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Automatic Classification of ECG Data Quality for Each Channel

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ABSTRACT In the analysis of ECG data, it is necessary to first automatically classify the quality of ECG data to facilitate the subsequent processing. PhysioNet/Computing in Cardiology Challenge 2011 and existing researches involve the quality of the entire record of ECG, which fails to maximize utilization of ECG data. In fact, single-lead ECG has been widely used in many fields, such as wearable devices, sleep apnea monitoring, and deriving respiratory rate. However, the present methods for evaluating the data quality by each channel only divide them into two categories: acceptable and unacceptable, which is relatively coarse. This paper proposes a new method for the automatic classification of ECG data quality by channel. This method divides them into four categories: (1) electrode shedding, marked as C3; (2) serious noise interference, under which it is difficult to detect R wave, marked as C2; (3) partial noise interference, under which part of R waves may not be detected correctly, marked as C1; (4) high quality signal, marked as C0. The 2011 competition data was re-marked according to the channel with the help of our designed auxiliary program. This paper defined some features and designed a tree classifier using One-Class Support Vector Machine(OCSVM). The test results of our method show that the detection accuracy of electrode shedding is 93.22%, serious noise interference is 90%, partial noise interference is 89.22%, and high quality signal is 97.19%. It shows that the method has a broad prospect in the automatic preprocessing of ECG data.

INDEX TERMS Data annotation, ECG quality assessment, feature extraction, OCSVM.

I. INTRODUCTION

With the increasing use of dynamic electrocardiograms in hospital and home [1], automatic analysis of ECG data plays a vital role. In the automatic analysis of ECG data, it is at least necessary to automatically classify the quality of ECG data into two categories: the available or the unavailable. In the ECG signal acquisition process, there are various interferences [2], which may lead to poor quality of the collected ECG signals [3]. If it can automatically identify and eliminate the bad signal, it can reduce the misdiagnosis of arrhythmia and save medical resources. Therefore, many researchers have developed various quality assessment techniques.

Regarding the automatic classification of ECG data quality, the CinC 2011 competition and many subsequent works mainly gave an acceptable or unacceptable conclusion on the quality of the entire ECG signal [4]–[12]. However, these methods are aimed at the whole ECG signal. Actually, single-lead ECG is widely used in many fields, such as wearable devices, sleep apnea monitoring and respiratory rate determination. Serious noise interference in one channel does not mean that the quality of the remaining channels is poor. Therefore, the quality assessment of the single-lead ECG signal is also very important.

For the single-channel signal quality, Li proposed an evaluation method using quantitative indicators (QI), which analyzed the influence of power line and EMG interference on the analog signal spectrum, only proved its feasibility but did not give a classification result [13]. J Behar added the noise from the Noise Stress Test Database to the clean data to balance the categories. Then the Gaussian kernel function was selected based on the libSVM library to classify the data into acceptable or unacceptable [14]. However, it not only destroys the original data but also divides the ECG data into two categories based on quality, which is relatively rough. According to different requirements, clinical use needs more specific signal quality categories [15].

This paper proposes a new method for the automatic classification of ECG data quality by channel. This method divides the channel quality into four categories: (1) electrode

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shedding, marked as C3; (2) serious noise interference, for which it is difficult to perform correct R wave detection, marked as C2; (3) partial noise interference, for which part of R waves may not be detected correctly, marked as C1; (4) high quality signal, for which R wave detection is unaffected completely, marked as C0. A total of six signal quality metrics are extracted from segments of ECG waveforms and sent to OCSVM for training. The final classification results are obtained through parameter optimization.

II. DATA ANNOTATION

A. DATA SOURCE

The data used in this paper is from the 2011 PhysioNet/Computing in Cardiology Challenge. There are 1500 groups of 12 lead ECG records in the database, which are divided into two data sets: training data Set_a and test data Set_b. The Set_a group consists of 1000 ECG records, of which 773 are recorded as "acceptable" by clinical experts and technicians, 225 as "unacceptable" records, and 2 as "uncertain" records. The Set_b group includes 500 ECG records, but unpublished category labeling results. The data sampling rate is 500Hz and the recording time is 10s. The dataset can be available for free download from http://physionet.org/challenge/2011/. The Set_a mentioned below does not include 2 "uncertain" records, that is, 998 ECG records.

