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ECG quality assessment based on a kernel support vector machine and genetic algorithm with a feature matrix*

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Abstract: We propose a systematic ECG quality classification method based on a kernel support vector machine (KSVM) and genetic algorithm (GA) to determine whether ECGs collected via mobile phone are acceptable or not. This method includes mainly three modules, i.e., lead-fall detection, feature extraction, and intelligent classification. First, lead-fall detection is executed to make the initial classification. Then the power spectrum, baseline drifts, amplitude difference, and other time-domain features for ECGs are analyzed and quantified to form the feature matrix. Finally, the feature matrix is assessed using KSVM and GA to determine the ECG quality classification results. A Gaussian radial basis function (GRBF) is employed as the kernel function of KSVM and its performance is compared with that of the Mexican hat wavelet function (MHWF). GA is used to determine the optimal parameters of the KSVM classifier and its performance is compared with that of the grid search (GS) method. The performance of the proposed method was tested on a database from PhysioNet/Computing in Cardiology Challenge 2011, which includes 1500 12-lead ECG recordings. True positive (TP), false positive (FP), and classification accuracy were used as the assessment indices. For training database set A (1000 recordings), the optimal results were obtained using the combination of lead-fall, GA, and GRBF methods, and the corresponding results were: TP 92.89%, FP 5.68%, and classification accuracy 94.00%. For test database set B (500 recordings), the optimal results were also obtained using the combination of lead-fall, GA, and GRBF methods, and the classification accuracy was 91.80%.

Key words: ECG quality assessment, Kernel support vector machine, Genetic algorithm, Power spectrum, Cross validation
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1 Introduction

ECGs collected via mobile phones are easily polluted by system noises, body movement, and circumstance interference. This corrupted data could lead to medical misdiagnosis and false alarms on cardiac monitors (Li and Clifford, 2012). So, there is an essential requirement to assess ECG quality before it is used for clinical applications. ECG quality assessment has been a focus recently (Clifford and Moody, 2012; Hayn *et al*., 2012; Johannesen and Galeotti, 2012; Redmond *et al*., 2012), and it is also the topic of the PhysioNet/Computing in Cardiology Challenge 2011 (Moody, 2011).

The general methods for ECG quality assessments are based mainly on the analysis of the ECG waveform features or using various pattern recognition methods. Liu *et al.* (2011) proposed an ECG quality assessment method based on multi-feature fusion. Langley *et al*. (2011) designed a classifier employing six features of ECG waveforms. These classifiers are simple to obtain and could achieve real-time analysis. However, they are not very robust

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since these methods rely mainly on the direct information from ECG waveforms (e.g., misplaced electrode, huge impulse, and baseline drifts). Some pattern recognition methods, such as ensemble decision trees (Zaunseder *et al*., 2011), independent component analysis (ICA) (Kasturiwale and Deshmukh, 2009), self-organizing neural network (Chen and Yang, 2012), and support vector machine (SVM) (Clifford *et al*., 2012), have also been used for ECG quality classification.

Zaunseder *et al*. (2011) proposed a method employing ensemble decision trees for ECG quality assessment. Thirty-five features were derived from the power spectra of different frequency bands and for the power ratio among these power spectra, an optimal accuracy of 90.4% was obtained using the ensemble decision trees. Obviously, this method relies exclusively on the use of ordinary spectral features. Thus, for all of the ECGs the Fourier transform of each lead has to be calculated, which makes this method slow and not very robust. Actually, many ECGs are not necessary for extracting the power spectrum features because they have obvious waveform features such as lead-fall (electrode falling off or electrode fracture), baseline drifts, and high amplitudes. So, expanding the feature space and making full use of waveform features help reduce computational complexity and could improve classification accuracy. Furthermore, decision trees may have a high risk of over-fitting to the training data and require rather complicated structures to solve simple problems satisfactorily. Considering various classification tasks, it has been shown that decision trees usually do not reach the performance level of more sophisticated approaches such as SVM (Zaunseder *et al.*, 2011). Chen and Yang (2012) integrated multiscale recurrence analysis into a self-organizing map for ECG quality assessment. This intelligent method can obtain satisfactory classification results. However, the design of a neural network is relatively complicated and relies on experience. Thus, this method is not suitable for inexperienced researchers. In addition, ECG feature selection needs to be further extended and refined in the above-mentioned pattern recognition methods. Clifford *et al*. (2012) employed SVM to classify ECG quality and proposed seven signal quality indices including power spectrum and features of waveforms, each quality index with the same importance. However, computational complexity can be reduced if the ECG features are considered to have different importance. According to the different importance of ECG features, certain obvious and simple features, such as lead-fall, can be used directly to assess ECG quality. In general, if any lead is considered to have a lead-fall feature, the recording is classified as 'unacceptable'. Other features are used in further ECG quality classification. Among several intelligent methods, SVM has been proven a promising method (Clifford *et al.*, 2012). However, its performance depends mainly on the kernel function and the parameter choice of SVM. Clifford *et al*. (2012) did not include the selection of the best free parameters of the classifier adopted. Optimization of the soft margin constant C (i.e., the penalty parameter) of SVM and Gaussian radial basis function (GRBF) kernel parameter σ usually helps improve SVM classification accuracy.

