Energy Storage State Identification Of Circuit Breaker Based On Fast Extraction Of Interval Feature Of Vibration Signal

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Abstract—Aiming at the problems of slow feature extraction and poor real-time diagnosis of some mainstream state identification methods in actual operation, a fast feature extraction method of vibration signal interval is proposed to identify the energy storage state of circuit breaker. Firstly, according to the kurtosis wavelet modulus maxima, the starting point of the energy storage state of the circuit breaker is detected. Then, the signal envelope sum is extracted as the feature vector by marking the obvious range of envelope amplitude difference through KS test, and the feature is filtered and dimensionally reduced by the reliefF-sfs method to get the optimal feature subset. At last, the fuzzy c-means clustering (KFCM) is used to pre-classify the features to obtain the optimal hyperplane with the least risk, and support vector machine (SVM) is used to establish the training model for state identification. The experimental results show that the energy storage state identification algorithm proposed in this paper only needs 0.2S to extract features on the premise of ensuring the accuracy, which is of great research value for on-line monitoring of circuit breakers.

1. Introduction
The current fault diagnosis methods of circuit breakers are mainly coil current, sound signal and vibration signal [1-3]. Coil current is difficult to fully reflect all kinds of mechanical faults. Although sound signal is easy to collect, it needs complex signal preprocessing, which affects the calculation speed. Some scholars have studied the diagnosis algorithm of acoustic vibration combination [4-6], and adopted the signal decomposition methods such as EEMD, cemmd, LMD, etc. after the signal decomposition, the characteristics such as entropy spectrum coefficient can be obtained, which makes the calculation process complex. Although the accuracy of diagnosis is improved, the cost of feature extraction is huge and the whole identification process takes too long. Vibration signal belongs to in vitro monitoring, with high signal-to-noise ratio and rich state information [7, 8], and the sensor is easy to install, without auxiliary power supply for signal acquisition, which is conducive to real-time monitoring on site.

Therefore, in this paper, the starting point of energy storage state is detected firstly, the vibration signal obtained is not decomposed, KS test method is introduced to search the difference range of envelope distribution of marker signal, relief SFS method is proposed to screen the mean value and characteristics of envelope, kfcm-svm model is used for state identification, and the accuracy and rapidity of the proposed method are verified. The overall diagnosis process is as follows:

![Overall diagnosis flow chart](image)

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2. Fault Diagnosis Method Based On Vibration Signal

2.1. starting point detection

During the energy storage process of the circuit breaker, the mechanical parts start, move and stop in a certain order, resulting in the change of signal impact. Kurtosis, as a dimensionless parameter, is particularly sensitive to signal shock, so it can be used to detect the peak of vibration signal envelope. Firstly, the envelope of vibration signal \( x(t) \) is calculated by the following formula:

\[
y(t) = H[x(t)] = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{x(\tau)}{t-\tau} d\tau
\]  

(1)

Through HT, the analytic signal \( Z(t) \), whose modulus \( m(t) \) is the envelope of the signal, is obtained as follows:

\[
m(t) = |z(t)| = \sqrt{x^2(t) + y^2(t)}
\]  

(2)

The envelope modulus value is divided into \( N \) continuous intervals, the kurtosis of each interval is calculated, and the kurtosis value of each interval signal envelope is compared to find the interval with obvious kurtosis value change difference, so as to determine the rough time of the change. The kurtosis is calculated as follows:

\[
K = \frac{E(x - \mu)^4}{\sigma^4}
\]  

(3)

Where \( E(x) \) corresponds to the expected value of the vibration signal, \( \mu \) is the envelope mean value, \( \sigma \) is the standard deviation.

In order to correct the position deviation of singular points and find the modulus maximum points of the same symbol in the upper and lower adjacent scales, two points are taken at the left and right ends as alternate mutation points, and the specific calculation process is referred to [10]. The selected starting point is determined according to the following formula:

\[
Q_1 \geq (1 + \lambda)Q_2
\]

Where \( Q_1 \) and \( Q_2 \) are the larger and smaller moduli of the difference value before and after the starting point of energy storage, and \( \lambda \) is the adjustment parameter.

2.2. KS inspection to extract vibration characteristics

KS test, as a nonparametric statistical method of goodness of fit test, can describe the similarity between samples. For vibration signal, the literature [9] has demonstrated KS is not sensitive to noise, so complex denoising process can be omitted. Set the empirical distribution functions of samples \( X \) and \( Y \) as \( F(x) \) and \( G(x) \), respectively. The test questions are as follows:

\[
H_0 : F(x) \equiv G(x) \iff H_1 : F(x) \neq G(x)
\]  

(4)

According to Glivenko, Smimov test statistics is used:

\[
D = \max_{i,j} \left| F_m(X_{(i)}) - G_n(Y_{(j)}) \right|
\]  

(5)

Where \( m, n \) represent the number of samples respectively, and \( X \) and \( Y \) represent the order statistics respectively, and the rejection domain of \( H_0 \) takes the maximum value. The significance level corresponding to \( D \) is represented by reliability distribution function:

\[
\alpha_D = R_D(\lambda) = 2 \sum_{j=1}^{\infty} (-1)^{j-1} e^{-j^2 \lambda^2}
\]  

(6)
Where \( \lambda = \left[ \sqrt{N_e} + 0.12 + \frac{0.11}{\sqrt{N_e}} \right] D \), \( N_e = \frac{mn}{m+n} \). If \( D \) is greater than the significance level \( \alpha \), it means that the distribution of the two samples is different.