B. LABELING BY CHANNEL

Label the above 1498 groups of 12-lead data (Set_a and Set_b) by channel. With the help of electrophysiologists, each channel of each group of data is labeled as one of four categories: "electrode shedding", "serious noise interference", "partial noise interference" and "high quality signal". Typical data of the four cases are shown in (a), (b), (c), and (d) of Fig. 1. When the ECG waveform of a channel at a full window length is almost constant or the standard deviation is very small, it is annotated as "electrode shedding". When the ECG waveform of a channel is not small within the full window length, and all R peak can not be recognized by naked eyes, it is marked as "serious noise interference". When part of R peaks on the ECG of a channel can not be recognized by the naked eye, it is marked as "partial noise interference". When all R peaks in the channel can be seen clearly with the naked eye, it is marked as "high quality signal".

In the data annotation, to improve efficiency, we design the Matlab GUI program, as shown in Fig. 2. The program selects the corresponding category of each ECG signal. The default option is "high quality signal". In Fig. 2, click the "lead name" button on the left side of each channel to display the corresponding lead enlargement below. Click the "Switch" button to switch the current ECG dataset to the next set of data for annotation. When all the data are marked, click the "Submit" button to store the marked information in the excel file for future use.

According to statistics, a total of 17976 channel data are marked, as shown in Table 1.

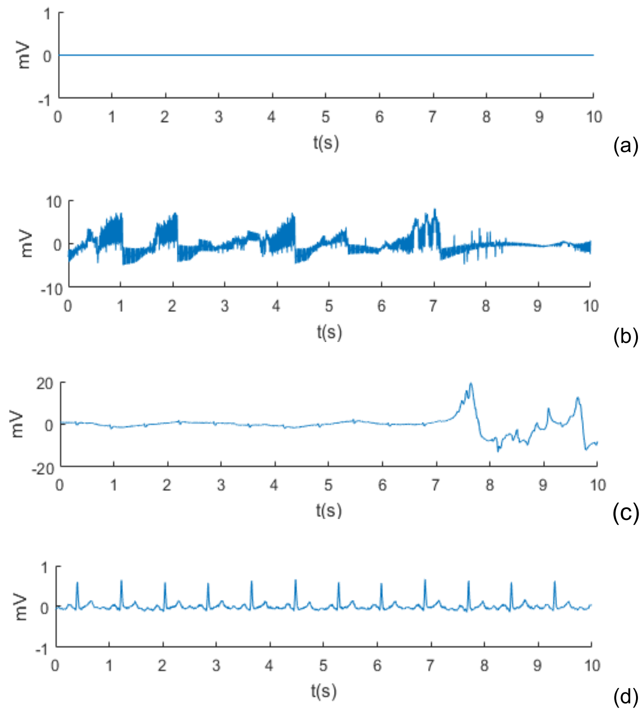

FIGURE 1. Typical signal diagram for the four label categories. (a) "electrode shedding", (b) " serious noise interference ", (c) "partial noise interference", (d) "high quality signal".

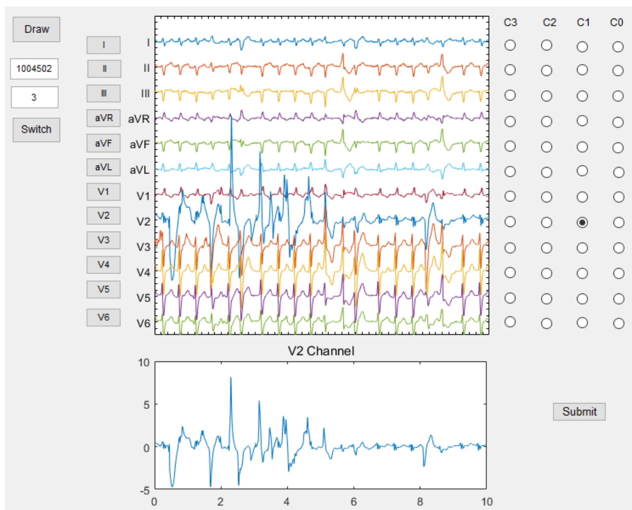

FIGURE 2. Schematic diagram of the GUI program interface for data annotation.

