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RESEARCH ARTICLE

Shape identification of electrocardiographic ST segment based on radial basis function neural network

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Abstract The types of myocardial ischemia can be revealed by electrocardiographic (ECG) ST segment. Effective measurement and electrocardiographic analysis of ST as well as calculation of displacement and shape change of ST segment can help doctors diagnose coronary heart disease and myocardial ischemia, especially for asymptomatic myocardial ischemia. Therefore, it is a very important subject in clinical practice to measure and classify the ECG ST segment. In this paper, we introduce a computerized automatic identification method of the electrocardiographic ST segment shape with radial basis function neural network based on adaptive fuzzy system, which has a better effect than other methods. It helps to analyze the reason of the ST segment change and confirm the position of myocardial ischemia, and is useful for doctor diagnosis.

Keywords radial basis function, fuzzy system, neural network, shape identification

1 Introduction

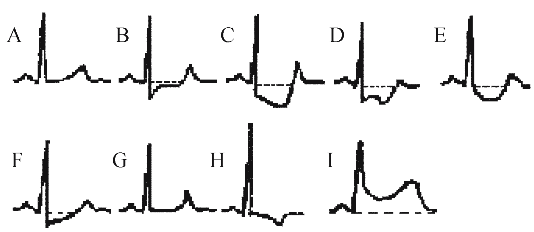
Electrocardiographic (ECG) ST segment is a wavelet from the end point of the QRS wave to the start point of the T wave. Its time span is related to heart rate and is approximately 50–120 ms. It is close to the equipotential line under normal conditions. Considering the process of myocardial depolarization/repolarization as well as the action potential mechanism of the myocardial cell, ST is actually a long unstable balance of the heart before repolarization according to the sequence of first depolarization and second repolarization. When the sequence of depolarization/repolarization is destroyed due to some reason or the heart is sick, changes such as rise, lowering and all kinds of shapes will occur in the body surface electrocardiographic ST segment.

Figure 1 shows the three common shapes of the ST segment:

1) Rise: type I in Fig. 1, usually in variant angina;

2) Horizontal straight acutely connected to T wave: type G in Fig. 1, injury of anterior wall, cardiac apex and endocardium as well as hypocalcemia;

3) Lowering: type B, C, D, E, F and H in Fig. 1. It is also divided into joint lowering, horizontal lowering, concave lowering, convex lowering and subsidence lowering. It may indicate mentally healthy heart; however it may also show inadequate coronary artery or sinus tachycardia. Sagging lowering (e.g., F) usually occurs in injury or ischemia of anterior lateral wall endocardium. Declined lowering (H) is a relatively typical myocardial ischemia lowering.



A): normal; B): ST segment lowering of horizontal type; C): ST segment lowering of sagging type; D): ST segment lowering of arch type; E): ST segment lowering of subsidence type; F): ST segment lowering of approximate ischemia type; G): ST segment horizon and ST-T joint at acute angle; H): left ventricular hypertrophy and injury; I): ST segment rise of variant angina and T wave rise.

Fig. 1 Various ECG ST segment

Therefore, the shape identification of the ST segment helps to analyze the reason for the ST segment change and confirm the location of ischemia. Thus, during the measurement of the ST segment, its characteristic parameters are determined according to its shape type, rising/falling level as well as joint to the front QRS segment and the back T segment (Yang, 2002).

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According to the shape features of the ST segment, we adopt the new method of radial basis function neural network based on the adaptive fuzzy system to identify the ST segment with great results.

2 Basic principles of the network

2.1 Principles of the radial basis function neural network

Radial Basis Function (RBF) Neural Network consists of three layers, the structure of which is shown in Fig. 2. Input layer nodes only transmit input signal to the hidden layer. Hidden layer nodes consist of radiating action function like Gaussian function [like Formula (1)], and output layer nodes are simple linear function [like Formula (2)].