In this paper we propose an automatic method to distinguish 'acceptable' and 'unacceptable' ECGs. Lead-fall detection can quickly recognize ECGs with an obvious lead-fall feature and obtain the initial classification. So, the computation time needed to obtain the initial classification can be reduced. KSVM is applied to ECG quality classification in this study. KSVM is essentially a nonlinear classifier. It has good performance in dealing with small samples, nonlinear and with high dimensions, and has a promising generalization capability (Khazaee and Ebrahimzadeh, 2010). This study combines the spectral feature with temporal features and forms a feature matrix. The proposed method employs the GA method to optimize the KSVM parameters since the efficiency and accuracy of GA outperform those of other state-of-the-art methods (Han and Kendall, 2003). Also, the classification results optimized by GA are compared with those by a grid search (GS) method.

2 Methods

2.1 Database

In this study, the database was from the MIT database of the PhysioNet/Computing in Cardiology Challenge 2011. This database consists of 1500 12-lead ECG recordings. All ECG recordings are divided into two datasets: training dataset A and test

dataset B (Moody, 2011). Set A includes 1000 ECG recordings and set B includes 500 ECG recordings. Each recording lasts 10 s and uses a 500 Hz sampling frequency. All recordings are identified by clinical experts and technicians as acceptable or unacceptable ECGs. The identification results of set A, including 775 acceptable recordings and 225 unacceptable recordings, are open to all researchers. However, the identification results of set B are not given. The automatic classification results can be assessed by uploading the experimental results to the PhysioNet/Computing database for comparison with the identification results given by clinical experts.

2.2 Method outline

The proposed method includes three modules (Fig. 1). The first one is the lead-fall detection module. An ECG recording can be regarded as an 'unacceptable' recording when any lead falls. The second one is the multi-feature analysis module. Six features are determined to form the feature matrix, including power spectrum, baseline drifts, amplitude difference, performance difference between two R-wave peak detection algorithms (i.e., R-wave peak detection algorithm based on difference (RDA) and R-wave peak detection algorithm based on wavelet transform (RWA) (Ramakrishnan and Saha, 1997)), and two features derived from the differences among all 12 leads detected by RWA. The third module employs a KSVM classifier to achieve the relatively accurate classification results for all ECG recordings. Actually, the KSVM classifier is used to deal with more difficult cases in which lead-fall detection is inefficient.

2.3 Lead-fall detection

When the amplitude of any lead in the ECGs almost keeps constant, lead-fall appears. As the lead-fall feature is easy to observe and identify, the lead-fall detection module is used for the initial ECG quality assessments in this study. The signal amplitude is determined to be within a small range around the constant value due to system noises. The difference between the maximum and minimum amplitudes of each lead is obtained. If the difference of any lead is less than five, the current recording is classified as 'unacceptable'.

2.4 Feature extraction and feature matrix

2.4.1 Extraction of the six features

1. Baseline drift

Considering the real-time requirement of clinical applications, we use an improved, fast median filtering algorithm (Ataman *et al.*, 1980) to extract the baseline curve. Denote $F_{i,1}$ as the feature of baseline drift of the *i*th ECG recording, which is defined as the maximum voltage of all its 12 leads.

2. Amplitude difference

In general, the amplitude peak in normal ECGs is 2.5–3.0 mV. There is always a huge impulse in many 'unacceptable' recordings. Denote $F_{i,2}$ as the amplitude difference of the *i*th ECG recording, which is defined as the maximum voltage of all the leads.