III. CLASSIFIER DESIGN

The overall architecture of the classifier is similar to the decision tree, as shown in Fig. 3. Firstly, The standard deviation characteristic is extracted from ECG data according to the characteristics of electrode shedding. If it is not the case of "electrode shedding ", a total of six linear and non-linear features are extracted and sent to the one-class support vector machine classifier OCSVM1 to determine whether it belongs to "serious noise interference" category. If not, it is sent to the

TABLE 1. Dataset annotation results.

Category	Number of channels for data annotation		
	Entire dataset	Set_a dataset	Set_b dataset
Electrode shedding	1871	1222	649
Serious noise interference	106	76	30
Partial noise interference	551	347	204
Good signal	15448	10331	5117

one-class support vector machine classifier OCSVM2, which is divided into two categories: "partial noise interference" or "high quality signal".

In Fig. 3, the two classifiers OCSVM1 and OCSVM2 are all one-class support vector machines. The reason for selecting the classifier is that the samples for the four categories are unbalanced, and the case of "serious noise interference" and "partial noise interference" is far less than the "high quality signal" category. Take into consideration that the balance using down-sampling [16] or oversampling [17], [18] will affect the originality and authenticity of the data. OCSVM maps the target samples to a high-dimensional space and maximizes the distance between the hyperplane and the origin in space, and the training data has only one type of positive (or negative), but no another [19], [20]. The principle of the OCSVM is shown in Appendix A.

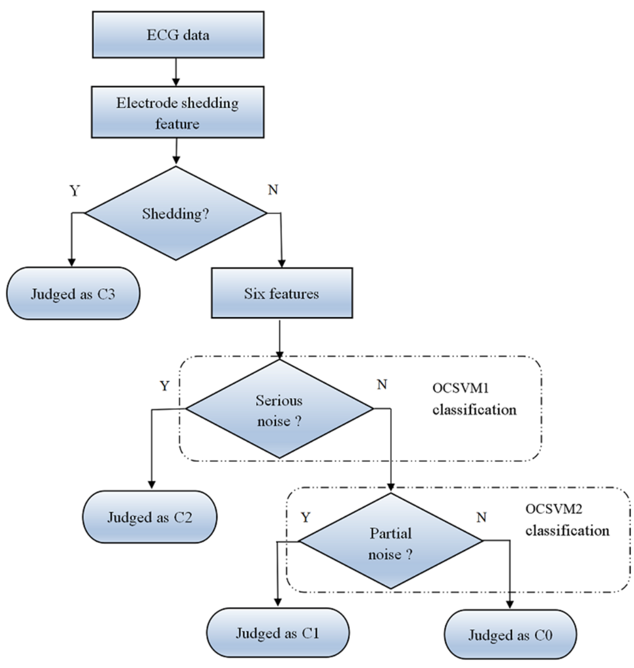

FIGURE 3. Overall flow chart of our classifier. C3: "electrode shedding", C2: "serious noise interference", C1: "partial noise interference", C0: "high quality signal".

A. ELECTRODE SHEDDING JUDGMENT METHOD

Firstly, the standard deviation feature is extracted. Each channel signal is divided into 10 segments, and calculate the standard deviation of each segment. The minimum value of the standard deviations for the 10 segments, denoted SD, is taken as the index for judging the electrode shedding. Fig. 4 shows the distribution of the SD of the electrode shedding channels (orange) and non-electrode shedding channels (blue) in the data Set_a, where Fig. 4(II) is an enlarged view of the junction area of the two kinds of channel data. Through observation and test, when the decision threshold is set to 0.005, the classification accuracy is the highest. Therefore, the channel with SD < 0.005 is considered as electrode shedding, otherwise, it is normal.

