Insulation fault identification of vacuum circuit breakers based on improved MFCC and SVM

Linhuan Luo1*, Xiao Liu1, Xiaohui Yan1
1Guangzhou Power Supply Bureau of China Southern Power Grid, Guangzhou, China

*Corresponding author e-mail: 160912453@qq.com

Abstract: Insulation faults in vacuum circuit breakers can produce physical phenomena such as visible sound, ultrasound, and electromagnetic waves. Through the real-time collection and analysis of the discharge sound during the internal insulation failure of the circuit breaker, the insulation state of the circuit breaker can be judged. This article proposes a method. The improved MFCC algorithm is used to extract the characteristic parameters of the discharge signal. The recognition of the flashover discharge sound signal is achieved by one-class SVM. The one-class SVM is constructed, so one-class SVM can be used to identify whether the signal is a surface discharge or not. The characteristic vectors of the audio signal of discharge have intrinsic similarity, and the distribution can be concentrated, which is significantly different from other abnormal sounds. The conclusion is verified by experimental data. The calculation results show that the it can effectively identify the insulation state of vacuum circuit breaker by the method of using of MFCC feature extraction based on Fisher criterion and one-class support vector machine.

1. Introduction

An insulator is used to securely connect electrical conductors of different potentials. Due to aging of materials, uneven distribution of humid air electric field, contamination, etc. The insulation capacity of the insulator is reduced [1-2], resulting in corona discharge and even partial discharge of the circuit breaker, which affects the safe operation of the circuit breaker.

In the aspect of judging the sound fault of electrical equipment, the state diagnosis of transformer is applied more, and the insulation fault and mechanical fault of the transformer are effectively discriminated. A transformer voiceprint based on improved Mel frequency cepstrum coefficient and vector quantization algorithm is proposed. The recognition model [3] uses the MFCC to extract the characteristic vector of the acoustic signal of the electrical equipment for fault diagnosis. Also, the corona discharge and the partial discharge state of the insulator on the high voltage line are detected by detecting the visible sound.

Some scholars [4] proposed Inverse MFCC (IMFCC) for high frequency information, and combined MFCC and IMFCC as new characteristic parameters. Some researchers proposed a filter bank for IF energy, and obtained a new parameter, combined with MFCC and IMFCC to form a mixed parameter for emotion recognition. Some researchers used an improved algorithm combining IMFCC, mid-frequency MFCC (Mid MFCC) and MFCC, and used a hybrid filter bank for speech recognition. There are generally two methods for evaluating the contribution of different components in the characteristic parameters to the recognition.

The Fisher's ratio of each component is used to obtain the distinguishing energy of each component, or the contribution of each component is judged by increasing or decreasing the component [5]. Using
Fisher’s criterion to analyze feature vectors and determine the reparability of feature components is a common feature selection method. This paper proposes a method to monitor the insulation state through the pickup built in the circuit breaker. When the insulator has serious problems, the surface will appear corona discharge or partial discharge, and the sound generated by the discharge will be collected by the recording device. By extracting the energy feature vector based on the improved Mel cepstrum algorithm, the MFCC parameters and IMFCC parameters are first calculated, and then the Fisher component is used to select the feature components with large degree of separation to form a new feature parameter. The signal is a discharge or an unrelated knocking sound or natural noise can be recognized, so, the feature vector is normalized, and the feature vector is input to the one-class SVM. The method can effectively judge whether corona discharge and partial discharge occur.

2. Signal feature extraction

2.1. Signal filtering

Because during the experiment, there is a large amount of unrelated noise that will interfere with the test results to some extent. The noise of people’s speech is about 4 kHz, and there is white noise distribution on the spectrum of the discharge signal. The high voltage equipment of the transformer also produces the sound signal of the power frequency and its harmonics.