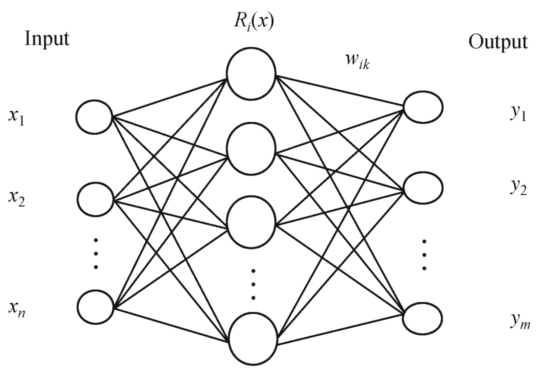


Fig. 2 Radial basis function neural network

The basis function in the hidden layer nodes locally responds to input signal. When the input signal is near the central range of the basis function, greater output will be generated in the hidden layer nodes. This network has local approximation ability. However, for the input sample away from the center of the hidden layer nodes, the network output approximates to 0. Therefore, when RBF network is used for classification, the decision area for each type will be local and the network can effectively refuse to decide new samples that do not belong to known types. It is an obvious feature by which the RBF network classifier differs from other neural network classifier. In comparison with Back Propagation (BP) network and in case of limited training samples, the training speed of the RBF network is 10–100 times faster than that of the BP network due to its local feature. The most common basis function is the Gaussian function:

$$R_i(x) = \exp\left[-\frac{\|x-c_i\|^2}{2\sigma_i^2}\right], \quad i = 1, 2, \ldots, m \tag{1}$$

$$y_k = \sum_{i=1}^{m} w_{ik} R_i(x), \quad k = 1, 2, \ldots, p \tag{2}$$

in which, x is n dimension input vector. c_i is the center of No. i basis function and a vector with the same dimension as x. σ_i^2 is called the shape parameter, or planning factor, which decides the width of the basis function around the center and measures the scope in which the input sample is similar to the typical one. $\|x-c_i\|$ is the Euclidean norm of $x-c_i$ and expresses the distance between x and c_i. $R_i(x)$ has only one maximum at c_i. As $\|x-c_i\|$ increases, $R_i(x)$ soon decreases to 0.

In order to obtain a smoother fuzzy boundary value, a calculation process of weighted average is added to the normal radial basis function network input. The network can be called general radial basis function network (or generalized regression network).

The normalized output $$y_k = \frac{\sum_{i=1}^{m} w_{ik} R_i(x)}{\sum_{i=1}^{m} R_i(x)}, \quad k = 1, 2, \ldots, p \tag{3}$$

in which p is the number of output nodes. The learning correction of connection weight can calculate the weight value of the linear output layer through the minimum sum squared error between network output y_k and target output d_k.

2.2 Fuzzy logic system

The fuzzy logic system is substantially an expert system that uses the fuzzy rule for inference and decision. A fuzzy system consists of four parts: fuzzy generator, knowledge, fuzzy inference engine and fuzzy remover (Zhang and Yan, 1998), which are shown in Fig. 3.

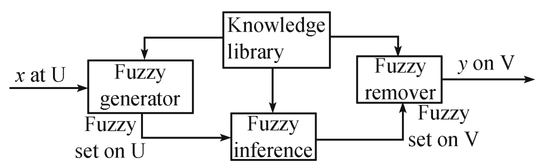


Fig. 3 Fuzzy logic system

2.3 Radial basis function neural network based on adaptive fuzzy system

The artificial neural network is good at adaptive learning of network parameters and is capable of parallel processing and generalizing. Nevertheless, the network output unit of the regular multilayer feedforward neural network classifier is fixed and constant so that the classifier can merely learn known types instead of new modes, i.e., lack of incremental learning. Fuzzy logic simulates the logical thinking of the human brain and deals with control problems with unknown or inaccurate models (Liu, 2001). We combine fuzzy logic and neural network into a system. A neural network realizes fuzzy logic inference so that the weight value of the network has a clear fuzzy logic meaning. Network structure is established according to fuzzy rule. Meanwhile, by means of the learning ability of the neural network, we carry out complex fuzzy inference and enhance calculation speed to automatically find the optimum weight value (Wang and Sun, 1998). In this way, we make full use of the advantages of neural networks and fuzzy logic and avoid their disadvantages.

The output of radial basis function neural network all results from each set of input value. Its value is a number from 0 to 1, and is equivalent to the total number of fuzzy rules from premise to conclusion in a fuzzy system. Each additional radial neuron means an additional fuzzy rule so that the fuzzy rules can be adjusted online (Wang et al., 1998).

3 Test methods

The difficulty of identifying the shape of the ST segment for which interfering signal has already been filtered lies in the accurate description of its diversification with a mathematical expression. A neural network is a powerful tool to solve problems such as establishing patterns that are not available by conventional method and requiring fault tolerance function, and so on. Combined with fuzzy systems, a neural network may be enhanced in learning and generalization capabilities (Wei et al., 2002). It is very suitable to adopt a radial basis function neural network based on fuzzy systems to sort shapes of the ST segment. Fig. 4 is the system block diagram of the shape identification of the ST segment.

