International Journal of Signal Processing, Image Processing and Pattern Recognition
Vol.7, No.2 (2014), pp.211-222
http://dx.doi.org/10.14257/ijsip.2014.7.2.20

# A Frame work of Automatic Analysis System of Electrocardiogram Signals

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***Abstract***

*The aim of this paper is twofold. First, we define an ECG feature parameter set (32 features) which could represent ECG signal as adequately as possible for diagnosing requirements. Second, we design an automatic classification framework. After benchmark point detection, feature parameter will be extracted. And then the classifier methods and its comparison based on SVM and QNN are presented. The long-term objective is to design a thorough system to realize the recognition of real-time ECG signal and enhance medical treatment.*

***Keywords:*** *ECG classification, RQS wave detection, Wavelet Transform, Principal component analysis, Rough sets, Support vector machine, Quantum Neural Network*

## 1. Introduction

Cardiovascular Disease which threatens human's life and causes death is one of the most serious diseases in the world. Long-term ECG-monitoring plays an important role in cardiovascular disease diagnosis. In recent years, the automatic classification of electrocardiogram (ECG) signal has received great attention from the biomedical engineering community.

The ECG is the signal of recording the variation of human cardiac bioelectric potential. It provides valuable information about the functional aspects of the heart and cardiovascular system. Early detection of heart diseases can prolong life and enhance the quality of living through appropriate treatment. The state of cardiac health is generally reflected in the shape of ECG waveform and heart rate. The ECG signal contains important pointers representing nature of diseases. Since the biological signal is unstable, the reflection may occur at random in the some time scale. And the ECG waves may differ for the same person at the different time. Sometimes, they are similar for different types of heart disease. In this situation, the automatic analysis of ECG signal keeps the research hotspot in medical Engineering. Computer based recognition of the ECG can achieve high accuracy and offer the potential of an affordable mass screening for cardiac abnormalities. Successful classification will be realized by achieving the characteristic parameter of the ECG shapes with the requirement of diagnostic. Conventionally, a typical heart beat is identified by the detection of component waves of the QRS, T and P. They are characterized using parameters measurement method such as amplitude, duration, magnitude and area. For many years, a large number of researches focus on automatic analysis of ECG signals and several methods have been developed to increase the accuracy and sensitivity. These methods include Wavelet

ISSN: 2005-4254 IJSIP

Coefficient, Autoregressive Modeling, Radial Basis Functions (RBF) Neural Networks, Support vector machine (SVM), Quantum Neural Network (QNN), Self-organizing Map, Rough Sets and fuzzy c-means clustering techniques [1-13].

In this paper, we design a framework of automatic analysis system of electrocardiogram signal (see Figure 1). We firstly define an ECG feature parameter set (with 32 features) which could represent ECG signal as adequately as possible for diagnosing requirements. Then feature extraction based on Wavelet Transform (WT) is implemented. After feature extraction, several methods of feature parameter selection will be presented. Next, we design two classifiers based on SVM and QNN. Our long-term objective is to design a thorough system to realize the recognition of real-time ECG signal and enhance medical treatment.

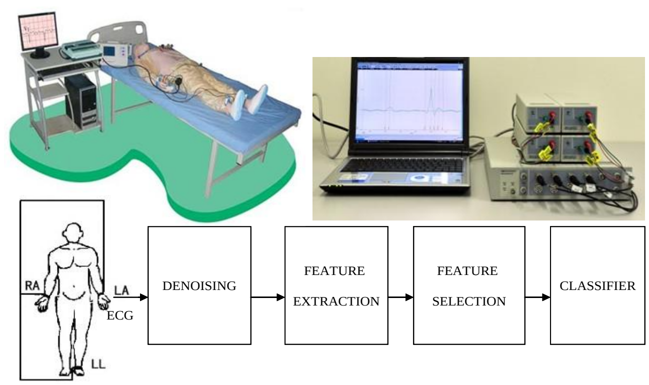


**Figure 1. The Procedure of the ECG Signal Analysis**

In the following sections, the method of feature extraction and selection will be introduced. Section 3 details the design of the classifiers. Experiment and result will be presented in Section 4. We state our conclusion and expectation in Section 5.