![Figure 1. Original signal and LMS filtered signal](image)

Signals below 4 kHz and above 20 kHz are filtered out by setting a bandpass filter, and white noise is filtered using a minimum mean square filter. The minimum mean square filter is an adaptive filtering method. The key to adaptive noise filtering is to obtain the best estimate of noise. The filter parameters obtained at the previous moment are used to adjust the control parameters at the next moment to obtain the error of the system. Function to improve the signal to noise ratio. As shown, the discharge noise signal is filtered out.

![Figure 2. Short-term energy of the discharge signal](image)
Extracting the feature of the signal in the sound is very necessary and useful. The start point and the end point of the discharge sound signal is extracted by FFT. Performing a signal of discharge to judge whether it is a discharge. The energy in the signal segment and the energy in the noise signal is little. The sound signal is used by the short-term energy, first divide the frame of the collected signal, set each frame to 960 points, shift 480 points each time, and obtain the short-time energy of each frame. Hanning window is used to be window functions.

2.2. Feature extraction by MFCC and IMFCC

The Mel Cepstral Coefficient (MFCC) simulates the auditory characteristics of the human ear, because the perceptual resolving power of low-frequency speech signals is stronger than that of high-frequency signals, converting the linear spectrum of speech into a nonlinear spectrum based on the Mel frequency, and then converting to the inverted Spectral domain [6]. The Mel scale and the Hz frequency scale approximately follow a linear relationship below 1000 Hz, while the Mel scale and the Hz frequency coordinate follow an approximate logarithmic relationship in the sound frequency range above 1000 Hz, and the transformation relationship between the two coordinates is as shown in Equation 1.

The MFCC is calculated by the filter bank method in Fig.3. A set of triangular bandpass filters are evenly distributed in the Mel domain, called the Mel filter bank, which is transformed into the Hz frequency domain. The center frequency and bandwidth of the filter vary with frequency. However, the filter distribution is dense below 1000 Hz, and the filter distribution is sparse above 1000 Hz.

The frequency domain filter distribution shows the MFCC mesoscale transformation relationship as shown in the figure, the human ear for different frequency sounds, The perceptual ability is different: the sound with a frequency below 1000 Hz basically satisfies the linear relationship of the human ear; when the frequency is higher than 1000 Hz, the human ear's perception of the sound and the frequency of the sound approximately satisfy the logarithm relationship. In the Mel frequency domain, the human ear approximately satisfies the linear relationship for sounds of different Mel frequencies. It is necessary to divide the frequency interval below 20 kHz, and the sampling frequency is 96 kHz, so it is necessary to divide the first quarter interval of the entire sampling frequency.

\[ F_{mc} = 1127 \times \ln(1 + f_{Hz}/700) \]  

(1)

Figure 3. Frequency response curve of IMel filter bank

MFCC parameter extraction process: After the speech signal is processed by windowing, it becomes a short-time signal, and these time domain signals are converted into frequency domain signals by using fast Fourier transform, and the short-time energy spectrum is calculated; The triangular filter bank performs filtering to obtain group filter coefficients, wherein the center frequency of each filter is evenly distributed on the Mel scale, and the bandwidth is the difference between adjacent center frequencies; the obtained filter coefficients are cosine transformed and removed by cosine transform The correlation between the various dimensional signals maps the signal to a low dimensional space to obtain the characteristic parameters.
\[ F_{\text{crit}} = 2146.1 - 1127 \times \ln \left( 1 + \frac{4000 - f_0}{700} \right) \]  

(2)

**Figure 4.** Frequency response curve of Mel filter bank

In MFCC, the filter bank is mainly distributed in the low frequency part, focusing on the low frequency spectrum of the sound signal, and the analysis ability of the spectrum information of the middle and high frequency is poor, while the corona discharge and partial discharge are in the intermediate frequency and high frequency range which has a wide distribution. In order to improve the calculation accuracy of the medium and high frequency, the inverse Mel Cepstral Parameter (IMFCC) and MFCC are combined. The IMFCC and the MFCC are each provided with 24 filters. After the MFCC filter bank is obtained, the IMFCC filter bank can be obtained by mirroring in Fig.4 and Equation 2.

