A Multi-classifier Fusion Approach for Capacitive ECG Signal Quality Assessment

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Abstract. Capacitive ECG (cECG), as a contactless solution for measuring ECG, has been extensively explored in existing works. However, the signal quality obtained by cECG can abruptly degrade due to body movement. Hence, it substantially increases the challenge in signal quality assessment of cECG. In this paper, a novel multi-classifier fusion approach is proposed to assess the cECG signal quality. It combines three commonly used classifiers namely, support vector machine (SVM), K-nearest neighbor (KNN) model, and decision tree (DT) and fuse these classifiers with a voting mechanism to provide a robust decision. With the proposed approach, the overall accuracy of 98.32% can be achieved in distinguishing the cECG signal quality into three categories, namely clear ECG signal, blurry ECG signal with clear R peaks, and noisy ECG signal. Experimental results exhibit that the proposed method outperforms existing works. The classification accuracy and F1-Score of this method are better than traditional methods. Meanwhile, the proposed method is expected to be integrated with cECG device for practical long-term heart monitoring.

Keywords: capacitive ECG · Signal quality assessment · Support vector machine · K-nearest neighbor model · Decision tree model

1 Introduction

Cardiovascular diseases (CVDs), as one of the main threat to human health, constitute the leading cause of morbidity and mortality. In China, the average number of sudden deaths caused by heart attacks exceeds 540,000 each year [1]. Early detection and timely treatment are vitally important to provide an early warning of sudden cardiac events or avoid the progressive deterioration of the CVDs [2]. ECG, as a significant tool to monitor cardiac rhythm for diagnosing CVDs, has been extensively used in the hospital and remote healthcare [3]. Figure 1 shows the waveform of the ECG signal in one cycle. A whole cycle includes P wave, QRS complex, T wave, U wave, P-R interval, Q-T interval, and other wavebands. The morphology of ECG contains detailed information about the condition of the heart. So accurately recording details of ECG weighs a lot in clinical settings.

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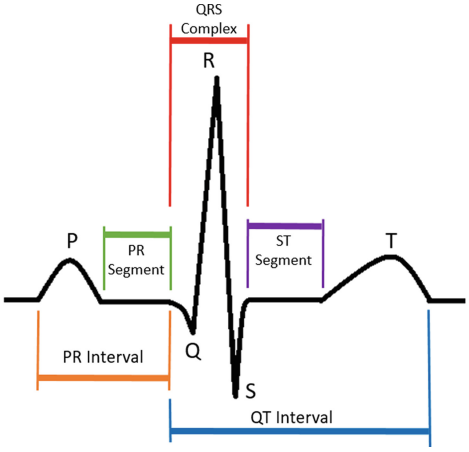

Fig. 1. ECG waveform in one cycle

Nowadays, the traditional method of measuring ECG uses the surface electrodes, such as Ag/AgCl electrodes, to acquire high-quality ECG signals. However, there are several limitations, mainly reflected as follows. Firstly, skin preparation such as removing hair and cuticle from the skin is necessary. Secondly, we need to use alcohol to clean the skin and apply gel to improve the conductibility of the skin. Then stick the electrodes on the patient's skin [4]. Obviously, the traditional measurement method is inconvenient, especially for people whose skin is fragile and sensitive, such as infants and elderly people [5]. Moreover, this method may arouse panic and anxiety of the patient, and then disturb the patient's heart rhythm, thereby raising questions about the authenticity of measurements. Thus, a contactless approach based on capacitively coupled electrodes for ECG monitoring has been proposed. According to Peng's article, it uses a non-contact ECG measurement device based on capacitively coupled electrodes and this device allows patients to take measurements with clothes in a comfortable way. The device uses a real-time denoising algorithm and stores the ECG signal automatically. This measurement method overcomes the limitations of traditional methods and provides possibilities for telemedicine and home health care. However, both contact measurement and non-contact measurement have noise and interference [6], which makes partial signals useless for clinical purposes. Especially for non-contact measurement methods, it is more sensitive to noise, such as power line interference, myoelectric signal, body movements, baseline drift, and so on. Therefore, it is necessary for us to assess the quality of the collected ECG signal in an automated way.