3. Performance difference between two R-wave peaks detection algorithms

When the recording includes strong noises, RDA usually has a poor anti-interference performance

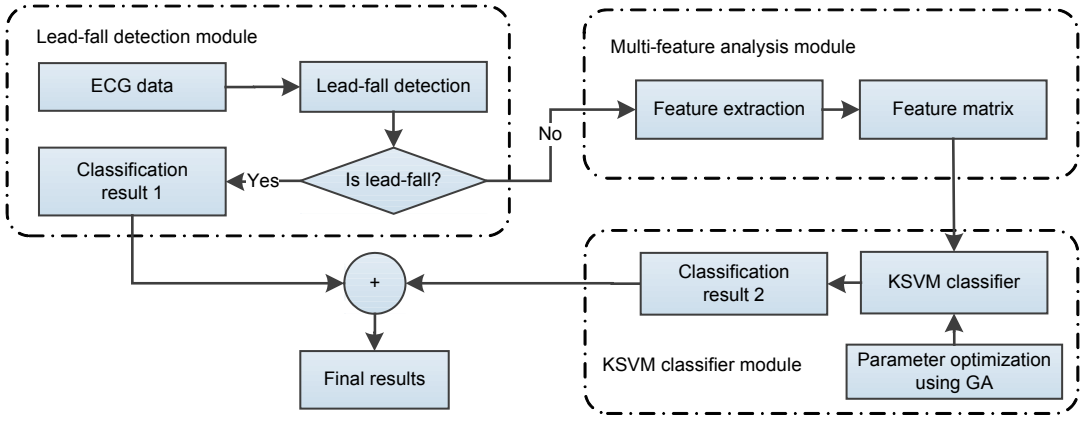

Fig. 1 The flowchart of the proposed method which includes three modules

whereas RWA (Ramakrishnan and Saha, 1997) remains accurate. So, the numbers of R-wave peaks extracted by RDA and RWA have an obvious difference.

Let N_{dj} and N_{wj} denote the numbers of R-wave peaks extracted by RDA and RWA respectively for the jth lead (j=1, 2, …, 12). Let i be the index of ECG recording (i=1, 2, …, n). Denote $F_{i,3}$ as the performance difference between RDA and RWA. $F_{i,3}$ can be calculated as follows:

$$F_{i,3}=\frac{1}{10}\left(\sum_{j=1}^{12}\text{Diff\_R}_j-\max(\text{Diff\_R}_j)-\min(\text{Diff\_R}_j)\right), \tag{1}$$

where $\text{Diff\_R}_j=|N_{dj}-N_{wj}|$.

The extreme values are removed by deleting the maximum and minimum absolute difference from the summation of Diff_R_j, which helps keep a stable outcome.

4. Difference of the numbers of R waves among all 12 leads detected by RWA

For 'acceptable' ECGs, the number of R-wave peaks extracted by RWA for each lead is approximately equal. However, for 'unacceptable' ECGs, the numbers have a large difference. $F_{i,4}$ and $F_{i,5}$ are used to reflect the difference of results among all 12 leads detected by RWA.

Let j (j=1, 2, …, 12) denote the index of lead, and i (i=1, 2, …, n) the index of ECG. For each ECG recording, the N_{wj} of all 12-lead R-wave peaks are obtained using RWA. Then, avg is calculated using

$$\text{avg}=\frac{1}{10}\left(\sum_{j=1}^{12}N_{wj}-\max(N_{wj})-\min(N_{wj})\right). \tag{2}$$

$F_{i,4}$ and $F_{i,5}$ are thus calculated as

$$F_{i.4}=\max(N_{wj})-\text{avg},\quad F_{i,5}=\min(N_{wj})-\text{avg}. \tag{3}$$

5. Power spectrum

ECG waveform usually has a frequency range of 0.01–100 Hz. The QRS complex is the main characteristic of ECGs. ECGs with high signal quality usually have a distinguishable QRS complex. The main energy of the QRS complex occurs at 3–40 Hz with the peak usually at 17 Hz (Thakor *et al*., 1984; Kligfield *et al*., 2007; Suh *et al*., 2011). So, the ratio of power spectral density (PSD) in the main energy band to that in the overall energy band provides a useful measure for ECG quality. In this study, this ratio is defined as $F_{i,6}$.

Let $P_{\text{part}\,j}$ denote the PSD at 10–24 Hz and $P_{\text{all}\,j}$ the PSD at 1–60 Hz for the jth lead (j=1, 2, …, 12). $F_{i,6}$ is defined as $F_{i,6}=\min(P_{\text{part}\,j}/P_{\text{all}\,j})$ for the ith ECG.

In this study the AR model spectrum estimation algorithm is adopted and the Burg algorithm is used for parameter estimation.