### 2.3. Fisher Ratio To Dimensionality Reduction

The above two characteristic parameters respectively characterize the sound signal of surface discharge, and can combine the two characteristics to describe the sound, but directly superimposing them will increase the dimension of the feature parameter and increase the calculation amount. Each dimension feature parameter has different contributions to the recognition. Some parameters may contain less information, and some may contain redundant information. If they are treated equally, the recognition performance will eventually be affected. Therefore, it is necessary to evaluate the degree of influence of each dimension parameter on the recognition result, and obtain the parameters that have the greatest influence on the recognition, and then combine the two sets of features as new feature parameters. The distinguishing ability of each component is obtained by calculating the Fisher ratio of the feature components.

Fisher's criterion is:

\[ r_{\text{Fisher}} = \frac{\sigma_{\text{between}}}{\sigma_{\text{within}}} \]  

(3)

\( r_{\text{Fisher}} \) is the fisher ratio of the feature component, \( \sigma_{\text{between}} \) is indicated the variance between classes of feature components, the variance of the mean of different speech feature components; \( \sigma_{\text{within}} \) represents the intraclass variance of the feature component, \( \omega_i \) also mean of the variance of the same feature component.

The \( k \) represents the dimension of the feature parameter, \( m_k \) represents the mean of the \( k \)th component of the phonetic feature on all classes, \( m'_i \) represents the mean of the \( i \) class of the \( k \)th component of the sound feature, \( \omega_i \) represents the sound feature sequence of the \( i \) class, \( n_i \) indicates the number of categories of feature sequences and the number of samples of each type, \( c'_k \) represents the \( k \)th component of the \( i \) class of sound features.
The inter-class variance of the MFCC parameters of the creeping discharge and the characteristic components of the IMFCC parameters reflect the degree of difference between different types of sounds signal, and the intra-class variance reflects the intensity of the same sound signal of surface discharge. The ratio of the intra-class variance and the inter-class variance of the characteristic parameter components characterizes the degree of differentiation of such characteristic parameter components of different kinds of sounds. This degree gives the relationship between the size and the Fisher ratio of the two characteristic parameters. It can be seen that the contribution of different feature parameter components to the recognition is different.

Fig. 5 and Fig. 6 is the 36-dimensional parameter of MFCC and IMFCC respectively. By performing MFCC and IMFCC on the data discharge along surface, 36-dimensional data is obtained respectively, and the fisher criterion is used to reduce the dimension, the number of characteristic parameters is reduced, and the parameter with larger ratio is used to form the feature vector, and the 7, 8, 15, 28, 33 MFCC parameters is selected, the 4, 10, 20, 26, 32 IMFCC parameters is selected, constitute a new 11-dimensional parameters vector \( T \), characterizing the characteristics of discharge along surface. Tab. 1 is the data of new characteristics vector.

\[
T = [S_1, S_2, S_3 \ldots S_{11}] \tag{4}
\]

3. SVM Identification

SVM is a machine learning algorithm that realizes the principle of structural risk minimization. It can classify sample data. The identification of the discharge signal is identified by one-class SVM. Only the sound of discharge signal and the non-discharge sound can be identification. The audio signal of discharged has statistical characteristics and is identified by the naturally generated sound. Construct one-class SVM. The one-class SVM is used to identify whether the sound is discharged or not, without further classification. The support vector machine maps the discharge feature vector of the insulator fault to the high-dimensional linear separable feature space through the kernel function.

The given training set, that is, the eigenvector calculated by the MFCC and fisher criteria, Nonlinear mapping \( \phi \) is a space from \( \mathbb{R} \) to a high dimensional feature \( \chi \), making \( \phi(X_i) \in \chi \), Search for a
supersphere with radius R and center a to cover $\phi(X_i)$ as much as possible, getting optimization problems:

$$
\min_{R,\xi} \left\{ R^2 + C \sum_{i=1}^{n} \xi_i \right\} 
$$

s.t. $\|\phi(X_i) - a\| \leq R^2 + \xi_i \geq 0 \forall i$

$\xi_i$ represents the slack variable. $C$ is the error penalty coefficient, and used to adjust the balance between target sample classification and algorithm complexity outside the sphere.