Currently, there are many machine learning algorithms for ECG signal quality assessment. For example, train an SVM model for classification by extracting multiple feature values of the ECG signal [7], calculate high-dimensional ECG features and use a KNN model based on Euclidean distance metric for classification [8]. Extract several non-benchmark features from the ECG signal and use the binary DT model to classify the signal [9]. ECG classification based on time and frequency domain features using random

forests [10]. Different classifiers have different classification standards. The classification accuracy is related to many factors such as the statistical distribution characteristics of the data it classifies, the size of the training data sample, and the structure of the classifier. Meanwhile, noncontact ECG signals is a non-stationary millivolt signal with a low signal-to-noise ratio. And it is easy to be interfered by other signals. Therefore, it is difficult for a single classifier to classify the capacitive ECG signals with high accuracy. In this article, based on the designed voting mechanism, we integrate three classifiers (SVM, KNN, and DT) to form an ECG classification system and achieve a high-precision classification of the cECG signals.

The rest of this article is organized as follows: Sect. 2 introduces the methodology and performance measurement. Section 3 introduces the experimental setup, results and comparison with the existing techniques. Conclusions are drawn in Sect. 4.

2 Methodology

2.1 Algorithm Framework

The whole system consists of the following three parts: signal acquisition, feature extraction, signal quality classification. Through the voting mechanism, the support vector machine (SVM), K-nearest neighbor (KNN) model, and decision tree (DT) model are combined to a fusion classifier and make classification decision together. The fusion model is shown in Fig. 2. It can effectively divide the ECG signal into three categories, namely clear ECG signal (classified as category A), blurry ECG signal with clear R peaks (classified as category B), and noisy ECG signal (classified as category C).

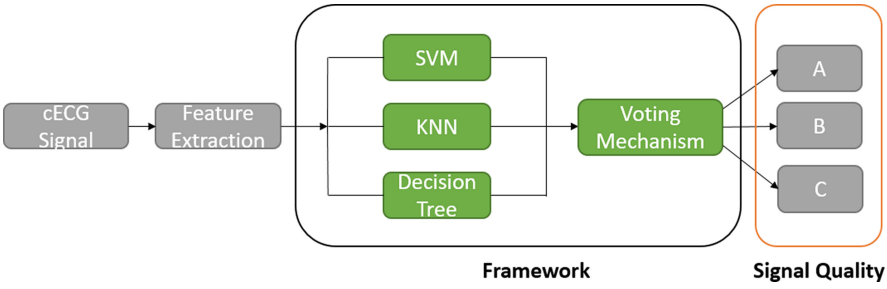

Fig. 2. Fusion classifier model

2.2 Feature Extraction

Six kinds of features of the cECG signal were extracted in total. The details of the features are explained below.

Kurtosis, also known as kurtosis coefficient, is the characteristic number that characterizes the peak height of the probability density distribution curve at the average

value [11]. Kurtosis is generally used to describe the statistics of the steepness of the distribution of all values in the population, the calculation formula is as follows:

$$K = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^4}{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^2\right)^2} \tag{1}$$

Skewness is a measure of the direction and degree of skewness in the distribution of statistical data. Its calculation formula is as follows:

$$S = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^3}{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^2\right)^{\frac{3}{2}}} \tag{2}$$

Range is used to count the difference between the maximum value and the minimum value in the data, which is represented by F_1.

The standard deviation can reflect the degree of dispersion of a data set. Standard deviation is a measure of the degree of data dispersion and is represented as F_2. The calculation formula is as follows:

$$F_2 = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \overline{x})^2}{n}} \tag{3}$$

The average RR interval refers to the average value of the time interval between the R waves in the sampled signal, and it is represented by F_3.

The number of R waves refers to the total number of R waves in the 5-s segment signal. And it is calculated based on QRS waveform detection algorithm (Pan and Tompkins (P&T) [12] and 'wqrs' algorithm [13]), represented by F_4.