3.1 Preprocessing of the ST segment

The ST segment is a period of time from point S to T wave. Since the accurate and rapid positioning of point S of every heartbeat is difficult to some extent, and detecting the location of the peak value of wave R is quite easy, we may take the peak value of wave R as reference point while intercepting the ST segment, and move backwards for 80–150 ms, since this interval must contain voltage values of all points within the ST segment and can reflect the mean accumulation degree of time for the ST segment of every heartbeat of patients suffering from myocardial ischemia.

1) Detect the Peak Value of QRS Wave

This paper adopts the R wave detection algorithm for ECG signal, which was put forward by Hamilton and Tompkins. First, eliminate the high and low frequency elements of non-QRS complex through a high pass-low pass filter. The low pass filter is realized by the following difference equation

$$y(nT) = 2y(nT-T) - y(nT-2T) + x(nT) \\ - 2x(nT-6T) + x(nT-12T)$$

In the formula, T refers to sampling period, and n is any integer. The high pass filter is realized by the following difference equation

$$y(nT) = y(nT-T) - x(nT)/32 + x(nT-16T) \\ - x(nT-17T) + x(nT-32T)/32$$

These two filters make up a band-pass filter. Such algorithm strengthens the QRS complex and restrains other elements of ECG. Since the change rate of the QRS wave of the ECG signal is the biggest, we may obtain the slope of the QRS wave through differential method, and the difference equation is as follows:

$$y(nT) = \left[2x(nT) + x(nT-T) - x(nT-3T) \\ - 2x(nT-4T)\right]/8$$

Then square the ECG signal of every point, turn all results into positive numbers, and nonlinearly amplify the output of the differentiation processor. By means of finding the maximum of the squared ECG signal, we may detect the position of the R peak.

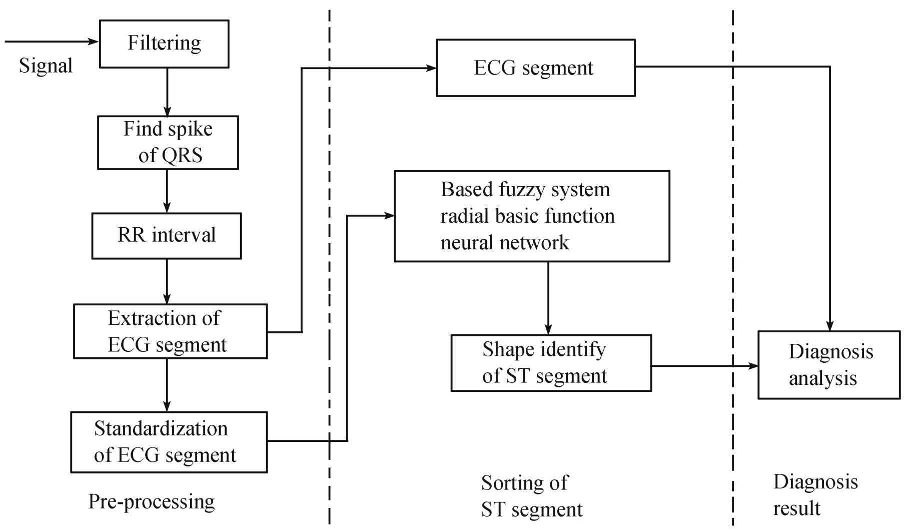


Fig. 4 System block diagram of shape identify of ST segment

2) Standardization for ECG segment

Through QRS peak value detection, we may accurately position the R wave and heart rate. The datum between the R-R interval is called Frame. People's heart rates differ, and the electrocardiographic amplitudes of different subjects vary greatly, so the handling of "normalization" should be carried out for heart rate and wave amplitude (Kwang and Wang, 1992). The heart rate of the ST sample for training the neural network is 60 times/min. The amplitude is normalized according to the following formula:

$$y_i(n) = \frac{x_i(n) - AL_i}{AH_i - AL_i}$$

In the formula, x_i and y_i is No. i frame datum respectively before and after the normalization, and AH_i and AL_i are the corresponding maximum and minimum. After normalization of amplitude, the highest amplitude if every frame signal is 1, and the least amplitude is 0.

Figure 5(a) is a normal electrocardiogram with 360 Hz sampling frequency and 66 times/min of heart rate. Figs. 5(b) and 5(c) show interception and standardization of the electrocardiosignal segment.