Introducing the Lagrangian function:

$$
L_p = R^2 - \sum_{i=1}^{n} \xi_i \beta_i + C \sum_{i=1}^{n} \xi_i - \sum_{i=1}^{n} \left( R^2 - \|\phi(x_i) - a\| \right) \alpha_i
$$

$a_i \geq 0, \beta_i \geq 0$ is a Lagrange multiplier. At the same time, the Mercer kernel function is used instead of the inner product in space.

Replace the spatial inner product with the Mercer kernel function:

$$
\max_{\alpha} L_D = \sum_{i=1}^{n} a_i K(x_i, x_j) - \sum_{i=1}^{n} \sum_{j=1}^{n} a_i a_j y_i y_j K(x_i, x_j)
$$

s.t. $0 \leq a_i \leq C, \sum_{i=1}^{n} a_i = 1$

The trained samples can be divided into three categories: the corresponding sample is in the sphere and becomes the inner point, and the corresponding sample is not inside the sphere, which is called the outer point.

$$
d^2(x) = \|\phi(x) - a\|^2
$$

is the distance function of any eigenvector to the center of the sphere:

$$
f(x) = \text{sgn} \left( R^2 - \|\phi(x) - a\|^2 \right) = \text{sgn} \left( R^2 - d^2(x) \right)
$$

R is the distance from the feature vector to the center of the sphere.

The classifier is trained by the support vector machine, and the newly tested data is input thereto for identification. Has a good recognition effect. It is shown that the discharge signal can be effectively identified by constructing a single classification vector machine. Training results as shown in Tab.2.

| TABLE 1. Surface discharge identification rate |
|---------------------------------------------|
| Identification                               | Recognition rate (%) |
| Sample of surface discharge                  | 92.15                |
| Sample of non-discharge                      | 94.43                |

**4. Conclusion**

Using the basis of the establishing theoretical model, so the conclusions are drawn, and the data is preprocessed by bandpass filtering and adaptive filtering. The MFCC and IMFCC are used to extract low and high frequency information respectively, and the dimension is reduced by the fisher criterion. The 11-dimensional data with higher discrimination is selected to form a new Characteristic vector as the training data of the one-class SVM. A new method for identification of insulation state is established.

**References**

[1] Xin Xiaohu, Luo Yongfen, Du Fei, Tang Xiao, “Li Yanming. Comparisons of Direction of Arrival Algorithms Applied to Ultrasonic Arrays for Partial Discharge Location in Oi,” Proceedings of the CSEE, vol.35, no.20, pp.5351-5359, 2015.
[2] Totzauer P, Hornak J, Trnka P, “Diagnostics of composite insulation materials for simple online diagnostics tools,” IEEE International Conference on High Voltage Engineering and Application, pp.1-4, 2016.

[3] Wang Fenghua, Wang Shaojing, Chen Song, Yuan Guogang, Zhang Jun, “Voiceprint Recognition Model of Power Transformers Based on Improved MFCC and VQ,” Proceedings of the CSEE, vol.37, no.5, pp.1535-1543, 2017.

[4] KE Y, SUKTHANKARR, “PCA-SIFT a more distinctive representation for local image descriptors,” Proceedings of the 2004 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, Washington, DC: IEEE Computer Society, vol.2, pp.506-513, 2004.

[5] LOWE D G, “Object recognition from local scale-invariant features,” Proceedings of the 7th IEEE International Conference on Computer Vision, Piscataway: IEEE, pp.1150-1157, 1999.

[6] LEONARDJJ, DURRANT-WHYTEHF, “Mobile robot localization by tracking geometric beacons,” IEEE Transactions on Robotics and Automation, vol.7, no. 3, pp.376 – 382, 1991.