## 2. Feature Extraction and Selection

The noise of ECG waveform contains power line interference with 60Hz, muscle electricity and baseline wander. The pretreatment of ECG wave is implemented based on a high-pass filter with 0.7Hz and low-pass filter with 100Hz [14]. Figure 2 shows an ECG segment before filtering. Figure 3 is the ECG segment after filtering, which has removed burrs and corrected baseline drift.

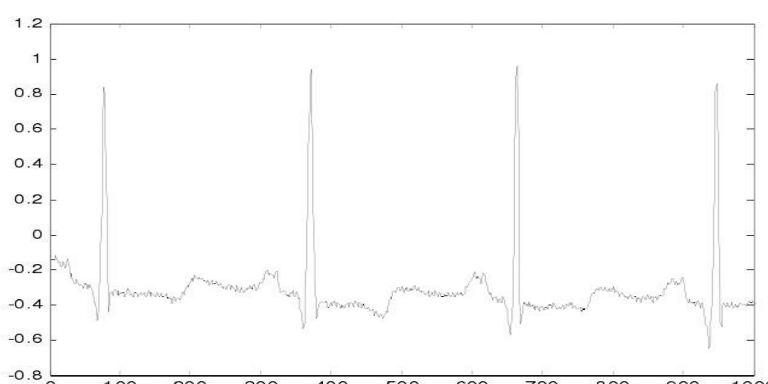


**Figure 2. ECG Original Signal**

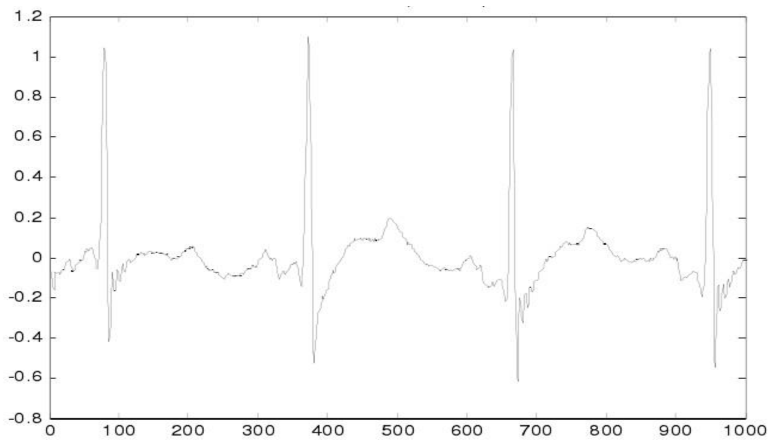


**Figure 3. The ECG Signal after De-noising**

### 2.1. Feature Extraction using Wavelet Transform

In order to classify the ECG signal, a reliable extraction of the characteristic ECG parameters is needed. The ECG is a non-stationary time signal. For such signal, time frequency features are desirable. The frequency characteristics as well as the temporal behavior can be described with Wavelet Transform. It can decompose the signals into various components depending upon the application and reassemble these components into the original signal without any information loss. So it is a powerful technique to analyze the physiological signals such as ECG and electroencephalogram (EEG). Basically wavelet transform is the convolution operation of the subject signal $f(t)$ and the wavelet function $\psi(t)$ [13]. The discrete wavelet transform is expressed as

$$X_{j,k} = \int_{-\infty}^{+\infty} f(t)\,\psi_{j,k}(t)\,dt \ . \tag{1}$$

The approximation coefficient of the signal $f(t)$ is represented as

$$A_{j,k} = \int_{-\infty}^{+\infty} f(t)\,\phi_{j,k}(t)\,dt \ , \tag{2}$$

where $\phi(t)$ is scaling function, $j$ and $k$ are scale and location respectively. For a range of scale $n$, the original signal $f(t)$ under discrete wavelet transform can be represented as

$$f(t) = f_n(t) + \sum_{j=1}^{n} d_j(t) \ , \tag{3}$$

where $d_j(t)$ is detail signal approximation in scale $j$ and $f_n(t)$ is mean signal approximation. $f_n(t)$ is given by $f_n(t) = A_{n,k}\phi_{n,k}(t)$.

