Ya-tao Zhang, Cheng-yu Liu, Shou-shui Wei, Chang-zhi Wei, Fei-fei Liu 2014. ECG quality assessment using a kernel support vector machine and genetic algorithm with a feature matrix. *Journal of Zhejiang University-SCIENCE C (Computers & Electronics),* **15**(7):564-573. [doi:10.1631/jzus.C1300264]

ECG quality assessment using a kernel support vector machine and genetic algorithm with a feature matrix

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

Corresponding author: Shou-shui Wei
E-mail: sswei@sdu.edu.cn

Motivation

- 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. So, there is an essential requirement to assess the quality of ECG before it is used for clinical applications.
- A method for ECG quality classification using the combination of lead-fall detection and the kernel support vector machine (KSVM) classifier has been presented in this paper.

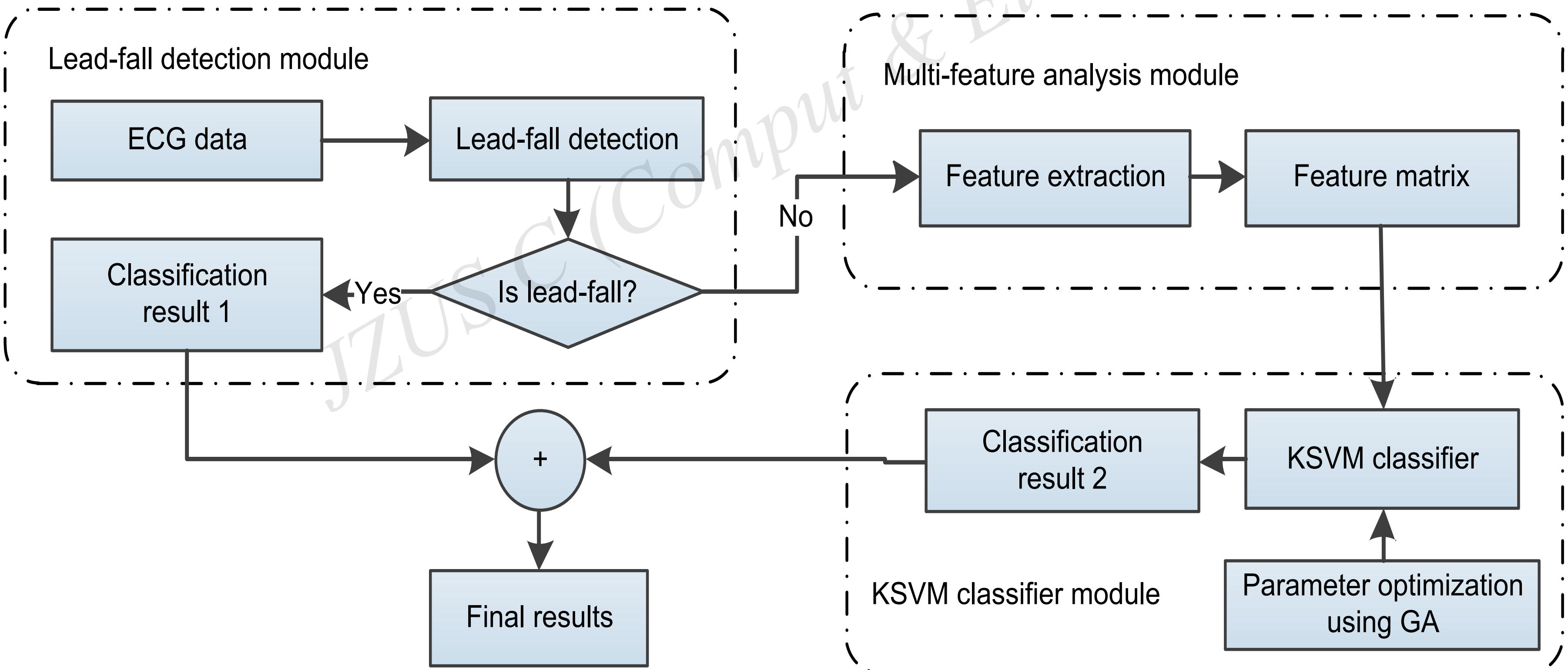
Features of our method

– Lead-fall detection can be used for the initial classification. So, the computation time can be reduced.
– Power spectrum and features of waveforms can comprehensively reflect the information of ECG.
– The KSVM classifier can further improve classification accuracy.
– Parameters are optimized using the genetic algorithm (GA).