3.2 Neural network design

Select point R and return backwards for 150 ms, take this ST segment as the RBF network input. The number of input neurons is 54 (sampling frequency is 360 Hz, and carry out standardization with heart rate of 60 times/min). The existing class identification number during training decides the number of output layer neurons, and the number of hidden layer neutrons equals the output neutrons. Therefore, a network structure with the preliminary set of $54 \times 9 \times 9$ is adopted.

In order to make the most out of the existing samples and shorten the study procedure, we have adopted a subnetwork structure: conduct one output for multi-input consisting of the already known patterns. An RBF network is a subnetwork that merely takes charge of identifying one pattern out of the already known pattern class. If a new sample is inputted to the combined network, all RBF subnetworks will reject to identify it. An output node, i.e., a RBF subnetwork, may be added to the classifier, and then the subnetwork will identify the new pattern. The subnetwork structure is shown in Fig. 6, and the ideal output of the sample is 1. If there exist several classes that meet the requirements, then divide X into the class with a maximum y according to the Maximum Principle.

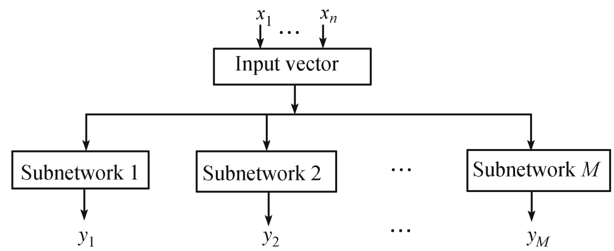


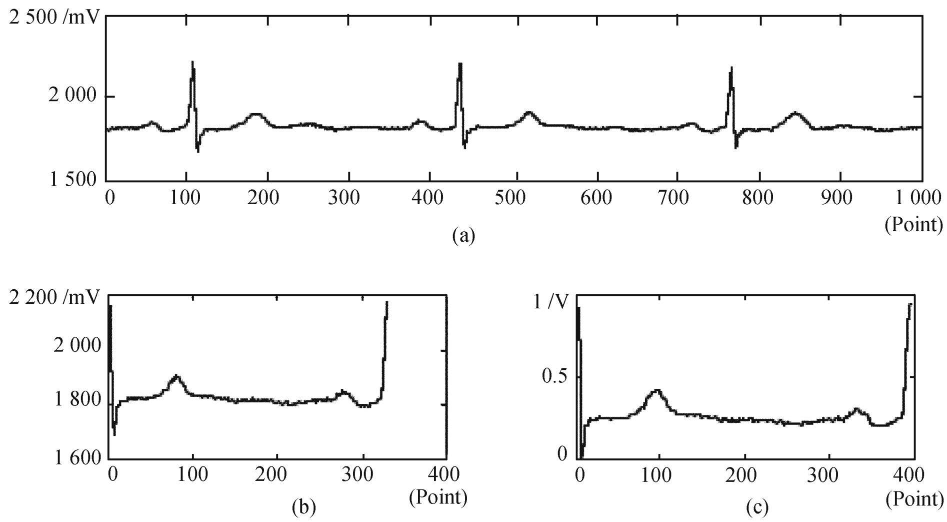
Fig. 6 Subnetwork structural diagram

3.3 Learning and identification

Corrective method for parameter vector: Based on the training mode, the learning algorithm is in light of the negative gradient descent of the error function and continuously renews network parameters, and the error parameter E_n of No. n training mode may be defined as

$$E_n = \frac{1}{2}(t_k - y_k)^2$$

in which k is the output neutron of the maximum.



(a): original ECG dignal; (b): intercepted ECG segment; (c): standardized R-R segment.

Fig. 5 Interception and standardization of ECG segment

According to the RBF structure relying on AFSI and the renewal and corrective principle for parameters, the output of No. k element is

$$y_k = \frac{\sum_{i=1}^{m} R_i(x) w_{ik}}{\sum_{i=1}^{m} R_i(x)} = \frac{u\left(c_{ji}, \sigma_{ji}, w_{ik}\right)}{z\left(c_{ji}, \sigma_{ji}\right)}$$

$$\Delta c_{ji} = -\frac{\partial E}{\partial c_{ji}} = -\frac{\partial E}{\partial y_k}\frac{\partial y_k}{\partial R_i}\frac{\partial R_i}{\partial c_{ji}} = \left(t_k - y_k\right)\frac{w_{ik} - y_k}{z} R_i \frac{x_j - c_{ji}}{\sigma_{ji}^2} \tag{4}$$

