Recognition of ST segment of electrocardiogram based on wavelet transform

Li Shi[1,*], Cenyu Yang[1], Jinying Zhang[2], Hui Li[1]

[1]Department of Electrical Engineering, Zhengzhou University, Zhengzhou, Henan 450001, China; [2]Department of Cardiology, The First Affiliated Hospital, Zhengzhou University, Zhengzhou, Henan 4500052, China

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Abstract

Objective. The aim is to research the extraction of R waves and ST segment feature points based on Wavelet Transform (WT), and propose an algorithm used to recognize the shapes of ST segment. *Method.* First, electrocardiogram (ECG) signals are decomposed by WT algorithm using a dyadic spline wavelet. Based on the relation between the feature points of ECG signals and the maximum pairs of the signals' WT, a scheme is developed to identify feature points at different wavelet decomposition scales. Then, an identification algorithm is presented to recognize the shapes of ST segments by lines fitting. At last, the proposed scheme is demonstrated by the datum from the standard MIT/BIH ECG database. *Results.* The automatic ECG analysis system based on the proposed scheme can extract the ECG feature points correctly and recognize the shapes of ST segment successfully. *Conclusion.* The proposed algorithm can be used to analyze ST segment of ECG correctly and reliably, and the result is greatly useful for clinical diagnosis of coronary heart disease (CHD). [Life Science Journal. 2007; 4(2): 90 – 93] (ISSN: 1097 – 8135).

Keywords: electrocardiogram; ST segment; wavelet transform; lines fitting

1 Introduction

With the improvement of people's living standard, coronary heart disease (CHD) recognized "the first killer of people", has become more and more dangerous for the human health.There are various methods to diagnose CHD, such as the coronary angiography, Holter monitoring and so on. Of all the diagnostic means, the coronary angiography is recognized as the "golden standard", but it costs money and brings some physical damage to patients. Holter monitoring is one of the most basic and popular diagnosis methods for its no hurt to patients, more economical and convenient.

ECG signals are recorded by Holter for 24 hours and often contain various noises in the detecting process, so doctors had to diagnose CHD by their experience, which causes many problems such as time-consuming diagnostic process and different diagnosis results. ECG automaticanalysis system is reevaluated to overcome these problems. The key point of the system is extracting the feature points of ECG signals correctly. Differential threshold algorithm[1] was often used to extract the characteristics, but it was extremely sensitive to high frequency noises and had low accuracy. Nowadays, wavelet transform (WT) which is used to detect ECG characteristic points via the multi-scales feature has some prominent merits, such as high accuracy and strong anti-interference capability[2–4].

In the paper, a WT method is proposed to identify feature points of the ECG signals. Then, an identification algorithm which can recognize the shapes of ST segments is presented. At last, the efficiency of the proposed algorithms is demonstrated by the standard MIT/BIH ECG database and clinical ECG data.

2 Materials and Methods

2.1 WT principle

WT, an emerging numerical analysis algorithm in re-

*Corresponding author. Tel: 86-371-6778-1407; Email: shili@zzu.edu.cn

cent years, has the good time-frequency localization property. Vividly speaking, it has the "micro" function in the high-frequency segment so that it has the unique superiority in dealing with ECG signals.

The extraction of signal's singularity is an important application of WT, and the singularity often corresponds to the extreme points or the zero points of wavelets[5]. In the paper, ECG signal is decomposed to $S = 2^1 - 2^4$ scales by WT algorithm using dyadic spline wavelets. In $S = 2^3$ scales, R wave has the highest amplitude while the high frequency noises are decreased greatly and the low frequency noises are weak, so the R wave is extracted at $S = 2^3$ scale. S wave is high-frequency low-amplitude, and its energy is mostly at $S = 2^2$ scale. So the S wave is extracted at $S = 2^2$ scale. Low-frequency and slow-changing T wave is usually influenced by low amplitude and high-frequency disturbances, which can be avoided at larger scales such as $S = 2^4$, $S = 2^5$. So it is extracted at $S = 2^4$ scale.

2.2 Extraction algorithm

R peak: Based on the relation between the signal singularity and its WT, QRS complex wave corresponds to minimax germinations at $S = 2^3$ scale, and R peak corresponds to the zero-crossing point of the minimax germinations with a fixed delay.

ST segment: ST segment is composed of S peak, J point, the beginning of the T wave, T peak and ST voltage. The extractive scheme of the feature points is illustrated in details as follows. S peak is located at the first downward peak after the zero-crossing point of R peak at $S = 2^2$ scale. T peak is the first zero-crossing point of minimax germinations after R peak at $S = 2^4$ scale. Let T_{on} be the beginning of the T wave. The segment from T_{on} to T peak can be seen as a slope function. The minimum point, which can be found at the time of extraction of T peak, is corresponded to the midpoint of the T wave rising edge. Suppose that T_a is the distance between the midpoint and T peak, we search the distance T_a leftward from the midpoint of the T wave rising edge, and then we detect the position of T_{on}. T_{off} is the ending of the T wave. T_{off} point detection is similar to T_{on} detection except that the search goes backwards from the maximum of T peak. $S = 2^2$ is used for J point detection. J point is the first singularity point within 20 ms after S point. If no peak is found, S point is viewed as J point. In order to obtain ST voltage accurately, we combine R+x with J+x method[6] and select the midpoint of J point and T_{on} as ST voltage.