Method outline (I)

The proposed method includes three modules:

1. Lead-fall detection module
2. Multi-feature analysis module
3. KSVM classification module



Method outline (II)

1. Lead-fall detection module

Step 1: The difference between the maximum and minimum amplitudes of the signal of each lead is calculated.

Step 2: If the difference between any lead is less than 5, the current recording is classified as ‘unacceptable’.

Method outline (III)

2. Multi-feature analysis module

The power spectrum, baseline drifts, amplitude difference, and other time-domain features for ECGs are analyzed and quantified to form the feature matrix.

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

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

where j (j=1, 2, …, 12) denotes the index of lead, and i (i=1, 2, …, n) the index of ECG.

Method outline (IV)

3. KSVM classification module

- KSVM classifier

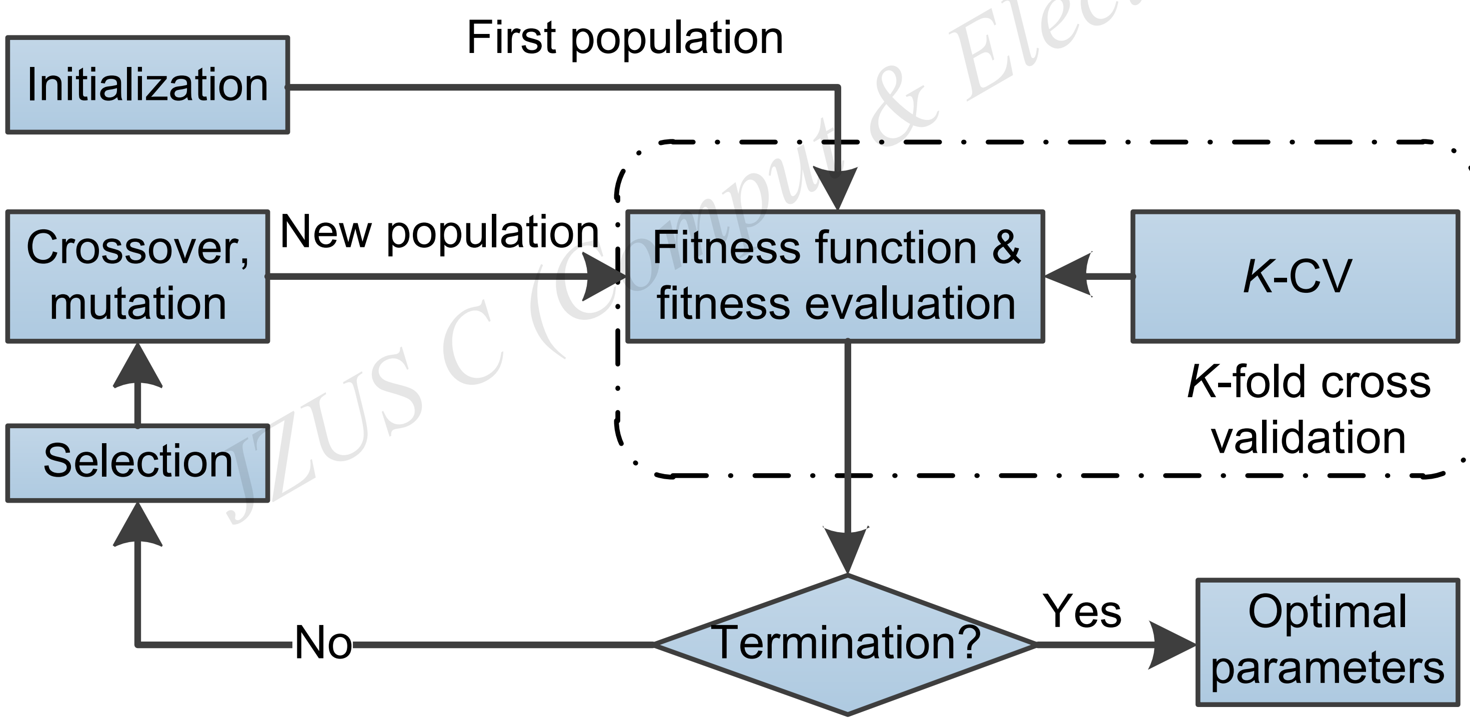
In this study, the KSVM classifier is trained using the feature matrix on training dataset A. After training, the optimal decision function (ODF) is obtained. Finally, classification results for test dataset B can be obtained by inputting their feature matrix to the ODF. The decision function is shown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

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

where sign() is the decision function, $\boldsymbol{x}_i$ 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.

Method outline (V)

➢ Parameter determination by GA



Major results

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