We redefine the ECG feature parameter set upon the Ref. [15]. Considering to the professional cardiovascular doctor's advice, we add T wave area and P wave area in the feature set. And R-S amplitude and Q-R amplitude are decomposed into P wave amplitude, Q wave amplitude and S wave amplitude. Figure 4 is a single heartbeat illustrating of the major landmarks of ECG with a heart beat. The feature parameter set (32 feature parameters) consists of 21 temporal features (distances between fiducial points), 5 amplitude features (values of P, Q, R, S, T peaks), 3 area features and 3 angle features, as shown in Figure 5 and Table 1.

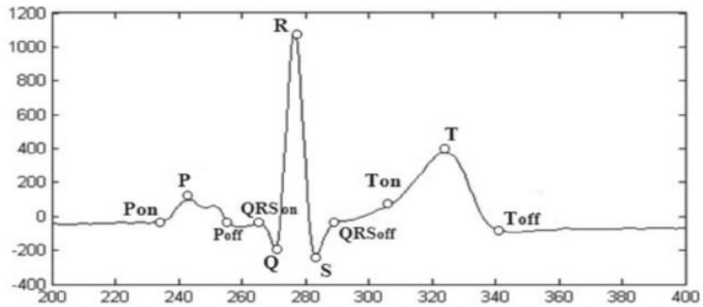


**Figure 4. Parameters of the ECG Signal in the Time Domain**

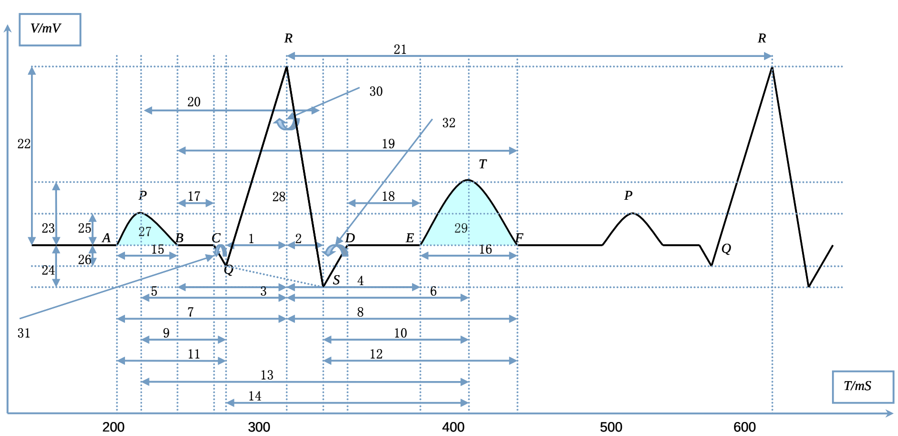


**Figure 5. 32 Fiducial Features in a Single Heartbeat Waveform**

**Table 1. Summary of the 32 Fiducial Features, Categorised according to Type of Features**

| Extracted features | Extracted features |
|---|---|
| Temporal features | 1. Q-R 2. R-S 3. B-R 4. R-E 5. P-R 6. R-T 7.A-R 8. R-F |
| | 9. P-Q 10.S-T 11. A-Q 12.S-F 13.P-T 14.Q-T 15. A-B 16. E-F |
| | 17.B-C 18.D-E 19. B-F 20.P-S 21.R-R |
| Amplitude features | 22. R high 23. T high 24. S high 25. P high 26. Q high |
| Area features | 27. P area 28. QRS area 29. T area |
| Angle features | 30. R angle 31. Q angle 32. S angle |

### 2.2. Feature Selection Methods

The goal of feature selection is to reduce dimensionality and enhance classification efficacy. There are many methods of feature reduction, such as Principle Component Analysis (PCA), Multiple Discriminant Analysis (MDA), Independent Component Analysis (ICA), Multidimensional Scaling (MDS), Self-Organizing Map (SOM), Rough Set Reduction (RSD) and Neural Network, *etc*. In this section, two methods of feature selection (PCA and RSD) are introduced briefly.