2.3 Multi-classifier Fusion

Our fusion classifier model is based on three classifiers, support vector machine (SVM), K-nearest neighbor (KNN), and decision tree (DT). Next, we explain the basic principles of the three classifiers respectively, and then explain the principles and composition of our fusion classifier, as well as the voting mechanism.

The basic model of SVM is to find the linear classifier of separation hyperplane with maximum interval in feature space. We use different kernel functions to improve the performance of the SVM classifier, such as linear, polynomial, and radial basis function (RBF) [14]. The KNN algorithm finds the k records closest to the new data from the training set, and then determines the category of the new data according to their features, and infers its category from the target's neighbors [8]. Decision tree model is a simple and easy-to-use nonparametric classifier and it does not require any prior assumptions about the data. The generation of the decision tree is a recursive process. The calculation

speed of the decision tree model is fast, the results are easy to explain, and its robustness is strong [7].

We use 1465 cECG data as the training set and 535 data as the test set. Taking 5 s as a cycle, we calculate six statistical characteristics of each sample signal. Through the voting mechanism, the three classifiers of support vector machine, KNN nearest-neighbor model, and decision tree model are combined to be an overall classification system. After many times of training and 13-fold cross-validation, the signal is divided into three levels: A, B, and C in a high-precision way finally. The voting mechanism is: if two or more classifiers regard signal as a certain level, we are confident to rate this segment of signal as that level. If the classification results of the three classifiers are inconsistent, we randomly select the classification result of one of the classifiers. Three classifier models are integrated through the voting mechanism. When the accuracy of the validation set is 99.1%, we use the 13-fold cross-validation method to determine the hyper-parameters of each classifier. The average classification accuracy obtained by the fusion classifier on the test set data is 98.3%.

2.4 Performance Measurement

Performance evaluation is done using Confusion Matrix. It is a performance measure for Machine Learning classification. To evaluate the trained model, we applied the confusion matrix and calculate the recall (Re), precision (P+), accuracy (Acc), and F1-Score of the fusion classifier model. The confusion matrix is a table that includes three indices represented by true-positive (TP), false-negative (FN), and false-positive (FP). The calculation formula of each index is as follows:

Accuracy (Acc): The fraction of correct predictions to the total predictions.

$$Acc = \frac{2 \times TP}{2 \times TP + FN + FP} \tag{4}$$

Precision (P+): It is the fraction of correct predicted positives to the total predicted positives.

$$P_+ = \frac{TP}{TP + FP} \tag{5}$$

Recall (Re): It measures the proportion of positives that are correctly identified.

$$\mathrm{Re} = \frac{TP}{TP + FN} \tag{6}$$

F1-Score: It gives a way to merge the Recall and Precision into a single quantity that captures both the properties [15].

$$F_1 - Score = \frac{2 \times Re \times P_+}{Re + P_+} \tag{7}$$

3 Experimental Setup and Results

This section firstly introduces the experimental process and data acquisition method. And then we explain the classification performance of the fusion classifier model through a confusion matrix, and measure the performance of the model through the method proposed in Sect. 2.4. Finally, we compare with the existing common methods such as SVM, KNN, DT, Random Forest.

3.1 Experimental Setup

The data of this article is collected by a non-contact cECG measurement system published in article [4]. The ECG acquisition device is jointly developed by the author's laboratory team. The cECG measurement system is based on capacitively coupled electrode and it can acquire ECG signal both in contact with skin and through clothes with real-time denoising algorithm and automatically store ECG data for later analysis.

Thirty volunteers (15 men and 15 women, average age 30 ± 10), were enrolled in this study. All subjects have good health and no history of cardiovascular disease. And all of them signed the informed consent. The cECG signals were measured at a sampling frequency of 500 Hz for 2 h. The collected signals were divided into five-second segments. 2000 of sampled signal with obvious statistical characteristics were selected. Each segment was la-belled as A, B, or C type by well-trained researchers according to its quality. We randomly select 1465 cases as the training set and 535 cases as the test set, including 172 cases of class A data, 183 cases of class B data and 180 cases of class C data.