2.4.2 Feature matrix

With the above six features $F_{i,1}$–$F_{i,6}$ of all the ECG recordings, the feature matrix is defined as

$$\boldsymbol{I}=[F_{i,j}]=\begin{bmatrix}F_{1,1},F_{1,2},F_{1,3},F_{1,4},F_{1,5},F_{1,6}\\F_{2,1},F_{2,2},F_{2,3},F_{2,4},F_{2,5},F_{2,6}\\\cdots\\F_{n,1},F_{n,2},F_{n,3},F_{n,4},F_{n,5},F_{n,6}\end{bmatrix}_{n\times 6}, \tag{4}$$

where n denotes the number of ECG recordings.

2.5 KSVM classifier and GA algorithm

2.5.1 KSVM classifier

For linearly separable cases, the data can be correctly classified by linear SVM. However, for nonlinearly separable cases, the kernel function must be used in the SVM classifier, which is KSVM. KSVM can map the training data to a high dimensional feature space, where linear separation can be used. The classification problems can be solved by constructing optimal separating hyper-planes (OSHs). Then a decision function is obtained by solving this OSH problem.

In this study, the KSVM classifier is trained using the feature matrix on set A. After training, the optimal decision function (ODF) is obtained. Finally, classification results for set B can be obtained by inputting their feature matrix to the ODF.

The nonlinear classification hyper-plane problem is described as follows:

$$\begin{aligned}&\min_{\boldsymbol{w},\xi_i}\left(\frac{1}{2}\|\boldsymbol{w}\|^2+C\sum_{i=1}^{l}\xi_i\right)\\&\text{s.t.}\quad y_i(\boldsymbol{w},\varphi(\boldsymbol{x}_i)+b)\ge 1-\xi_i,\ \xi_i\ge 0,\ i=1,2,...,l,\end{aligned} \tag{5}$$

where $\boldsymbol{w}$ indicates the weight vector, b the bias, C the penalty parameter, ξ_i a non-negative slack variable

used to realize soft margins, $\boldsymbol{x}_i$ the training data (i.e., feature matrix $\boldsymbol{I}$), l the number of training data, y_i the known category of $\boldsymbol{x}_i$, and $\varphi(\boldsymbol{x}_i)$ a nonlinear function mapping $\boldsymbol{x}_i$ to a high dimensional space (Zhang, 2012).

This dual optimization problem can be achieved by Lagrange transformation:

$$\max_{\alpha}\left\{\sum_{i=1}^{l}\alpha_i-\frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l}\alpha_i\alpha_j y_i y_j K(\boldsymbol{x}_i,\boldsymbol{x}_j)\right\},$$
$$\text{s.t.}\quad 0\le\alpha_i\le C,\ \sum_{i=1}^{l}\alpha_i y_i=0, \tag{6}$$

where α_i is the Lagrange multiplier and K is a nonlinear function usually named the kernel function. The training procedure of KSVM is essentially a constrained quadratic optimization problem. After training, the decision function is shown as

$$f(\boldsymbol{x})=\operatorname{sign}\left(\sum_{\boldsymbol{x}_i\in\mathrm{SV}}\alpha_i y_i K(\boldsymbol{x}_i,\boldsymbol{x})+b\right), \tag{7}$$

where $\boldsymbol{x}_i$ is the ith support vector, α_i is the Lagrange multiplier, α_i and b are obtained during the training process, and $\boldsymbol{x}$ is the data to be classified.

2.5.2 Kernel function

The kernel function determines the classification performance of the KSVM classifier (Wang *et al*., 2005; Zhang, 2012). GRBF is a popular kernel function for the SVM application, defined as

$$K(\boldsymbol{x}_i,\boldsymbol{x})=\exp\left(\frac{-\|\boldsymbol{x}-\boldsymbol{x}_i\|^2}{\sigma^2}\right), \tag{8}$$

where σ is the parameter of GRBF. The selection of σ and error penalty factor C significantly affects the precision of KSVM.

We also test another kernel function, the Mexican hat wavelet kernel function, which is defined as (Biswal *et al*., 2013)

$$K(\boldsymbol{x}_i,\boldsymbol{x})=\frac{1}{\sqrt{2\pi\sigma^3}}\left(1-\frac{\|\boldsymbol{x}-\boldsymbol{x}_i\|^2}{\sigma^2}\right)\exp\left(\frac{-\|\boldsymbol{x}-\boldsymbol{x}_i\|^2}{\sigma^2}\right), \tag{9}$$

where σ is the parameter of the Mexican hat wavelet kernel function.

