Decision Tree-based Model for Signal Quality Scanning in Wearable ECG

Caiyun Ma[1], Zhongyu Wang[1], Meicheng Yang[1], Jianqing Li[1], Chengyu Liu[1]*

[1]State Key Laboratory of Bioelectronics, School of Instrument Science and Engineering, Southeast University, Nanjing, China

Abstract

With the development of wearable electrocardiogram (ECG) monitoring equipment, the ECG signal quality assessment algorithm is becoming critical. At present, there is no unified classification standard for signal quality assessment. Signal quality can be divided into three categories in this work: Class A, ECG waveform (P wave and T wave, QRS complex wave) is visible. Class B, the signal can only reliably detect QRS. Class C, the signal is not suitable for analysis. Eighteen features were analyzed. Three models based on the decision tree were trained according to diagnostic requirements for wearable ECG. The first model uses twelve practical features to select Class A and B. The single-lead wearable ECG monitoring device is a convenient means of monitoring arrhythmia, which can be used for disease screening only by RR interval analysis. The second model, uses eight practical features to screen out Class A signals. Clean ECG waveforms are essential for the diagnosis of the disease. In the third model, seven practical features are used to classify Class A, B, and Class C. The test results from the first model are as follows: Sp is 97.97%, and Se is 99.80%. The results from the second model are 92.12% and 92.19%. The third model report that the Acc of A, B, and C are:90.74 %, 89.72%, and 97.60%. The results showed that models could evaluate the ECG signal quality to meet the need for disease screening and diagnosis.

1. Introduction

With the development of health medical technology, more and more wearable electrocardiogram (ECG) devices appear in people's lives, which are used to monitor and screen arrhythmia [1]. Middle-aged and older people choose to wear wearable devices to monitor their ECG signals for disease screening. Patients with occult arrhythmia generally need to carry out long-term wearable ECG monitoring to capture abnormal ECG signals [2]. Clean ECG waveforms and important ECG feature points are typically required for diagnostic algorithms of cardiac rhythm diseases [3]. Compared with traditional ECG monitoring devices, the signals collected by wearable devices will have more noise. The ECGs contaminated by noise will bring significant problems to the ECG diagnosis algorithm, such as affecting the recognition of QRS, resulting in the misjudgment of the ECG diagnosis algorithm [4, 5]. Therefore, it is vital to evaluate the quality of wearable ECG signals.

Studies have developed signal quality indicators (SQIs), including time-domain, frequency-domain and nonlinear features. Classical signal quality indicators (SQI) include sSQI, kSQI, pSQI, SDN-SQI, purSQI, LpSQI, HpSQI et al [6-9]. The 2011 PhysioNet Computing in Cardiology Challenge aimed at improving the quality of ECGs collected using mobile phones. It provided a database with assigned ECGs a letter grade (A (0.95): excellent, B (0.85): good, C (0.75): adequate, D (0.60): poor, or F (0): unacceptable) for signal quality [10]. Since then, a lot of SQIs have been developed.

At present, there is no unified classification standard for signal quality assessment. Due to the analysis of different arrhythmia diseases, ECG feature points required are different. The quality of ECG signals is usually classified differently according to the requirement of heart disease analysis. The single-lead wearable ECG monitoring device is a convenient means of monitoring arrhythmia, and it can be used for disease screening only by the RR interval analysis. It is necessary to require the ECG signal to have a clear QRS complex wave. For the screened arrhythmia disease, it is necessary to diagnose the disease according to the critical feature points of the ECG waveform [11]. Signal quality can be divided into three classes in this work, as shown in Table1.

Table 1. The three classes of wearable ECG signal quality

Class	Define
A	ECG waveform (P wave and T wave, QRS complex wave) is visible.
B	ECG signals can only reliably detect QRS complex waves.
C	ECG signal is not suitable for analysis.

This work analyses the effects of different SQIs on wearable signals. The first task is to analyze the indicators used to choose Class A and B, which is vital for screening for arrhythmia. The second analysis is to explore the practical features used to screen out Class A signals,

 ISSN: 2325-887X DOI: 10.22489/CinC.2022.121

which are essential for diagnosing the disease. The third task analyzes the indicators used to distinguish between Class A, B, and C. The quality evaluation model based on the decision tree is built on the basis of practical index analysis.

2. Methods

2.1. Database

The Brno University of Technology ECG Quality Database (BUT QDB) is a database created by the cardiology team at the Department of Biomedical Engineering, Brno University of Technology, to evaluate ECG quality [12]. The data was collected using a mobile ECG with a sampling frequency of 1,000 Hz, including 18 long-term recordings of single-lead ECGs. Three signals were fully annotated in terms of ECG signal quality. The sliding window of 10 s was used to intercept data, and each window overlapped for 5s. The data details are shown in Table 2.