The ECG signals are divided into three categories according to the needs of medical diagnosis. Especially for cECG signals, it is necessary for us to decide whether the piece of signal is useful or not for further data processing [16]. Through manual labeling, the ECG signals can be divided into the following three categories. 1) Type A: clear ECG signal which is clear enough for medical diagnosis, as shown in Fig. 3; 2) Type B: blurry ECG signal with clear R peaks and a little bit of noise, which needs further processing before further medical usage, as shown in Fig. 4; 3) Type C: noisy ECG signal with obvious noise and unobvious ECG waves, which is useless from a medical perspective, as shown in Fig. 5.

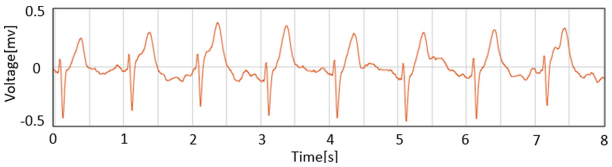

Fig. 3. Type A signal waveform

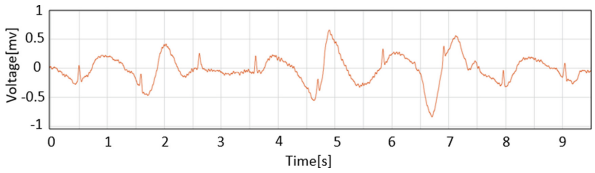

Fig. 4. Type B signal waveform

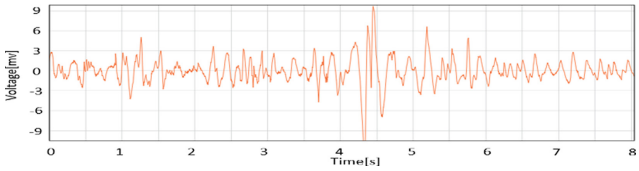

Fig. 5. Type C signal waveform

3.2 Result

Based on the 6 feature values obtained in Sect. 2.2, we establish the feature matrix: $\vec{F} = [K, S, F_1, F_2, F_3, F_4]$ and each set of data has a level label corresponding to it. The range of the six characteristic values of the three types ECG signals are shown in Table 1.

Table 1. A/B/C signal quality characteristics distribution (mean ± standard deviation)

Feature	A	B	C
K	0.36 ± 0.32	0.15 ± 0.28	0.42 ± 1.86
S	0.45 ± 0.98	-0.23 ± 0.82	2.12 ± 1.25
F_1	0.82 ± 0.20	1.40 ± 0.34	8.25 ± 4.35
F_2	0.22 ± 0.20	0.52 ± 0.47	1.59 ± 2.23
F_3	0.60 ± 0.21	0.90 ± 0.45	1.52 ± 2.21
F_4	8.00 ± 2.00	5.00 ± 2.00	3.00 ± 2.00

We use the fusion classifier to classify the cECG signals on the test set and the confusion matrix of the classification results are shown in Fig. 6.

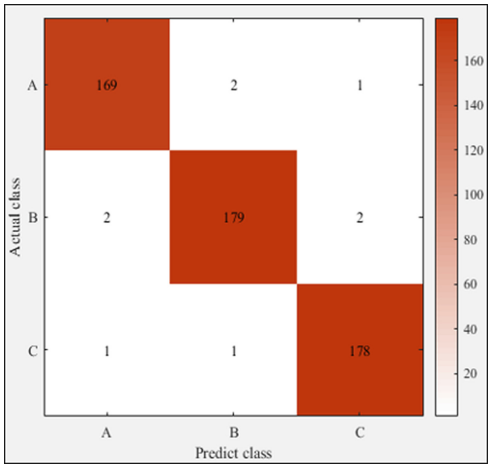

Fig. 6. Confusion matrix of the fusion classifier

It can be known from the confusion matrix that in the 535 test set data, the fusion classifier model can accurately identify 526 sample data, and there are only 9 prediction errors. For our cECG test set data, the fusion classifier model can achieve 98.3% classification accuracy. This method has higher classification accuracy and better performance than the conventional single classifier [9]. Especially for noise-sensitive ECG signal, the fusion model can achieve more stable and reliable results.