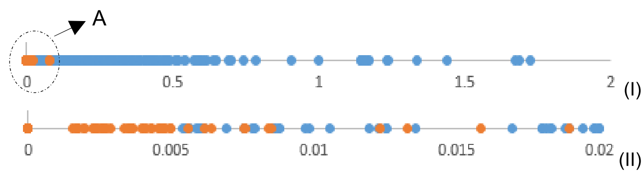

FIGURE 4. Distribution of standard deviation SDs of electrode shedding and non-shedding channel data. (I) Distribution of entire data Set_a, (II) Enlargement of local area A.

B. SIX FEATURES GENERATION

1) PEAK-TO-PEAK CHARACTERISTICS

Generally, the amplitude of an ECG is less than 2.5-3.0mV [21], and the channel with poor signal may have a larger pulse. Firstly, each channel signal is divided into 10 segments, and the quality indicator F1 is defined as the largest peak-to-peak value in all segments.

2) BASELINE DRIFT CHARACTERISTICS

This feature is used to verify that the signal waveform has periodic or non-periodic fluctuations. The median filtering algorithm is used to extract the baseline [22], and the quality index F2 is defined as the maximum value of the baseline.

3) SHORT-TERM ENERGY CHARACTERISTICS

First, each channel signal is divided into 10 segments, and the data volume is N. The average amplitudes of each segment are subtracted before processing. Let the signal of the n^{th} segment be x_n and $\overline{x_n}$ is the average value of the signal amplitude, then its short-time energy E_n is:

$$E_n = \sum\nolimits_{m=1}^{N} \left(x_n\left(m\right) - \overline{x_n}\right)^2 \tag{1}$$

Take the maximum of the short-term energy in the 10 segments as the quality index F3.

4) SIGNAL TO NOISE RATIO CHARACTERISTICS

The QRS complex is the main feature of the ECG signal, and its main spectrum is distributed between 0.5-40 Hz [23]. Let SF denote energy of 0.5-40 Hz and NF denote energy of 40-100 Hz. Divide each channel signal into 10 segments and calculate the signal-to-noise ratio of each segment:

$$\mathrm{SNR} = \mathrm{SF}/\mathrm{NF} \tag{2}$$

Take the minimum of these 10 segments as the quality indicator F4.

5) CHARACTERISTICS RELATED TO R WAVE

According to the different sensitivity of R-wave detection algorithms to signal noise, the quality index can be obtained. The number of R-wave in the jth channel detected by the two algorithms are set to Nj and Mj respectively, and their difference Diff = |Nj - Mj| is calculated as the quality index F5. The noise-sensitive R-wave detection algorithm used in this paper is an adaptive threshold detection algorithm [24], and the insensitive one is a double orthogonal spline-based QRS detection [25].

6) SAMPLE ENTROPY CHARACTERISTICS

The sample entropy indicates the degree of random variation of the data on a single scale [26], and the algorithm is shown in Appendix B. The experiment shows that when the scale τ is 4, the separability is the best, Therefore, the quality index F6 defines the sample entropy with a scale of 4.

Since the above six features may have different dimensions, each feature should be normalized first. For feature x, let u be its mean value of the learning samples and σ is the standard deviation, then the normalized feature is as follows:

$$\mathrm{Y} = (x - u)/\sigma \tag{3}$$

Then, to eliminate the correlation between features, the processed feature matrix is subjected to PCA dimension reduction [27]. The number of reserved dimension k can be obtained by:

$$\sum\nolimits_{i=1}^{k} Si/\sum\nolimits_{i=1}^{n} Si \geq 0.99 \tag{4}$$

Si is the eigenvalue of the normalized sample correlation matrix. After the experiment, k was taken 5 in this paper.