KS test expects that there are obvious differences in amplitude distribution of vibration signals in different states. Extract signal envelope, and then obtain obvious range of envelope amplitude difference through KS test. Take the mean sum of envelope in each range as feature vector, and the feature extraction process is shown in figure 2:

Divide the signal envelope into \( N \) sections according to 1.1, and calculate the mean value of each section envelope

KS test is used to compare the amplitude envelope distribution of each interval and mark the interval with large difference

The mean sum of the envelope of the marker interval is taken as the feature, and the diagnostic effect is recorded after the feature screening

**Figure 2 KS inspection feature extraction flow chart**

2.3. **ReliefF-SFS feature selection method**

Relieff selects a sample \( R \) from the training set each time, and then finds out the \( k \) nearest neighbors \( R_1 \) and \( R_2 \) of \( R \) from the samples of the same kind and different kind with \( R \), and calculates the weight of each feature \( a \), the formula is as follows:

\[
W(a) = W_m(a) - \sum_{j=1}^{k} \text{diff}(a, R, R_{1j})/(mk) + \sum_{j=1}^{k} \left[ \frac{p(c)}{1-p(c(R_j))} \right] \text{diff}(a, R, R_{2j})]/(mk)
\]

\[
\text{diff}(a, R, R_i) = \frac{|R(a) - R_i(a)|}{\max(a) - \min(a)}
\]

Where \( \text{diff}(a, R, R_i) \) is the distance between \( R \) and \( R_i \) on feature \( a \), \( c \) is the category of \( R \), \( p(c) \) is the prior probability of \( c \), and \( m \) is the number of random sampling.

The characteristic evaluation criteria function is set as follows:

\[
FDR = \frac{1}{M} \sum_{j} \sum_{i} \frac{(\mu_i - \mu_j)^2}{\sigma_i^2 + \sigma_j^2}
\]

Where \( M \) is the number of sample categories, \( \mu_i \) and \( \mu_j \) is the mean value of class \( i \) and class \( j \) eigenvectors, \( \sigma_i^2 \) and \( \sigma_j^2 \) M represents the intra class variance of class \( i \) and class \( j \) samples, respectively.

2.4. **KFCM-SVM diagnostic model**

Kernel based fuzzy c-means clustering algorithm (KFCM) is a kind of unsupervised learning clustering algorithm. By introducing kernel function for spatial mapping, the feature differences of samples can be highlighted [10].

For the data set \( X \) composed of \( n \) vectors, set the number of categories \( c \) to be classified and define the membership matrix. The process is as follows:

(1) Set the fuzzy coefficient \( m \), the number of categories \( c \), the type and parameters of kernel function, and the precision of objective function is \( \epsilon \).

(2) The membership matrix is initialized to conform to normalization.

(3) Calculate cluster center:
\[
\sum_{k=1}^{m} u_{ik} K(X_k, V_i) X_k
\]
\[
c_i = \frac{\sum_{k=1}^{m} u_{ik} K(X_k, V_i) X_k}{\sum_{k=1}^{m} u_{ik} K(X_k, V_i)} \quad (10)
\]

Where \( c_i \) is the fuzzy clustering center of group \( i \), \( u_{ij} \) is the membership value of \( x_j \) in group \( i \), \( 0 \leq u_{ij} \leq 1 \). Gauss kernel function is used,
\[
K(x, y) = \exp(-\|X - Y\|^2 / \sigma^2).
\]

Update membership matrix:
\[
u_{ik} = \frac{[1 - K(X_k, V_i)]^{-1/(m-1)}}{\sum_{j=1}^{c} [1 - K(X_k, V_j)]^{-1/(m-1)}} \quad (11)
\]

(4) Compare the iterative membership matrix according to the matrix norm. If it converges, stop the iteration, otherwise return to the previous step.

In this paper, KFCM is used to pre-classify the feature set and establish the membership mapping between the feature set and the fault category. On this basis, SVM is used for training and comprehensive evaluation to get the final results. Cluster validity index \( \lambda_{\text{KFCM}} \) is used to check,
\[
\lambda_{\text{KFCM}} = 1 - \frac{C}{1 - C} \left( 1 - \frac{1}{N} \sum_{i=1}^{C} \sum_{j=1}^{N} u_{ic} \right),
\]
where \( u_{ic} \) is the membership degree of the c-th sample to the i-th category, \( C \) is the number of clusters, \( N \) is the number of samples.