$$\Delta \sigma_{ji} = -\frac{\partial E}{\partial \sigma_{ji}} = -\frac{\partial E}{\partial y_k}\frac{\partial y_k}{\partial R_i}\frac{\partial R_i}{\partial \sigma_{ji}} = \left(t_k - y_k\right)\frac{w_{ik} - y_k}{z} R_i \frac{\left(x_j - c_{ji}\right)^2}{\sigma_{ji}^3} \tag{5}$$

$$\Delta w_{ik} = -\frac{\partial E}{\partial w_{ik}} = -\frac{\partial E}{\partial y_k}\frac{\partial y_k}{\partial u}\frac{\partial u}{\partial w_{ik}} = \left(t_k - y_k\right)\frac{1}{z} R_i \tag{6}$$

1) The algorithm of the learning process is as follows:

Step 1: use a small random number to initialize weight-value w_{ik}, and the initial value of shape parameter is $\sigma_{init} = 0.25$;

Step 2: take the training sample X_i as the center c_i of radial basis function network respectively, and the corresponding subnetwork expected output of every sample $t_i = 1$;

Step 3: use the No. i input pattern to estimate $\left|y_i - t_i\right|$, y_i and t_i are respectively the subnetwork output value and expected value of No. i sample;

Step 4: if $\left|y_i - t_i\right| > \varepsilon$, and ε is error bound, then turn to step 5, otherwise to step 6;

Step 5: adjust the weight vector according to the corrective method of formula (6), and turn to step 3;

Step 6: input new training sample, then turn to step 2.

2) The algorithm of the identification process is as follows:

The node number of the hidden layer

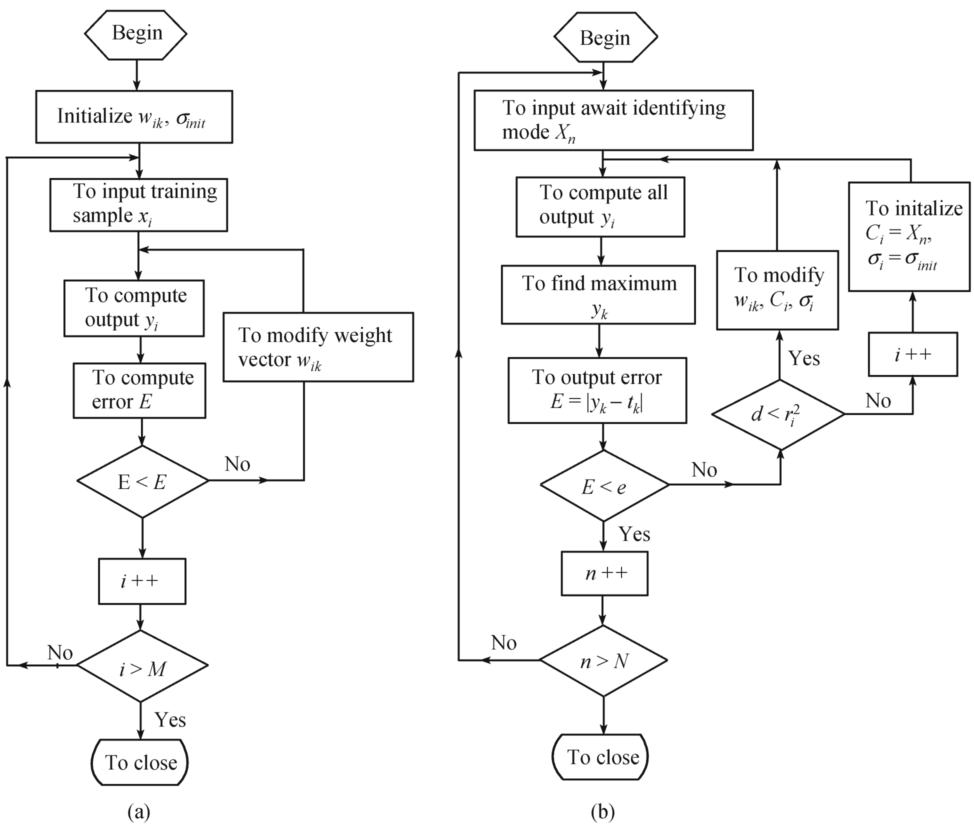
$i = 9$. Set effective radius r_i;

Step 1: input pattern X_n that needs to be identified;

Step 2: use No. n input pattern to estimate $\left|y_k - t_k\right|$, $y_k = \max(y_1, y_2, \ldots, y_i)$, $t_k = 1$, y_k and t_k are respectively the network output value and expected value of No. n sample.