**2.2.1. Principle Component Analysis (PCA):** Principle component analysis (PCA) is a useful statistical technique to reduce the dimension of the data. New variables are generated by linear composites of the original variables and they are orthogonal to each other. The new variables still reserve the critical information, while the calculation is largely reduced. PCA provides us a means to represent a data set of $n$ variables in a lower $m$ -dimensional space where $m$ is less than $n$ . In general, the PCA technique transforms $n$ vectors $(X_1, X_2, \ldots, X_n)$ from a $m$ -dimensional space to a new $n$ vectors $(X_1', X_2', \ldots, X_n')$ from $m'$ -dimensional space [16, 17]:

$$X_i' = \sum_{k=1}^{d'} a_{k,i} e_k, \; m' \le m , \qquad (4)$$

where $e_k$ are the eigenvectors corresponding to the $m'$ largest eigenvalues for the scatter matrix $S$ . $a_{k,i}$ are the projection of the original vectors $X_i$ on $e_k$ the eigenvectors. These projections are called principal components of the original data set. Both $m'$ and $m$ are positive integers, and the $m'$ dimension cannot be greater than $m$ . The $m$ -by- $m$ scatter matrix $S$ for the original data set $(X_1, X_2, \ldots, X_n)$ is defined as:

$$S = E\left[X_i X_i^T\right], \; for \; i = 1 \; to \; n.$$

Where $E\left[X_i X_i^T\right]$ is the statistical expectation operator applied on the outer product of $X_i$ and its transpose.

**2.2.2. Rough Set Reduction (RSD):** Attribute reduction based on the theory of rough sets has proved to be a very useful approach for knowledge discovery [18]. An information system (IS) is a pair $(U, A)$ , where $U$ is a non-empty finite set of objects. The set $A$ composed of $C$ and $D$ is a non-empty finite set of attributes. Each subset of attributes $p \subseteq A$ determines a binary indistinguishable relation $IND(p)$ as: $IND(p) = \{(u,v) \in U \times U \,|\, \forall a \in p, a(u) = a(v)\}$ . Suppose $R$ is an equivalence relation cluster and $x \in R$ . If $IND(R) = IND(R - |a|)$ , $a$ is dispensable in the set $R$ , otherwise it is indispensable. If $p = R - |a|$ is independent, $p$ is a reduction in the set $R$ .

In this work, we use rough set method to reduce the feature parameters.

***Algorithm: Feature Reduction Alg***

**Input:** decision table $S = (U, C, F, D, V)$

**Output:** the attribute reduction result $red(C)$ of the decision table $S$ .

**Step 1:** (Initiating)

Calculate the degree of dependency of conditional attributes $r_C(D) = \dfrac{card(POS_C(D))}{card(U)}$ , If $r_C(D) = 1$, the decision table is consistent and we go to the next step.

If $r_C(D) \neq 1$, the decision table is inconsistent. It will be divided into several consistent decision tables. For each table, repeat step 1.

**Step 2:** (Eliminating redundant attribute)

Compute every degree of dependency of $C - a_i$ respectively, $a_i \in \{a_1, a_2, \cdots, a_m\}$. For each $a_i \in A$, if $r_{C-a_i}(D) \neq 1$, end.

Then $a_i$ is indispensable in the set $C$, we could obtain the reduction set $red(C) = C$.

**Step 3:** If $a_i \in A$, $r_{C-a_i}(D) = 1$, then $a_i$ is dispensable in the set $C$, we note $B_i = C - a_i$.

**Step 4:** (Redefine the attribute set $C$)

Redefine $C = B_i = C - a_i$ and return to step 3.

Repeat step 3 (from $i = 1$ to $m$) until the decision is inconsistent, i.e., $r_{C-a_i}(D) \neq 1$.