Table 2. The details of the database

Class	Sample size	Percentage
A	33,279	51,6%
B	20,663	32.1%
C	10,510	16.3%
Total	64,452	100%

2.2. Processing

To facilitate the processing of the ECGs, this work used the minimum-maximum normalization measure to regularize the filtered ECG segments to the interval (0, 1). Due to the high computational complexity of nonlinear indicators, the signal was sampled down to 200 Hz.

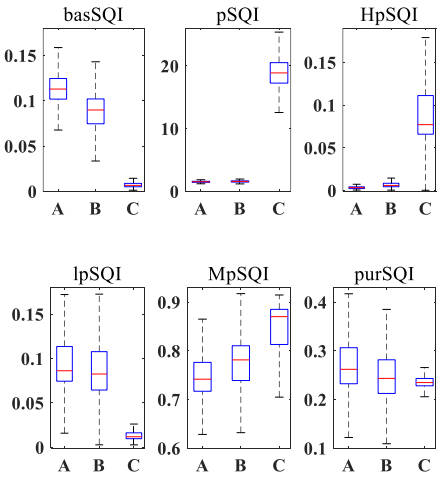

Figure 1 The boxplot of frequency-domain feature.

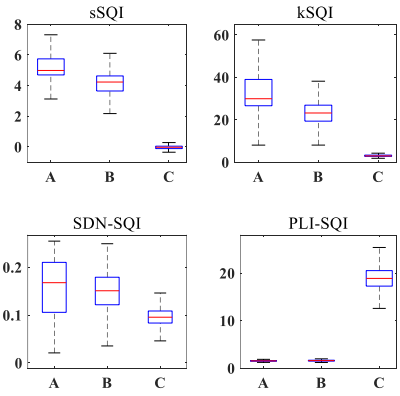

Figure 2 The boxplot of time-domain feature.

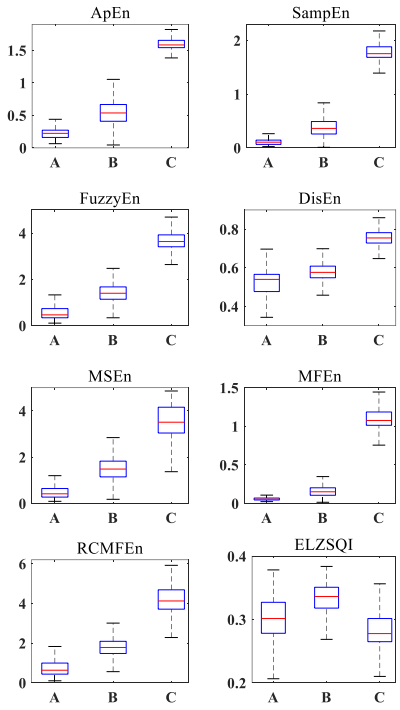

Figure 3 The boxplot of nonlinear feature.

2.3. Signal quality indicators

This work extracted 18 features for signal quality evaluation, including six frequency-domain features [7, 9]: basSQI, pSQI, HpSQI, LpSQI, MpSQI, purSQI, four time-domain features [6-8]: sSQI, kSQI, SDN-SQI, PLI-SQI. And 8 nonlinear features [13-16]: ApEn, SampEn, FuzzyEn, DisEn, MSEn, MFEn, RCMFEn, and ELZSQI. The distribution of each feature is plotted by boxplot, as shown in Figure1, Figure2, and Figure3.

2.4. Model building

After the boxplot analysis, 12 practical features are used to choose Class A and B, including sSQI, kSQI, PLI-SQI, basSQI, pSQI, HpSQI, LpSQI, ApEn, SampEn, FuzzyEn, MSEn, MFEn. 8 practical features are screening Class A, including sSQI, kSQI, ApEn, SampEn, FuzzyEn, MSEn, MFEn, RCMFEn. The seven features are helpful features for the classification of Class A, B and C, including sSQI, kSQI, ApEn, SampEn, FuzzyEn, MSEn, RCMFEn. Due to the imbalanced training samples, we choose the decision tree algorithm to train three models respectively when selecting classifiers.

2.5. Evaluation methods

For classification of two category, there are four evaluation indicators used: Sensitivity (*Se*), Specificity (*Sp*), Accuracy (*Acc*), and Measure of Accuracy (*Macc*). According to the positive or negative of the label, two indexes were used: true positive (*TP*), true negative (*TN*), false positive (*FP*), and false negative (*FN*).