C. DESIGN OF OCSVM CLASSIFIER

1) DESIGN METHOD

With training set $\mathrm{D} = \{x_i\}_{i=1}^{n}$, $x_i \epsilon R^N$, the dual optimization problem required by One-Class SVM is as follows:

$$\begin{aligned} &\min \frac{1}{2}\sum\nolimits_{\mathrm{i}=1}^{\mathrm{n}}\sum\nolimits_{\mathrm{j}=1}^{\mathrm{n}} \alpha_{\mathrm{i}}\alpha_{\mathrm{j}}\mathrm{K}\left(\mathrm{x_i},\mathrm{x_j}\right) \\ &\text{s.t.} \sum\nolimits_{i=1}^{n} \alpha_i = 1 \\ &\quad 0 \leq \alpha_i \leq 1/(vn), \quad \mathrm{i} = 1, 2, \ldots, \mathrm{n} \end{aligned} \tag{5}$$

where K is the kernel function and v is the balance parameter. This paper selects the most commonly used Gaussian kernel function, defined as follows:

$$\mathrm{K}(x_i, x_j) = \exp[-\frac{\left\|x_i - x_j\right\|^2}{2\sigma^2}] \tag{6}$$

where σ is the bandwidth of the Gaussian kernel. Through optimization, the final classification decision function is determined as follows:

$$\mathrm{f(x)} = \mathrm{sgn}(\sum\nolimits_{i=1}^{n} \alpha_i K(x_i, x_j) - \rho) \tag{7}$$

In formulas (5) and (6), the selection of hyperparameter σ and equilibrium parameter v determines the classification performance of the classifier to some extent [11]. The discussion in this paper discusses their optimization.

2) OCSVM1 CLASSIFIER

OCSVM1 is used to distinguish "serious noise interference" from "high quality signal" and "partial noise interference". According to the One-Class SVM principle, the "high quality signal " and "partial noise interference" channels with a large number of samples are used as training sets for a single-classification classifier design. The training data comes from the annotated data Set_a, with a total of 10678 samples. The experimental results show that when the hyperparameter v is 0.008 and the g is 0.19, the accuracy is the highest.

3) OCSVM2 CLASSIFIER

Different from OCSVM1, the OCSVM2 classifier is designed to distinguish "high quality signal" from "partial noise interference". Since the number of samples in the former category far more than the latter, the "high quality signal" samples are used to train the OCSVM2 single classifier. The training data comes from the annotated dataset Set_a, with a total of 10331 samples. The experimental results show that when the hyperparameter v is 0.003 and the g is 0.08, the accuracy is the highest.

IV. TEST EXPERIMENT

The test is based on the Set_b dataset. Firstly, the standard deviation threshold determined by Set_a is used to judge whether the Set_b data belongs to "electrode shedding" category. If not, six characteristics are calculated from the dataset that is judged as non-electrode shedding, and then the feature matrix is normalized and dimensionality is reduced. Finally, the processed features are sent to the OCSVM classifier module for testing

A. EVALUATION INDICATORS

TP: positive class is judged as the positive class.

TN: negative class is judged as a negative class.

FP: negative class is judged as the positive class.

FN: positive class is judged as a negative class.

At present, ECG signal quality assessment is mainly expressed by the following three indicators:

$$\mathrm{Se} = \mathrm{sensitivity} = \mathrm{TP}/(\mathrm{TP} + \mathrm{FN}) \tag{8}$$

$$\mathrm{Sp} = \mathrm{specificity} = \mathrm{TN}/(\mathrm{TN} + \mathrm{FP}) \tag{9}$$

$$\mathrm{Acc} = \mathrm{accurancy} = (\mathrm{TP} + \mathrm{TN})/(\mathrm{TP}+\mathrm{TN} + \mathrm{FP} + \mathrm{FN}) \tag{10}$$

B. CLASSIFICATION RESULTS

TABLE 2. Classification result of Set_B.