2.5.3 Parameter determination for GRBF by GA

In fact, there is not a unified theory for the selection of parameters σ and C for GRBF. In this study GA is used to specify these parameters. GA is an adaptive heuristic search algorithm based on the process of natural evolution and selection. For GA, a solution to the problem is encoded by a certain structure, such as a chromosome or genome. GA creates a population of genomes, and then applies crossover and mutation to the individuals in the population to generate new individuals. An objective function is defined to determine how 'good' each individual is. So, GA can pick the best individuals for mating and mutation. At last, GA finds the best individual by evolving the solution.

The process of GA is designed as follows:

Step 1: chromosome coding and population initialization.

In this study all feasible solutions are searched using binary representation. A 40-bit binary code chromosome (individual) is used to encode a pair of parameters (σ, C) in each GA population. Fig. 2 shows an example of chromosome encoding.

g_σ^1	g_σ^2	…	g_σ^{20}	g_C^1	g_C^2	…	g_C^{20}

Fig. 2 Example of chromosome encoding

g_σ^i (i=1, 2,…, 20) is a 20-bit binary code representing kernel parameter σ, and g_C^j (j=1, 2, …, 20) is a 20-bit binary code representing penalty parameter C

Finding an adequate population size is a complex task. If the population size is too small, GA may not be able to achieve high quality solutions and is easily trapped into a local optimum. If it is too large, unnecessary computational resources are used. In fact, selecting the population size usually relies on experience and habit. In this study the population size is set to 30.

Step 2: setting the fitness function f.

The fitness function value is treated as classification accuracy, namely individual fitness. The higher the pair of parameters (σ, C) corresponding to the classification accuracy of KSVM, the better the

individual fitness. The fitness function is defined as

$$f(\mathrm{Ch}_i) = \mathrm{CA}\,, \tag{10}$$

where Ch_i is the ith chromosome code and CA is a pair of parameters (σ, C) corresponding to the classification accuracy.

Step 3: selection.

According to the individual fitness, roulette wheel selection is employed to pick individuals for mating. For each individual, the probability of being selected is

$$p_i = f_i \Big/ \sum_{i=1}^{n} f_i\,, \tag{11}$$

where n is the number of individuals and f_i is the value of the ith individual fitness.

Step 4: crossover and mutation.

This step is to generate a second generation population of solutions from those individuals selected in the previous step through genetic operators, crossover and/or mutation. The crossover operator is performed between two selected individuals, and two next generation individuals are generated. An individual is randomly selected for mutation. The crossover and mutation probabilities are set to 0.9 and 0.05, respectively.

Step 5: termination.

This evolution process does not stop until a termination condition is reached. Common termination conditions include: the maximum number of generations is reached; the highest ranking population's fitness is reaching or has reached a plateau such that successive iterations no longer produce better results. A maximum of 240 generations is chosen as the termination condition.

Fig. 3 shows the flowchart of parameter optimization using GA. The evolutionary process starts from a randomly initialized population and is run for a maximum of 240 generations with a population size of 30, a mutation rate of 5%, and a crossover rate of 90%.

Results are over-fitting if the training sample is used as the validation sample. However, K-fold cross validation (K-CV) can avoid over-fitting because the training sample is independent of the validation sample. A K-fold partition of the dataset is created. For each of the K experiments, K-1 folds are used for training and the remaining ones for testing. At last, the average of the K classification accuracies is used for classifier performance evaluation. So, we use K-CV to verify each pair of parameters (σ, C) and its corresponding classification accuracy.

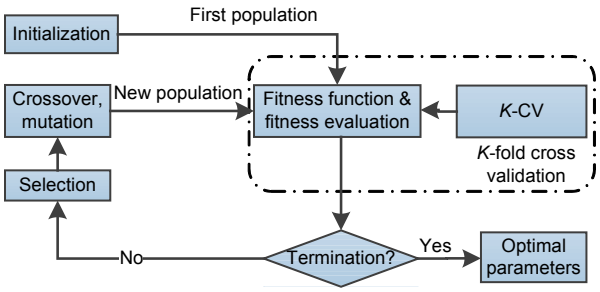

Fig. 3 The flowchart of KSVM parameter optimization using GA

2.6 Evaluation method

The classification outcomes are referred to as A_1, A_2, N_1, and N_2. A_1 represents the total number of unacceptable ECG recordings that are truly identified as unacceptable ECG recordings, A_2 represents the total number of unacceptable ECG recordings that are falsely identified as acceptable ECG recordings, N_1 represents the total number of acceptable ECG recordings that are truly identified as acceptable ECG recordings, and N_2 represents the total number of acceptable ECG recordings that are falsely identified as unacceptable ECG recordings.