Se is defined as:

$$Se=TP/(TP+FN).$$

Sp is defined as:

$$Sp=TN/(TN+FP).$$

Acc is defined as:

$$Acc=(TP+TN)/(TP+FN+TN+FP).$$

Macc is defined as:

$$Macc=(Se+Sp)/2.$$

For classification of three categories, *Aacc*, *Bacc* and *Cacc* are the proportion of the total number of correct labels predicted for Class A, B and C respectively. Accz is the proportion of the sum of predicted correct labels A, B and C to the total.

Maccz is defined as:

$$Maccz=(Aacc+Bacc+Cacc)/3.$$

3. Results

3.1. Results of the Class A and B

When selecting Calss A and B signals, Class A and B signal are positive and Class C signals are negative. 5-fold cross-validation was perfsormed, and the experimental results are shown in Table 3. The average of the results is to be evaluated, and *Macc*, *Acc*, *Se*, *Sp* are 98.89%, 99.51%, 99.80%, 97.97%.

3.2. Results of the Class A

When chooseing Class A signals, Class A signals are positive, and Class B and C signals are negative. The results from the 5-fold cross-validation are shown in Table 4, reporting *Macc* of 92.16%, *Acc* of 92.14%, *Se* of 92.19%, *Sp* of 92.12%.

Table 3. The result of the screening class A and B

Fold	*Macc* (%)	*Acc* (%)	*Se* (%)	*Sp* (%)
1	98.72	99.43	99.77	97.67
2	98.90	99.57	99.89	97.91
3	98.84	99.53	99.85	97.86
4	99.00	99.48	99.71	98.29
5	98.97	99.53	99.80	98.14
Mean	98.89	99.51	99.80	97.97
SD	0.08	0.05	0.07	0.24

Table 4. The result of the screening class A

Fold	*Macc* (%)	*Acc* (%)	*Se* (%)	*Sp* (%)
1	92.24	92.14	91.77	92.70
2	91.85	91.85	91.84	91.85
3	91.98	91.99	92.46	91.50
4	92.25	92.26	92.47	92.03
5	92.48	92.47	92.41	92.54
Mean	92.16	92.14	92.19	92.12
SD	0.20	0.24	0.35	0.49

3.3. Results of three classification

This work train the model on Class A, Class B, and Class C signals, and the results from 5-fold cross-validation are shown in Table 5, achieving *Maccz* of 92.68%, *Accz* of 91.52%, *Aacc* of 90.74%, *Bacc* of 89.72%, *Cacc* of 97.60%.

Table 5. The result of the three classification

Fold	*Maccz* (%)	*Accz* (%)	*Aacc* (%)	*Bacc* (%)	*Cacc* (%)
1	92.86	91.61	90.43	90.85	97.29
2	92.65	91.45	90.70	89.40	97.86
3	92.62	91.37	90.04	90.44	97.38
4	92.61	91.54	91.26	88.72	97.95
5	92.66	91.63	91.28	89.18	97.53
Mean	92.68	91.52	90.74	89.72	97.60
SD	0.09	0.09	0.54	0.89	0.29

4. Discussion

For the Class A and B signals quality assessment, the accuracy is relatively high. The signal from Class A and B can be ued to screen for arrhythmia by RR interval analysis. For example, the single-lead wearable ECG monitoring devices have been used for long-term monitoring of patients with atrial fibrillation. The

abnormal rhythm can be determined through RR interval. For Class A signals quality assessment, the accuracy is only 90%. Class A signals are the complete signal and used to the diagnosis of diseases directly, which is very valuable. The accuracy rate of Class A, B, and C classification is only 90%, it is not very meaningful to only carry out the three classifications. In practical application, the signal quality can be screened according to the needs of disease diagnosis.

In this work, 18 features were analyzed for ECG signal quality assessment. Based on the needs of clinical diagnosis, feature analysis and model building were made for the signal quality assessment for disease screening and diagnosis, as well as for the three-stage signal quality assessment. Among them, the accuracy of signal quality assessment for disease screening can reach more than 97.5%, and the accuracy of signal quality assessment for disease diagnosis can get more than 90%, which is a guarantee for the analysis of wearable ECG monitoring algorithm.

Acknowledgement

The study was partly supported by the National Key Research and Development Program of China (2019YFE0113800), the National Natural Science Foundation of China (62171123, 62071241 and 81871444), the Natural Science Foundation of Jiangsu Province (BK20190014 and BK20192004) and Postgraduate Research & Practice Innovation Program of Jiangsu Province (KYCX21_0089).

References

[1] U. Satija, B. Ramkumar, and M. S. Manikandan, "A review of signal processing techniques for electrocardiogram signal quality assessment," *IEEE Reviews in Biomedical Engineering*,vol. 11, pp. 36-52, 2018, DOI: 10.1109/RBME.2018.2810957.