Category	Number of channels for data marked	Number of channels in each category in the results				Correctly classified percentage(%)
		C3	C2	C1	C0	
C3	649	605	40	4	0	93.22
C2	30	0	27	3	0	90
C1	204	0	14	182	8	89.22
C0	5117	0	98	46	4973	97.19

Note: C3: electrode shedding, C2: serious noise interference, C1: partial noise interference, C0: high quality signal.

C. COMPARISON WITH LITERATURE METHODS

According to the channel quality classification algorithm provided by J Behar *et al.*, data is divided into two categories: acceptable and unacceptable [14]. For the convenience of comparison, this paper takes "electrode shedding" and "serious noise interference" as unacceptable, and "partial noise interference" and "high quality signal" as acceptable, as shown in Table 3:

TABLE 3. Simplify test results.

Category	Number of categories for data marked	Number of categories in the results	
		unacceptable	acceptable
unacceptable	679	672	7
acceptable	5321	112	5209

For the convenience of comparison, Set_b data combine test results into two categories

The comparison between the results of this paper and the literature [14] is shown in Table 4. It can be seen from Table 4 that the classification accuracy of this method is slightly higher.

TABLE 4. Algorithm comparison.

Paper	Se	Sp	Acc
Literature[14]	0.977	0.965	0.971
This paper	0.979	0.989	0.98

V. DISCUSSION

A. ANALYSIS OF EXPERIMENTAL RESULTS

Compared with the literature [14], although the OCSVM classifier has been used for learning twice, but it does not deal with the problem of class imbalance by introducing noise, thereby ensuring the originality of the data to a certain extent.

From the four categories in this paper, the classification accuracy of the "partial noise interference" detection module is slightly lower. The main reason is that these channel signals are in a critical state, that is, there is a large interference, but part of the R-wave is still visible. This situation may be classified as "severe noise interference".

B. SELECTION OF SCALE FACTOR FOR SAMPLE ENTROPY FEATURE

The sample entropy feature mentioned in the third section involves scale parameters. To select the optimal scale, for the Set_a dataset, the sample entropy of "high quality signal" channels and other channels (excluding the channel marked as "electrode shedding") at different scales are calculated, and then their average values are taken. As shown in Fig. 5 and Table 5.

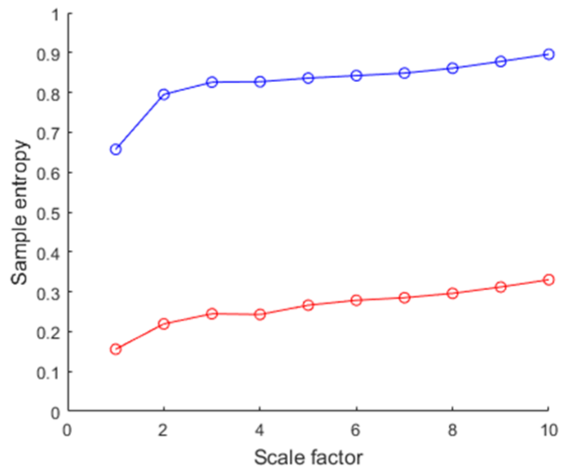

FIGURE 5. Scale factor - sample entropy map. Red is the mean of sample entropy of channels with high quality signal and blue is the sample entropy mean of the remaining channels.

TABLE 5. Sample entropy difference.

Scale	D-value
1	0.5014
2	0.5757
3	0.5811
4	0.5841
5	0.5698
6	0.5637
7	0.5636
8	0.5650

Differences in sample entropy mean of channels with high quality signal and remaining channels at different scales

It can be seen from Table 5 that when τ is taken as 4, the separability is the best. Therefore, the quality index F6 is defined as the sample entropy value with a scale factor of 4.

C. OPTIMIZATION OF OCSVM HYPERPARAMETERS

The above OCSVM classifiers both involve the optimization of the hyperparameter g($g = 1/(2\sigma^2)$) and the penalty parameter v. We use the grid search method to calculate the classification results under the corresponding parameters (g, v) of each grid point [28]. In searching, the value of v ranges from 0.001 to 0.015 in steps of 0.001, the value of g ranges from 0.05 to 0.35 and the step size is taken 0.01.