Three indices, true positive (TP), false positive (FP), and classification accuracy, are used as the evaluation indices:

$$\mathrm{TP} = \frac{A_1}{A_1 + A_2} \times 100\%, \tag{12}$$

$$\mathrm{FP} = \frac{N_2}{N_1 + N_2} \times 100\%, \tag{13}$$

$$\mathrm{Accuracy} = \frac{A_1 + N_1}{A_1 + A_2 + N_1 + N_2} \times 100\%. \tag{14}$$

These three indices can be obtained for set A since the identification results of set A are open to all researchers. For set B, only the classification accuracy can be obtained by uploading the results to the PhysioNet/Computing database for online assessment.

3 Results and discussion

3.1 Classification results using lead-fall detection

Table 1 shows the classification results obtained using the lead-fall detection module. TP, FP, and classification accuracy were obtained for set A and classification accuracy for set B. For set A, by lead-fall detection 130 recordings were correctly identified as 'unacceptable' from 225 'unacceptable' ECG recordings and 8 recordings incorrectly identified as 'unacceptable' from 775 'acceptable' ECG recordings.

TP for set A is 57.78%, which is not high because lead-fall is not the only reason for poor quality ECGs. Some interferences such as baseline drift, high amplitude, low-frequency noise, and high-frequency noise may reduce the quality of ECGs. Thus, some poor quality ECGs cannot be identified by lead-fall detection. FP for set A is 1.03%. The classification accuracy is 89.70% for set A and 88.40% for set B.

Table 1 Classification results using lead-fall detection

TP* (%)	FP* (%)	Classification accuracy (%)	
		Set A	Set B
57.78	1.03	89.70	88.40

* For set A only

3.2 Determination of the optimal parameters for KSVM

To solely test the performance of the KSVM classifier, we first removed the ECG recordings with lead-fall in set A and set up a new training dataset named set C, which contained 767 acceptable ECGs and 95 unacceptable ECGs selected from set *A* and no lead-fall ECGs.

3.2.1 Selection of *K* for *K*-CV

The objective of this test was to determine the optimal value of *K* for the *K*-CV method. Different values of *K* may lead to different classification accuracies and efficiencies. So, it is important to select a proper *K* value. We selected different *K* values to perform the *K*-CV for set C, and then calculated the corresponding optimal parameters, the *K*-CV classification accuracies for set C, and the time costs. Fig. 4a shows the *K*-CV classification accuracy for set C with different *K* values, and Fig. 4b shows the corresponding time cost. Taking into account the classification accuracy and time cost, among the values of 2 to 10, K=4 was selected for the following analysis, which leads to an optimal classification accuracy of 93.97% for set C.

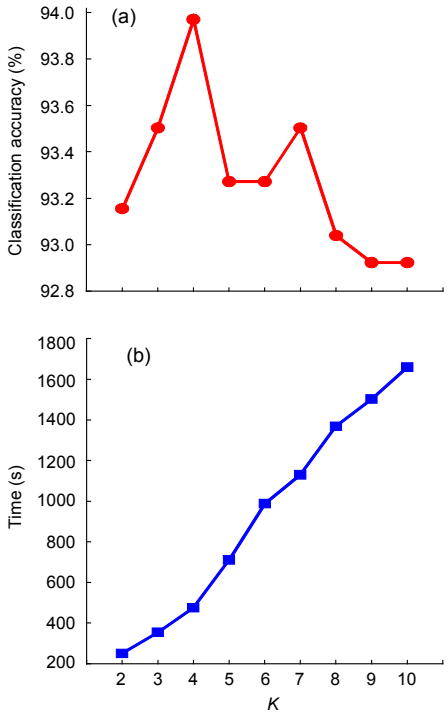

Fig. 4 The corresponding classification accuracy for set C using *K*-CV (a) and the time cost (b) with the increase of *K*

3.2.2 Determination of optimization parameters

In this test, GA was employed to optimize the parameters of the KSVM classifier. Parameters σ and C were both selected from 0 to 2^{20}. Fig. 5 shows the curve of fitness using the GA method with different generations when K equals 4. The optimal fitness, namely the *K*-CV classification accuracy, reaches 93.97% for set C. In fact, the optimal fitness was obtained when $\sigma=0.43\times10^{-3}$ and $C=1.14\times10^{5}$. During the process of parameter optimization, some corresponding classification accuracies for set C using *K*-CV are low because the chosen σ and C are not the optimal parameters. This is also why the average fitness is lower than the optimal one. Finally the optimal parameters ($\sigma=0.43\times10^{-3}$, $C=1.14\times10^{5}$) were obtained by GA and *K*-CV (K=4).