Step 3: if $\left|y_k - t_k\right| > e$, and e is error bound, then turn to step 4, otherwise to step 7;

Step 4: if a node in the hidden layer make the training sample fall into hyper-sphere H, then turn to step 5, or turn to step 6 if a new hidden layer node occurs. The parameter of the new node is determined in accordance with the following method



(a) Learning flow process diagram; (b) Identification flow process diagram.

Fig. 7 Algorithm flow process diagram

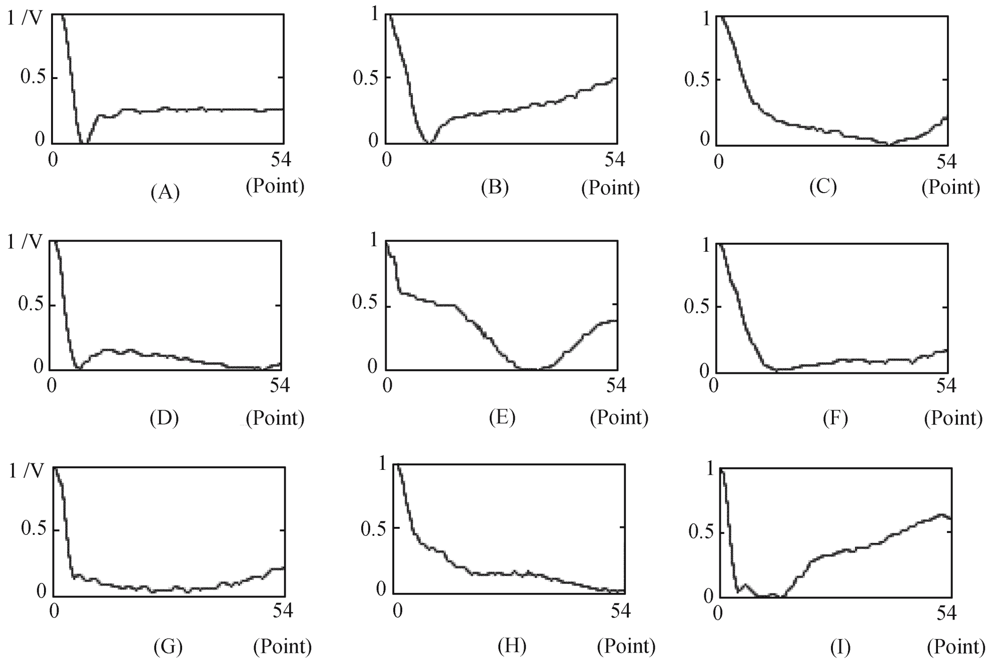


Fig. 8 Nine ST segments in MIT/BIH data base

Set $i = i + 1$; center vector c_i = input of training sample; shape parameter $\sigma_i = \sigma_{init}$;

Step 5: adjust parameter vectors according to the corrective methods of (4), (5) and (6);

Step 6: turn to step 2;

Step 7: wait for new data samples, and then turn to step 1.

The algorithm flow process diagram of the learning and identification processes is shown in (a) and (b) of Fig. 7.

4 Test results and discussion

This paper chose nine typical ST segments from the MIT/BIH database for emulation test, as shown in Fig. 8. A–H were regarded as eight typical patterns already known for the learning process. To each pattern, we chose one patient from whom ten frames were intercepted for network training, so the initial structure of the network was $54 \times 8 \times 8$. I was the new pattern in the course of identification during which we chose electrocardiosignals of ten patients from the above nine ECG records, and identified one frame of ST segment for each patient.

In this paper, we adopted MATLAB6.1 programming. After repeated tests, we chose error bound $\varepsilon = 0.001$, $e = 0.2$, and effective radius $r_i = 3$. We tested the ST segments of 90 frames, and the identification results are shown in Table 1.

The identification results given by the above table are satisfactory. The choosing of error bound e and effective radius r_i is very essential. The error bound e determines the adjustment degree of parameters, and the effective radius r_i determines the range of the same class. But there is no fixed formula for choosing these two threshold values, so they can be achieved only by repeated tests and adjustment.

Table 1 Shape Identification result of the ST segment

Type	*A*	*B*	*C*	*D*	*E*	*F*	*G*	*H*	*I*
Accurate Ness/%	99.2	96.1	86.8	92.5	89.6	93.7	92.1	86.4	91.6

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