interval} = (\text{the starting position of next R-wave} - \text{R-wave starting position}) / f_s \quad (4)$$

The formula of heart rate is:

$$HR = 60 / RR\text{ interval} \quad (5)$$

The corresponding heart rate can be calculated through the RR interval.

In clinic, the duration of ventricular rate caused by any cause is less than 60 beats per minute, which is called bradycardia. Bradycardia can be caused by the origin, conduction and the combination of origin and conduction of cardiac excitation. When the pacing function of sinoatrial node is low or the vagus nerve which dominates the heart is hyperfunction, it can cause sinus bradycardia. The former belongs to organic disease, and the latter can become a part of sick sinoatrial syndrome. Similarly, the duration of ventricular rate is higher than 100 /min, which is called tachycardia.

According to the upper limit (100) and the lower limit (60), the input heart rate is determined by determining the range and forcing conversion. The results of tachycardia and bradycardia are output through the structure of true and false conditions. If it is within the normal range, no warning light is given.

4. Conclusion

This article proposes a multi-resolution wavelet peak detection method for R waves location. The algorithm has been verified by MIT-BIH database and achieves very good detection performance, for nsrdb, SE = 99.92% and $+P = 99.93\%$, although on chfdb, our algorithm presents SE = 99.72%, $+P = 99.79\%$, meanwhile, dynamic ECG diagnostic system is implemented for RR interval, heart rate counting, bradycardia and bradycardia on LabVIEW platform.
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