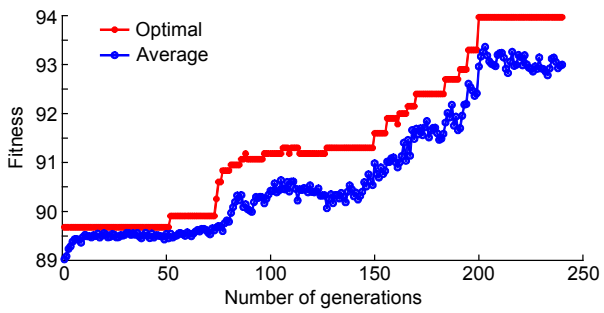

Fig. 5 The curve of fitness vs. different numbers of generations using the GA method (*K*=4, terminal generation=240, population size=30)

As a comparison, the optimization parameters using the GS method were also obtained. Fig. 6 shows the 3D view of the GS optimization parameters. The value ranges of σ and C are both between 2^{-20} and 2^{20}, and the search step is 0.8. Fig. 6 also shows the change trend, relationship between σ and C, and the corresponding K-CV classification accuracy. Satisfactory results have been achieved as the search step decreases along with the expansion of the parameter range.

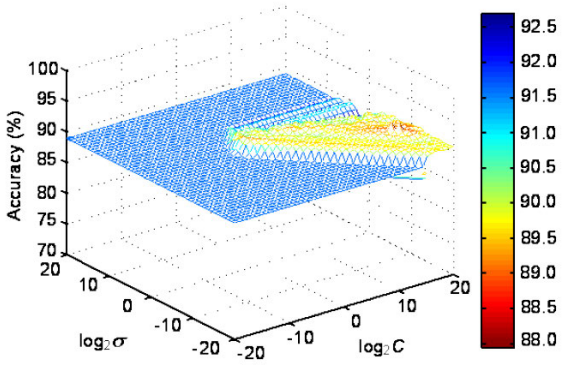

Fig. 6 The 3D view of optimization parameters using the GS method

Red and blue regions show the high and low classification accuracies respectively using K-CV. References to color refer to the online version of this figure

3.3 Classification results using the KSVM classifier

3.3.1 Comparison between GA and GS

The GA and GS methods were used respectively to determine the optimization parameters for GRBF in the KSVM classifier. Tables 2 and 3 show the search parameters, classification accuracy, and time cost for set C using the KSVM classifier based on GS and GA, respectively. In Table 2, 21 pairs of (σ, C) were selected among the range of 2^{-20} to 2^{20} with different search steps. The time cost increased with the decrease of the search step. Comparison of Tables 2 and 3 shows that GA is more effective than GS in obtaining optimal parameters, since it needs less time. The classification results of GA had more fluctuations due to the randomness of the classical GA. A higher optimal classification accuracy was obtained using GA (i.e., 93.97% for GA and 92.69% for GS), while the time cost of GS was about twice that of GA. According to the trend of the classification accuracy and the corresponding parameters, GS obtained better classification results as the search step decreased, but the time cost of GS would be very high.

3.3.2 Comparison between GRBF and MHWF

We also compared the classification performance of SVM between two kernel functions, GRBF and MHWF, using GA with 40 to 240 generations. In each generation, 30 tests were carried out to obtain sensible and reliable data. The Gaussian radial basis SVM was a normal SVM, and the Mexican hat wavelet SVM was a wavelet SVM. The classification performance of the Mexican hat wavelet SVM was slightly inferior to that of the Gaussian radial basis SVM (Fig. 7).

Generalization ability is another important factor for SVM to select the kernel function. The normal SVM has better generalization performance than the Mexican hat wavelet SVM.

3.4 Classification results of the combination of different methods

Table 4 shows the classification results of the combination of different methods for sets A and B. For set A, the best results (TP 92.89%, FP 5.68%, and classification accuracy 94.00%) were obtained from the combination of lead-fall, GRBF, and GA. For set B, the best classification accuracy 91.80% was also obtained from the combination of lead-fall, GRBF, and GA.