Table 6 and VII show the optimization results of OCSVM1 and OCSVM2, respectively. Among them, the top

TABLE 6. OCSVM1 parameter optimization results.

V	g	Se(%)	Sp(%)	Acc(%)
0.008	0.19	97.89	90	97.95
0.009	0.19	97.88	90	97.94
0.009	0.18	97.90	86.67	97.94
0.008	0.20	97.86	90	97.92
0.009	0.20	97.82	90	97.88
0.010	0.19	97.80	90	97.87

TABLE 7. OCSVM2 parameter optimization results.

V	g	Se(%)	Sp(%)	Acc(%)
0.003	0.08	99.10	96.08	98.98
0.003	0.09	99.08	96.08	98.97
0.004	0.04	99.04	96.08	98.93
0.005	0.04	98.98	96.57	98.89
0.005	0.03	99.00	96.08	98.89
0.004	0.05	98.98	96.08	98.87

six good combinations are listed according to the accuracy rate from high to low. From the classification results in Table 6 and Table 7, we choose v = 0.008, g = 0.19 as the optimal parameter of OCSVM1 classifier, and v is 0.003 and g is 0.08 as the optimal parameter of OCSVM2 classifier.

VI. CONCLUSION

This paper studies the method of evaluating and classifying ECG signal quality by channel. The ECG data is divided into four categories according to the channel: electrode shedding, serious noise interference, partial noise interference, and high quality signal. The 2011 competition data has been re-annotated by channel. On the whole, an overall tree classification framework is proposed. First of all, according to the characteristic of standard deviation, it is judged whether the electrode shedding. If not, six features are defined and the other three categories are identified by the OCSVM classifier. According to the competition data test, the classification results of the designed classifier are as follows: the classification accuracy of electrode shedding is 93.22%, the classification accuracy of serious noise interference is 90%, the classification accuracy of partial noise interference is 89.22%, and the classification accuracy of high quality signal is 97.19%, which is better than the literature method.

The feature of this paper is to evaluate the quality of a single channel. Firstly, each channel is remarked and divided into four categories according to its characteristics. Besides, when dealing with the problem of category imbalance, the OCSVM classifier is used to ensure the originality of the data. A certain effect was finally achieved.

The disadvantage of this paper is that the " partial noise interference" category may be misjudged as "serious noise interference" category. These signals are critical, that is, there is a large interference in the channel, but part of the R-wave can still be clearly seen. Besides, the number of samples in the "serious noise interference" category is too small, and subtle faults may lead to low classification accuracy. The author thinks that in the future, we can further tap the potential to improve the accuracy of the partial noise interference module.

APPENDIX A
PRINCIPLES OF OCSVM

Bernhard Scholkopf *et al.* proposed a classification problem based on the principle of support vector machine [29], aiming to find a hyperplane to maximize the interval between the sample and the origin. Given a training dataset D $= \{x_i\}_{i=1}^{n}$, $x_i \epsilon R^N$, there is a non-linear mapping ϕ from R^N to a high-dimensional feature space χ, making $\phi(x_i)\epsilon\chi$. A hyperplane w $\cdot\phi(\mathrm{x})-\rho = 0$ is established in the high dimensional space, and the mapping sample is separated from the origin by an interval ρ, where w is the normal vector of the hyperplane and ρ is the intercept of the hyperplane. To increase the robustness and introduce a relaxation factor $\xi_i \geq 0$, the optimization problem of OCSVM is as follows:

$$\begin{aligned} &min\frac{1}{2}||\mathrm{w}||^2 + \frac{1}{vn}\sum\nolimits_{i=1}^{n} \xi_i - \rho \\ &\mathrm{s.t.}(w\cdot \emptyset\,(x_i)) \geq \rho - \xi_i, \quad (\xi_i \geq 0,\ \mathrm{i} = 1, 2, \ldots, \mathrm{n}) \end{aligned} \tag{A1}$$

Among them, v ϵ (0,1) is a balanced parameter, which is similar to the penalty coefficient C in the standard support vector machine. It determines the punishment degree of the misclassified sample. n represents the number of samples.