**Step 5:** (Return and output reduction) (see Tab.2)

**Table 2. Reduced Feature Set**

| Extracted features | Extracted features |
|---|---|
| Temporal features | 1. Q-R 2. R-S 3. B-R 4. R-E 5. P-R 6. R-T 7.A-R 8. R-F |
| | 10.S-T 11. A-Q 12.S-F 13.P-T 14.Q-T 15. A-B 16. E-F 20.P-S |
| | 21.R-R |
| Amplitude features | 22. R high 23. T high 24. S high 25. P high |
| Area features | 28. QRS area 29. T area |
| Angle features | 30. R angle |

## 3. Classifier Design

In order to standardizing the input parameters of classifier, these data need to be normalized. The range of all features was scaled to a range from 0 to 1. Suppose $\min_A$ and $\max_A$ are minimum and maximum value of feature parameter $A$. The value of feature parameter $A$ is mapped to the interval $[0,1]$ from the formulas

$$v' = \frac{v - \min_A}{\max_A - \min_A}. \qquad (5)$$

### 3.1. SVM Classifier

An assumption is made that there are two types of points in input training set $S = \{(x_i, y_i)\}_{i=1}^{n}$. Where $n$ is the number of input samples, $x_i \in R^m$ is an $m$ -dimensional input vector, and $y_i = \{-1, +1\}$ is the label of $x_i$. For a two-class classification problem, the decision function of the SVM is given by [19, 20]

$$f(x) = \operatorname{sgn}\left(\sum_{i=1}^{Ns} a_i k(x_i, x) + b\right). \qquad (6)$$

Where $a_i$ is the corresponding weight of the support vector $x_i$, $x$ is the input pattern to be classified, $Ns$ is the number of support vectors, and $b$ is the bias. Figure 6 is the sketch map of SVM rationale.

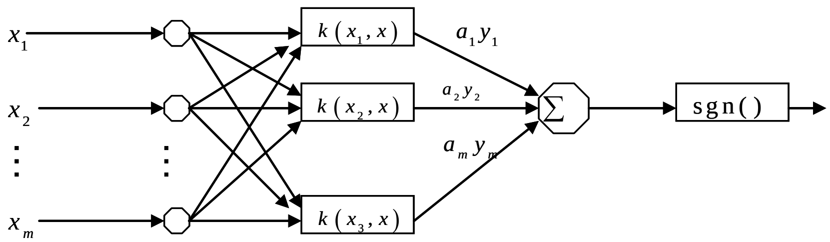


**Figure 6. Sketch Map of SVM Rationale**

For multi-class classification problem, one-against-all and one-against-one are two very commonly methods. In one-against-all support vector machines, a $k$ -class problem is converted to $k$ two-class problems. For $i$ -th two-class problem, class $i$ is separated from the remaining classes. In one-against-one support vector machines, a $k$ -class problem is converted to $k(k-1)/2$ two-class problems.

## 3.2. QNN Classifier

Quantum Neural Network (QNN) is a youthful and energetic science built upon the combination of quantum computing and artificial neural network [21-26]. The output of the multi-layer excitation function of hidden neurons in QNN can be written as:

$$\frac{1}{ns}\sum_{s=1}^{ns} f\left[\beta * \left(W^{T}X - \theta_{s}\right)\right] \tag{7}$$

where $f(x) = 1/\left(1+\exp(-x)\right)$, $W$ is the network weights vector, $X$ is the network input vector, $\beta$ is the slope factor and $ns$ is the number of levels or sigmoid in the hidden unit. Figure 7 is the activation functions of quantum neural net work.

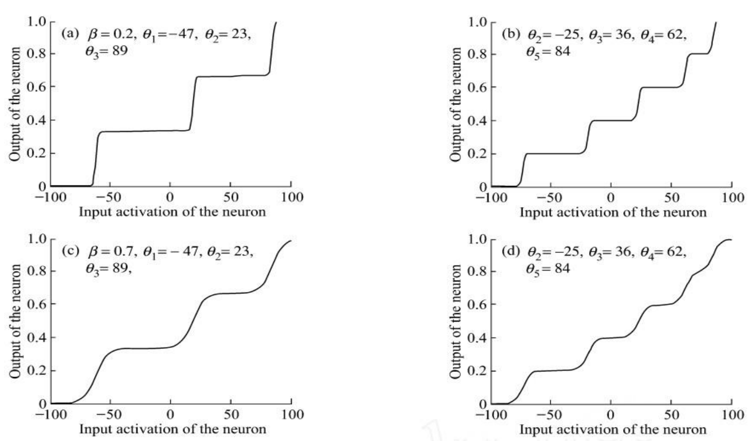


**Figure 7. Activation Functions of Quantum Neural Net Work**

The gradient descent method is used to train the QNN of multi-layer excitation function. In each training cycle, the training algorithm revises both the connection weight between the different level neuron and quantum intervals of the hidden layer. When the synaptic weights have been obtained, hidden neurons quantum intervals can be learned by minimizing the class-conditional variances at the outputs of the hidden units [27, 28].