Table 2 The searched parameters, classification accuracy, and time cost for set C using the KSVM classifier based on the optimization parameters searching algorithm GS

Search step	C ($\times10^5$)	σ ($\times10^{-4}$)	Classification accuracy (%)	Time (s)
4.0	10.49	2.44	90.26	42.37
3.5	0.33	13.81	91.19	41.63
3.0	0.66	39.06	91.19	40.35
2.5	1.85	1.73	91.53	69.57
2.4	0.86	5.23	91.65	37.85
2.3	2.63	1.14	91.53	54.47
2.2	7.95	4.25	91.42	76.01
2.1	9.78	3.22	91.53	82.27
2.0	2.62	0.61	91.53	99.86
1.9	2.62	1.85	91.53	101.69
1.8	2.57	1.40	91.53	98.43
1.7	0.16	11.22	90.49	86.83
1.6	3.46	7.40	91.65	135.77
1.5	0.66	4.88	91.53	105.66
1.4	2.28	1.22	91.53	152.01
1.3	0.66	4.88	91.53	203.96
1.2	0.81	4.07	92.23	238.26
1.1	0.81	4.25	92.23	334.93
1.0	2.62	1.22	92.23	504.52
0.9	2.28	1.40	92.69	609.97
0.8	0.66	7.40	92.69	728.29

Table 3 The searched parameters, classification accuracy, and time cost for set C using the KSVM classifier based on the optimization parameters searching algorithm GA

Number of generations	C	σ ($\times10^{-3}$)	Classification accuracy (%)	Time (s)
40	6649.97	140500.10	89.68	81.75
50	801.94	11038854.30	88.98	118.92
60	60.61	443.50	90.37	110.31
70	55.08	450.13	91.53	114.59
80	24.68	664.71	91.53	116.04
90	4.44	2164.80	91.18	149.81
100	48.83	140124.00	89.68	218.75
110	1779.00	19906.3	90.02	261.58
120	19.89	679.02	91.65	190.75
130	25.75	630.38	91.65	212.95
140	22.53	680.92	92.23	207.87
150	95.79	362.40	92.23	201.93
160	12.88	803843.00	92.23	344.01
170	10.67	139363.40	91.53	375.35
180	19.00	718.12	92.58	232.95
190	8738.69	750.00	92.58	410.53
200	68732.50	0.86	93.97	379.45
210	32768.31	3.76	93.62	300.35
220	94374.30	0.50	93.97	421.41
230	85389.00	0.74	93.97	323.57
240	114104.80	0.43	93.97	574.72

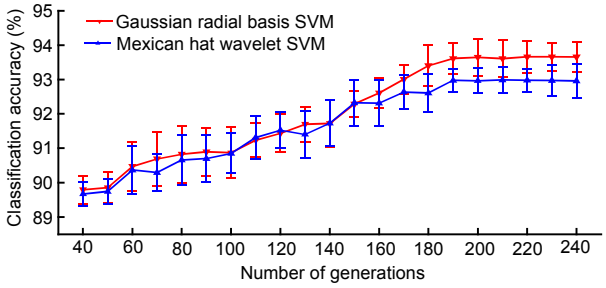

Fig. 7 Comparison of classification accuracy between the Gaussian radial basis SVM and Mexican hat wavelet SVM

Table 4 Classification results of the combination of different methods

Methods	TP* (%)	FP* (%)	Classification accuracy (%)	
			Set A	Set B
Lead-fall+ GRBF+GA	**92.89**	**5.68**	**94.00**	**91.80**
Lead-fall+ GRBF+GS	90.67	6.45	92.90	90.08
Lead-fall+ MHWF+GA	92.00	6.06	93.50	91.40
Lead-fall+ MHWF+GS	90.67	6.45	92.90	90.08

* For set A only. The best results are highlighted in bold

4 Conclusions

We have proposed a method for ECG quality classification using the combination of lead-fall detection and the KSVM classifier. Lead-fall detection used as an initial classification could decrease data volume and computation load for further analysis. The results after lead-fall detection were TP 57.78%, FP 1.03%, and classification accuracy 89.7% for set A and classification accuracy 88.40% for set B, which are acceptable results. The spectral feature, in combination with temporal features, provides comprehensive and useful information for assessing ECG signal quality. GA was used to optimize the parameters σ and C. The optimal results for set A were obtained using the combination of lead-fall, GA, and GRBF methods with TP 92.89%, FP 5.68%, and classification accuracy 94.00%. The optimal classi-

fication accuracy 91.80% for set B was also obtained using the combination of lead-fall, GA, and GRBF methods.

Future work should focus on the methods for expanding the feature space, feature fusion, and further optimization of KSVM parameters.

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