To solve the quadratic programming problem, Lagrangian function is introduced:

$$\begin{aligned} \mathrm{L}(\omega, \rho, \xi, \alpha, \beta) = \frac{1}{2}\,\|\mathrm{w}\|^2 + \frac{1}{vn}\sum\nolimits_{i=1}^{n} \xi_i - \rho \\ - \sum\nolimits_{i=1}^{n} ((w\cdot\emptyset(x_i)) - \rho + \xi_i)\alpha_\mathrm{i} \\ - \sum\nolimits_{i=1}^{n} \xi_i\beta_i \end{aligned} \tag{A2}$$

where $\alpha_i \geq 0$, $\beta_\mathrm{i} \geq 0$, $\beta_\mathrm{i} \geq 0$ is the Lagrangian multiplier

Let L(ω, ρ, ξ, α, β) have a partial derivative of w, ρ, ξ respectively be zero:

$$\mathrm{w} = \sum\nolimits_{i=1}^{n} \alpha_i\emptyset(x_i) \tag{A3}$$

$$\sum\nolimits_{i=1}^{n} \alpha_i = 1 \tag{A4}$$

$$\alpha_i = 1/(vn) - \beta_i \tag{A5}$$

Substituting the formulas (A3)-(A5) into the formula (A2), the dual problem described in the formula (5) can be obtained, and then the classification decision is obtained.

APPENDIX B
SAMPLE ENTROPY SOLVING STEPS

For the time series X = [x1,x2..., x_N] composed of N data, the sample entropy is calculated as follows:

(1) Form a set of vectors sequence of dimension m by sequence number, $X_m(1)$,..., X_m(N-m+1), where vector $X_m(i) = [x_i, x_{i+1} \ldots, x_{i+m-1}]$, the range of i is [1, N−m+1]. These vectors represent the values of m consecutive x from the ith point.

(2) Define d [X_m(i), X_m(j)] $= max(|x_{i+k} - x_{j+k}|)$, which represents the distance between the vector X_m(i) and X_m(j), the value of k is [0, m-1], and the value of i and j in [0, N-m+1], Where i $\neq$ j.

(3) Given a threshold r, for each value of i, count the number of elements whose d [Xm (i), Xm(j)] is less than r, denoted as Ni, and define:

$$C_i^m(r) = \frac{N_i}{N-m} \tag{A6}$$

(4) Calculate the average value of $C_i^m\,(r)$ as:

$$\emptyset_m(\mathrm{r}) = \frac{1}{N-m+1}\sum\nolimits_{i=1}^{N-m+1} C_i^m(r) \tag{A7}$$

(5) Increase m dimension to m+1 dimension, calculate Ø(m+1)(r), and the sample entropy is defined as:

$$\mathrm{SampEn(m,\,r)} = \lim_{N\to\infty}\left\{-\mathrm{In}\left[\frac{\emptyset_{m+1}(\mathrm{r})}{\emptyset_m(\mathrm{r})}\right]\right\} \tag{A8}$$

When N is a finite value, it can be estimated by:

$$\mathrm{SampEn(m,\,r,\,N)} = -\mathrm{In}\left[\frac{\emptyset_{m+1}\,(\mathrm{r})}{\emptyset_m\,(\mathrm{r})}\right] \tag{A9}$$

When increasing from m dimension to m+1 dimension, the distance d[X_m(i), X_m(j)] between the two vectors is relatively increased, so the more complex the time series, the larger the value of the sample entropy.

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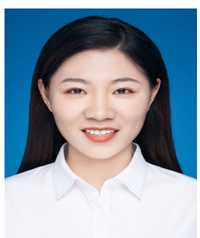

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