The variance of the output of the $ith$ hidden unit for class $C_m$ is

$$\delta_{i,m}^2 = \sum_{x_k \in C_m} (\langle O_{i,m} \rangle - O_{i,k})^2, \tag{8}$$

where $O_{i,k}$ is in the input of the $ith$ neuron in hidden layer when the input vector is $x_k$. $\langle O_{i,m} \rangle = \frac{1}{|C_m|} \sum_{x_k \in C_m} O_{i,k}$, $|C_m|$ is the cardinal number of $C_m$, $m$ is pattern class number.

By minimizing $\delta_{i,m}^2$, we can get the update equation for $\theta_{i,s}$ as follows. For each hidden unit $i$ and its $sth$ quantum level $(s = 1, 2, \cdots, ns)$,

$$\Delta \theta_{i,s} = \alpha \frac{\beta}{ns} \sum_{m=1}^{n_0} \sum_{x_k \in C_m} (\langle O_{i,m} \rangle - O_{i,k}) * (\langle v_{i,m,s} \rangle - v_{i,k,s}). \tag{9}$$

In the forum, $\alpha$ is the learning rate, $n_0$ is the number of output layer nodes, namely the total class number; $n_s$ is quantum interval of layers, $x_k \in x_m$ means that among all samples belong to the class $C_m$; $\langle v_{i,m,s} \rangle$ and $v_{i,k,s}$ obtained by the following two equations:

$$\langle v_{i,m,s} \rangle = \frac{1}{|C_m|} \sum_{x_k \in C_m} v_{i,k,s} \tag{10}$$

$$v_{i,k,s} = O_{i,k,s} * (1 - O_{i,k,s}). \tag{11}$$

Where $O_{i,k,s} = f\left[\beta * (w^T x_k - \theta_s)\right]$ and $f(x) = 1/(1 + \exp(-x))$. When the input vector is $x_k$, it is the output of $s$ of the $ith$ neuron in the hidden layer.

## 4. Experiment and Comparison

For evaluation of experiment result, internationally-recognized ECG signals databases need to be used. Usually, there are three databases served for QRS detection:

MIT DB: The Massachusetts Institute of Technology Beth Israel Hospital Arrhythmia Database [28]

AHA DB: The American Heart Association ECG Database [ECRI, www.healthcare.ecri.org.]

ESC DB: The European Society of Cardiology ST-T Database [30]

In this paper, MIT–BIH arrhythmia database is used as source of experimental data (http://physionet.org/physiobank/database/). ECG signal detection and feature extraction algorithms are implemented with Matlab/Simulink. We selected the part waveform signals $T_{100}, T_{105}, T_{106}, T_{108}, T_{111}, T_{112}, T_{217}, T_{219}, T_{220}, T_{221}$ from MIT-BIH to do the experiment. For each signal, we randomly selected 40 wave forms to analyze. And we randomly selected 20 wave forms to train the network.

 

### 4.1. Experiment result with BP and RBF Neural Network Classifiers

Table 3 is the experiment result with BP and RBF neural network classifiers [31].