3. Experimental Verification

3.1. Experimental signal acquisition

In the energy storage experiment of ZN65-12 circuit breaker in the laboratory, AC144 piezoelectric acceleration sensor (0.6-10000HZ) is selected, and the sampling rate is set as 52kHZ. 30 sets of energy storage data are collected respectively under the conditions of high voltage, low voltage, spring falling off and normal state. The training set is set to 20 groups and the test set to 10 groups. Figure 3 shows the time domain and envelope waveform of the collected energy storage process:

![Time domain waveforms of four kinds of energy storage states](image-url)
From figure 3, it can be seen that the amplitude and envelope of energy storage process signal are different, and the difference can be used to quickly distinguish the type of energy storage state.

3.2. signal feature editing
Using the method proposed in 1.2, set the interval width of 5ms and the energy storage time of no more than 5S, so set the interval to 1000 and the significance level $\alpha$ to 0.01, respectively test the distribution of sample envelope amplitude under each state, and mark the intervals with different envelope distribution. The number of marking intervals under the four states is shown in the table below:

| Status type                  | Number of marked intervals / piece |
|------------------------------|-----------------------------------|
| Normal condition             | 78                                |
| High energy storage voltage  | 196                               |
| Low energy storage voltage   | 310                               |
| Energy storage spring shedding| 243                               |

As an example, the probability density of normal state and low energy storage voltage is shown below. The probability density curve of the two is obviously different, so it can be used as the preferred characteristic quantity.

![Figure 4](image-url) Envelope probability density in normal state and low energy storage voltage state

The grid search method is used to select the number of iterations $m$ and the number of nearest neighbors $k$, and the weight of feature table is obtained after $m$ iterations of ReliefF. Among them, $m$ and $k$ are set to 100 and 10, respectively, and the ReliefF threshold $\eta$ is set to 0.1 for the first feature selection. According to SFS, the dimension of the selected feature set is reduced, and the intersection of the marked feature intervals after dimension reduction is taken as the final feature vector. After normalization, some characteristic results are shown in Table 2:

| Fault type                  | Characteristic parameter |
|-----------------------------|--------------------------|
|                             | Second interval | Thirty-eighth interval | 453rd interval | 480th interval | 485th interval | 982nd interval |
| Normal condition            | 0.234          | 0.385                    | 0.723          | 0.816          | 0.689          | 0.416          |
| High voltage                | 0.420          | 0.479                    | 0.856          | 0.923          | 0.711          | 0.535          |
| Low voltage                 | 0.189          | 0.257                    | 0.521          | 0.602          | 0.489          | 0.330          |
| Spring shedding             | 0.012          | 0.125                    | 0.246          | 0.289          | 0.195          | 0.132          |
3.3. diagnosis results
KFCM is used for clustering, the number of clusters C is set to 4, and the three-dimensional spatial clustering results are shown in figure 5.

![KFCM 3D spatial clustering effect](image)

Figure 5 KFCM 3D spatial clustering effect

SVM (C-SVC) uses RBF radial basis function, penalty factor C is set to 3.8, kernel function parameter g is set to 0.15. Set the sample eigenvalue label of normal state as 1 (1-10 groups), 2 (11-20 groups) for high energy storage voltage, 3 (21-30 groups) for low energy storage voltage, and 4 (31-40 groups) for spring falling off. The diagnosis results are shown in figure 6:

![SVM classification results](image)

Figure 6 SVM classification results

It can be seen from the results that a group of test samples under the condition of spring falling off are wrongly divided into low energy storage voltage, all other samples are correctly classified, and the diagnostic accuracy is 97.5%. Therefore, the method proposed in this paper can accurately reflect the energy storage state of the circuit breaker.

3.4. comparative analysis
The decomposition of vibration signals by EEMD, CEEMD and LMD is a research hotspot. In order to highlight the advantages of the algorithm proposed in this paper, the algorithm proposed in this paper is compared with the above several feature extraction methods. The results are shown in Table 3:
Table 3 Comparison of feature extraction methods

| Feature extraction method | Time/s | Accuracy rate/% |
|--------------------------|--------|-----------------|
| EEMD                     | 75     | 95.0            |
| CEEMA                    | 230    | 100             |
| LMD                      | 8.5    | 97.5            |
| Proposed method          | 0.2    | 97.5            |

4. Conclusion
(1) In this paper, a fast feature extraction method of vibration signal based on KS test is proposed, which does not need to decompose the original signal and greatly shortens the time of feature extraction.

(2) In this paper, the ReliefF-SFS method is proposed to effectively edit the feature parameters and classify them by KFCM-SVM model, which greatly improves the accuracy of state identification.

(3) According to the characteristics of on-site operation, a new starting point detection method based on kurtosis and wavelet modulus maxima is proposed, which is helpful for on-line monitoring.

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