Baseline: We select the average of the ECG signal between T_{off} and P wave as the baseline.

2.3 Recognition algorithm

ST segment and the baseline should be at the same level in normal condition. When the depolarization/repolarization is in disorder, the shapes of the ST segments will change. The recognition of ST segment shapes is very helpful for doctors, and it is significant to diagnose CHD[7].

After ST segments are thoroughly studied, their shapes may be basically divided into six kinds: normal, horizontal depression, downsloping depression, upsloping depression, concave elevation and convex elevation[8]. An identification algorithm which can recognize the shapes of ST segment is proposed as follows:

First: ST voltage denoted as $a(st)$ is compared with the baseline, and the ST segment is divided into normal, depression and elevation.

Second: The data between the J point and the midpoint of the ST segment, the midpoint and the T_{on} point is fitted by straight lines respectively, and then the slope values of two straight lines recorded as d_1, d_2 are obtained.

Third: According to $a(st)$, d_1, d_2 and medical standards, the following judgments are carried on:

if $a(st) \le 0.1$ mV and $a(st) > -0.1$ mV, then the shape of ST segment is normal;

if $a(st) \le -0.1$ mV and $d_1 \ge -0.5$ and $0 \le d_2 \le 1$, then the shape of ST segment is horizontal depression;

if $a(st) \le -0.1$ mV and $d_1 \ge 0.5$ and $d_2 \ge 1$, then the shape of ST segment is upsloping depression;

if $a(st) \le -0.1$ mV and $d_1 \le -1$ and $d_2 \ge 1$, then the shape of ST segment is downsloping depression;

if $a(st) \ge 0.1$ mV and $d_1 > 0.5$ and $d_2 \ge 1$, then the shape of ST segment is concave elevation;

if $a(st) \ge 0.1$ mV and $d_1 < -1$ and $d_2 < -1$, then the shape of ST segment is convex elevation.

3 Results

The test data mainly come from standard MIT/BIH ECG database and clinical ECG data. As the limitation of recording lead numbers in database, ECG signals are analyzed mainly at MLII lead.

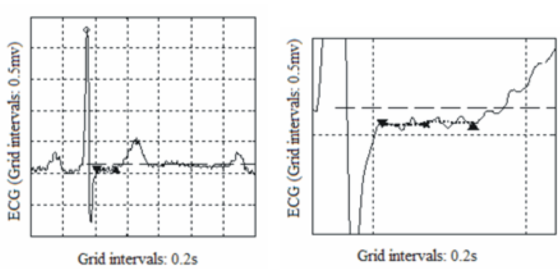
To evaluate the efficiency of the proposed automatic extractive algorithm, the feature points are also obtained by experienced cardiologists. The comparisons are shown in Table 1, in which E and e express mean and variance of error respectively. In Table 1, E and e are very small, and these fully show that the extractive accuracy by the proposed algorithm is high.

The recognized results are illustrated from Figure 1 to

Table 1. The comparison between the feature points identification of ECG from the proposed scheme and from the manual identification

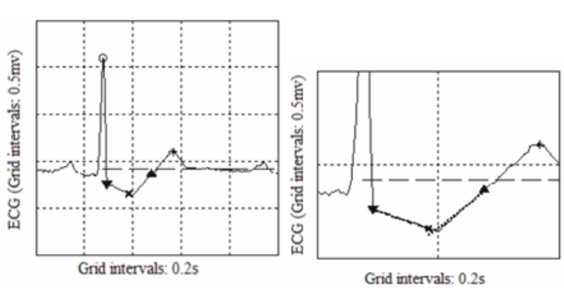
Position deviation (ms)	ECG records					
	300	302	307	310	312	327
$E_r \pm e_r$	1.43 ± 0.06	0.17 ± 0.08	1.18 ± 0.07	0.91 ± 0.08	0.45 ± 0.09	0.45 ± 0.06
$E_s \pm e_s$	2.28 ± 0.07	1.52 ± 0.07	2.03 ± 0.10	2.04 ± 0.10	1.6 ± 0.17	2.6 ± 0.12
$E_{T_{on}} \pm e_{T_{on}}$	2.77 ± 0.28	1.62 ± 0.45	2.62 ± 0.24	2.38 ± 0.34	1.04 ± 0.33	2.29 ± 0.16
$E_T \pm e_T$	1.86 ± 0.13	1.19 ± 0.09	1.19 ± 0.08	1.15 ± 0.12	1.47 ± 0.11	1.62 ± 0.29
$E_{T_{off}} \pm e_{T_{off}}$	2.46 ± 0.15	1.32 ± 0.27	2.05 ± 0.18	2.29 ± 0.30	1.43 ± 0.21	2.14 ± 0.30