**Table 3. The Experiment Result of BP and RBF Neural Network**

| Sig. No | Waves learned | Waves tested | Precision(trained) | Precision (BP) | Precision (RBF) |
|---|---|---|---|---|---|
| $T_{100}$ | 20 | 40 | 100% | 95.2% | 95.2% |
| $T_{105}$ | 20 | 40 | 100% | 81.8% | 81.0% |
| $T_{106}$ | 20 | 40 | 100% | 77.3% | 69.2% |
| $T_{108}$ | 20 | 40 | 100% | 57.1% | 75.0% |
| $T_{111}$ | 20 | 40 | 100% | 87.0% | 95.0% |
| $T_{112}$ | 20 | 40 | 100% | 95.0% | 100% |
| $T_{217}$ | 20 | 40 | 100% | 64.3% | 82.6% |
| $T_{219}$ | 20 | 40 | 100% | 90.5% | 87.0% |
| $T_{220}$ | 20 | 40 | 100% | 100% | 100% |
| $T_{221}$ | 20 | 40 | 100% | 85.7% | 81.0% |
| Average | 20 | 40 | 100% | 83.4% | 86.6% |

### 4.2. Experiment Result with SVM Classifier

Radial Basis Functions (RBF) $k(x_i, x) = \exp\left[-\frac{|x - x_i|^2}{\sigma^2}\right]$ is selected as the kernel function of classifier. One-against-one support vector machine is used for designing the classifier. Classification experiment is implemented with Libsvm software [Software can be got at http://www.csie.ntu.edu.tw/~cjlin/libsvm.]. Table 4 is the experiment result with SVM classifier.

**Table 4. The Experiment Result of SVM**

| Sig. No | Waves learned | Waves tested | Rate(trained) | Precision (SVM) |
|---|---|---|---|---|
| $T_{100}$ | 20 | 40 | 100% | 97.5% |
| $T_{105}$ | 20 | 40 | 100% | 90.0% |
| $T_{106}$ | 20 | 40 | 100% | 82.5% |
| $T_{108}$ | 20 | 40 | 100% | 80.0% |
| $T_{111}$ | 20 | 40 | 100% | 95.0% |
| $T_{112}$ | 20 | 40 | 100% | 97.5% |
| $T_{217}$ | 20 | 40 | 100% | 92.5% |
| $T_{219}$ | 20 | 40 | 100% | 92.5% |
| $T_{220}$ | 20 | 40 | 100% | 100% |
| $T_{221}$ | 20 | 40 | 100% | 92.5% |
| Average | 20 | 40 | 100% | 92.0% |

### 4.3. Experiment Result with QNN Classifier

**Table 5. The Experiment Result with QNN Classifier**

| Sig. No | Waves learned | Waves tested | Rate(trained) | Precision (QNN) |
|---|---|---|---|---|
| $T_{100}$ | 20 | 40 | 100% | 96.3% |
| $T_{105}$ | 20 | 40 | 100% | 87.7% |
| $T_{106}$ | 20 | 40 | 100% | 80.2% |
| $T_{108}$ | 20 | 40 | 100% | 79.3% |
| $T_{111}$ | 20 | 40 | 100% | 96.4% |
| $T_{112}$ | 20 | 40 | 100% | 100% |
| $T_{217}$ | 20 | 40 | 100% | 91.8% |
| $T_{219}$ | 20 | 40 | 100% | 93.4% |
| $T_{220}$ | 20 | 40 | 100% | 100% |
| $T_{221}$ | 20 | 40 | 100% | 92.3% |
| Average | 20 | 40 | 100% | 91.7% |

## 5. Conclusion and Expectation

The aim of this paper is to design a classification system for ECG signal. We firstly defined a new ECG feature parameter set (32 features) with the professional cardiovascular doctor's advice. After benchmark point detection, feature parameters were extracted based on Wavelet Transform. Rough set theory was used to reduce the feature parameters. Then a reduction set (24 features) was reserved with diagnosing requirements. Classification results with BP, RBF, SVM and QNN were presented in Section 4. It is obvious that the SVM and QNN method is superior to the BP and RBF method. The classification result of the SVM is similar with the QNN.

The next step for our work is to improve recognition precision and accomplish classification with 13 kind of arrhythmia of all the 48 waveforms in MIT–BIH arrhythmia database. A thorough classification system of real-time ECG signal is the final goal for the biomedical engineering community.

## Acknowledgements

We would like to thank all the referees for their valuable comments in improving this paper. This work is supported by The Foundation of Sichuan Normal University (Grant No. 13KYL15).

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