[2] C. Ma, S. Wei, T. Chen, J. Zhong, and C. Liu, "Integration of results from convolutional neural network in a support vector machine for the detection of atrial fibrillation," *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1-10, 2021, DOI: 10.1109/TIM.2020.3044718.

[3] F. Liu, C. Liu, L. Zhao, X. Jiang, Z. Zhang, J. Li, *et al.*, "Dynamic ECG signal quality evaluation based on the generalized bSQI index," *IEEE Access*, vol. 6, pp. 41892-41902, 2018, DOI: 10.1109/ACCESS.2018.2860056.

[4] C. Liu, X. Zhang, L. Zhao, F. Liu, X. Chen, Y. Yao, *et al.*, "Signal quality assessment and lightweight QRS detection for wearable ECG smartvest system," *IEEE Internet of Things Journal*, vol. 6, pp. 1363-1374, 2018, DOI: 10.1109/JIOT.2018.2844090.

[5] G. D. Clifford and G. B. Moody, "Signal quality in cardiorespiratory monitoring," *Physiological Measurement*, vol. 33, no. 9, 2012. DOI: 10.1088/0967-3334/33/9/E01.

[6] Q. Li, R. G. Mark, and G. D. Clifford, "Robust heart rate estimation from multiple asynchronous noisy sources using signal quality indices and a kalman filter," *Physiological Measurement*, vol. 29, no.1, pp. 15-32, 2008, DOI: 10.1088/0967-3334/29/1/002.

[7] G. D. Clifford, J. Behar, Q. Li, and I. Rezek, "Signal quality indices and data fusion for determining clinical acceptability of electrocardiograms," *Physiological Measurement*, vol. 33, no. 9, pp. 1419-1433, 2012, DOI: 10.1088/0967-3334/33/9/1419.

[8] E. V. Estrella, M. M. Francisco, B. V. Manuel, G. B. Francisco, S. P. Salvador, R.-á Josę, *et al.*, "Noise maps for quantitative and clinical severity towards long-term ECG monitoring," *Sensors*, vol. 17, no. 11, pp. 2448-, 2017, DOI: 10.3390/s17112448.

[9] S. Nemati, A. Malhotra, and G. Clifford, "Data fusion for improved respiration rate estimation," *Eurasip Journal on Advances in Signal Processing*, vol. 2010, p. 926305, 2010, DOI: 10.1155/2010/926305.

[10] G. D. Clifford, D. Lopez, Q. Li, and I. Rezek, "Signal quality indices and data fusion for determining acceptability of electrocardiograms collected in noisy ambulatory environments," in *2011 Computing in Cardiology*, 2012.

[11] C. Ma, C. Liu, X. Wang, Y. Li, S. Wei, B. S. Lin, *et al.*, "A multi-step paroxysmal atrial fibrillation scanning strategy in long-term ECGs," *IEEE Transactions on Instrumentation and Measurement*, pp. 1-9, 2022, DOI: 10.1109/TIM.2022.3164138.

[12] A. Nemcova, Smisek, R., Opravilová, K., Vitek, M., Smital, L., & Maršánová, L., "Brno university of technology ECG quality database (BUT QDB) (version 1.0.0)." *PhysioNet*, 2020.

[13] W. Chen, J. Zhuang, W. Yu, and Z. Wang, "Measuring complexity using FuzzyEn, ApEn, and SampEn," *Medical Engineering & Physics*, vol. 31, no.1, pp. 61-68, 2009, DOI: 10.1016/j.medengphy.2008.04.005.

[14] P. Li, C. Liu, K. Li, D. Zheng, C. Liu, and Y. Hou, "Assessing the complexity of short-term heartbeat interval series by distribution entropy," *Medical & Biological Engineering & Computing*, vol. 53, no. 1, pp. 77-87, 2015, DOI: 10.1007/s11517-014-1216-0.

[15] Hamed, Azami, Alberto, Fernández, Javier, and Escudero, "Refined multiscale fuzzy entropy based on standard deviation for biomedical signal analysis," *Medical & Biological Engineering & Computing*, vol. 55, no. 11, pp. 2037-2052, 2017, DOI: 10.1007/s11517-017-1647-5.

[16] Y. Zhang, S. Wei, H. Liu, L. Zhao, and C. Liu, "A novel encoding Lempel–Ziv complexity algorithm for quantifying the irregularity of physiological time series," *Computer Methods & Programs in Biomedicine*, vol. 133, pp. 7-15, 2016, DOI: 10.1016/j.cmpb.2016.05.010.

Address for correspondence:

Chengyu Liu
Sipailou 2, Nanjing, 210096, Jiangsu Province, P.R.China
Southeast University
E-mail: chengyu@seu.edu.cn