Figure 6. In the figures, the position of R peak is donated by "○", the position of S peak is donated by "●", the position of T peak is donated by "*", the position of the level measure of cardiac cycle is donated by "×", the position of T_{on} is donated by "▲", the position of J point is donated by "▼", the position of the baseline of cardiac cycle is donated by "--", the fitting line is donated by "—", the fitting line is donated by "…". The figures show that the feature points are extracted accurately and the shapes of ST segment are well recognized by the fitting lines' slopes.



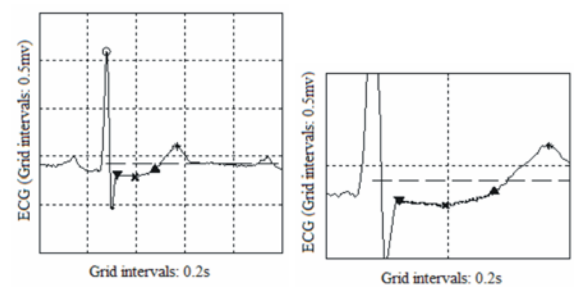
(a) (b)

Figure 1. (a) The feature points of normal ECG signal; (b) The partial amplificatory figure of ST segment.



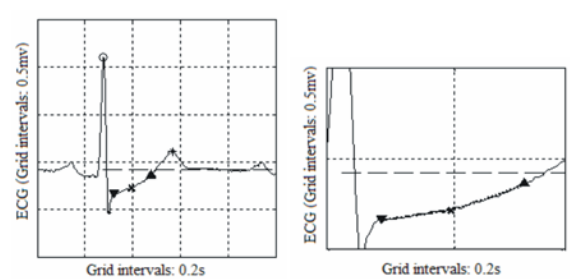
(a) (b)

Figure 2. (a) The feature points of downsloping ST segment depression; (b) The partial amplificatory figure of ST segment.



(a) (b)

Figure 3. (a) The feature points of horizontal ST segment depression; (b) The partial amplificatory figure of ST segment.



(a) (b)

Figure 4. (a) The feature points of upsloping ST segment depression; (b) The partial amplificatory figure of ST segment.

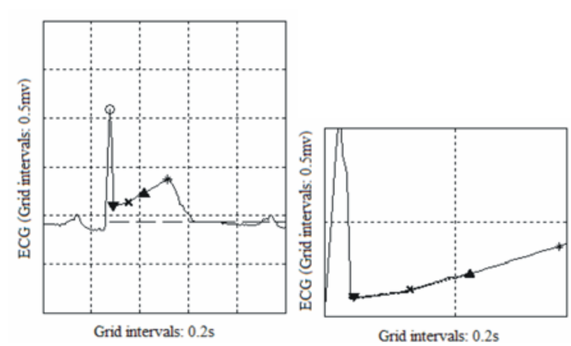


Figure 5. (a) The feature points of concave ST segment elevation; (b) The partial amplificatory figure of ST segment.

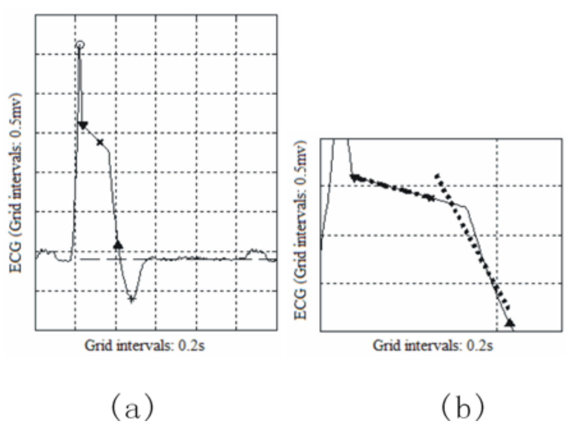


Figure 6. (a) The feature points of convex ST segment elevation; (b) The partial amplificatory figure of ST segment.

4 Conclusion

The proposed extractive algorithm based on WT can extract feature points automatically and accurately. It may successfully distinguished R wave from high T wave, noise and baseline drift, so the accuracy of the extraction of the feature points can be highly improved. If the noises in ECG signal are serious, the signal will be filtered by a series of hardware and software filters first. The tests prove the extractive algorithm has strong anti-interference capability and high accuracy.

Based on the feature points' correct extraction, the proposed lines fitting scheme can recognize the six shapes of ST segments accurately. Compared to the curve fitting method and neural network, it is simpler, quicker and has high accuracy rate.

The automatic ECG analysis system based on the proposed scheme can analyze ST segment of ECG correctly and reliably, and the result is very helpful for doctors to make quick and correct diagnosis of CHD.

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