According to the statistical analysis of the confusion matrix results, we can calculate the P_+ value of type A is 98.26%, and the value of Re is 98.26%; the P_+ value of type B is 98.35% and the value of Re is 97.81%; the P_+ value of type C is 98.34% and the value of Re 98.89%; The F1-Score of A, B, and C are: 98.26%, 98.08%, 98.61%. The average classification accuracy obtained by the fusion classifier on the test set data is 98.32%. The performance measure is shown in Table 2.

Table 2. Performance measures

Type	Acc	P_+	Re	F1-Score
A	98.26%	98.26%	98.26%	98.26%
B	97.81%	98.35%	97.81%	98.08%
C	98.89%	98.34%	98.89%	98.61%
Average	98.32%	98.32%	98.32%	98.32%

3.3 Comparison with the Single Classifier

Compared to existing classifiers and methodologies, the fusion classifier has given better accuracy, whereas Ö. Özaltın et al., [17] have used SVM to classify ECG signals that were converted into two-dimensional images using continuous wavelet transform and got an accuracy of 95%. In contrast, P.Michael Infant Lincy et al., [18] extracted ECG signal features and used KNN to classify the signal and obtained an accuracy of 93.40%. B. B.U. Demirel et al., [9] used DT algorithm to classify ECG signals on the PhysioNet/Computing in Cardiology Challenge 2011 database and obtained an accuracy of 94.70%, Li Xiaolin et al., [19] used the CNN algorithm on the Physionet MIT-BIH database to classify the arrhythmia of the ECG signal and got an accuracy of 98.12. But the proposed model can achieve the accuracy, Recall, F1-score, and precision of 98.32%, 98.32%, 98.32%, and 98.32% respectively. Because the data sets are different, it is less rigorous to directly compare the results of the method proposed in this article with the results of traditional methods. However, we can still know from Table 3 that the fusion classifier model has higher classification accuracy than traditional methods in classifying the quality of capacitive ECG signals. Meanwhile, we can know from Table 3 that the fusion classifier model has higher classification accuracy than traditional methods in classifying the quality of capacitive ECG signals, and the fusion model has higher stability and stronger robustness.

Table 3. Comparison with existing techniques

Author	Algorithm	Performance metrics			
		Recall (%)	Precision (%)	F1-score (%)	Accuracy (%)
Ö. Özaltın [17]	SVM	95.00	83.33	89.76	89.17
P. M. Infant Lincy [18]	KNN	**99.59**	88.32	93.62	93.40
B. B.U. Demirel [9]	DT	93.30	**99.00**	96.07	94.70
X. L. Li [19]	CNN	98.07	92.33	95.04	98.12
The proposed method	fusion classifier	98.32	98.32	**98.32**	**98.32**

4 Conclusion

Owing to the non-contact measurement, cECG shows great potential in long-term monitoring. However, it also causes critical issues that the signal quality is unstable due to body movement. To promote the use of cECG, an effective and robust multi-classifier fusion model for cECG signal quality classification is proposed in this paper. The model

consists of three commonly used classifiers (SVM, KNN, and DT) and fuse these classifiers with a voting mechanism to achieve the three-classes classification (Type A, Type B, and Type C) of cECG signal quality. Firstly, 6 features of the ECG signal are extracted in the time domain and non-linear domain. Secondly, 1465 ECG signal are randomly selected as the training set and 535 samples as the test set. Finally, a classification accuracy of 98.32% is obtained after many times of training and validation. Comparative results demonstrate the superior performance of this multi-classifier fusion model over traditional methods. As a potential field, the proposed method can be incorporated with cECG device for practical long-term heart monitoring and may help with the noninvasive detection of CVDs.

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