A Classification System for Insulation Defect Identification of Gas-Insulated Switchgear (GIS), Based on Voiceprint Recognition Technology

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Abstract: Insulation defects that occur in gas-insulated switchgear (GIS), which is one of the most important types of equipment in the power grid, can lead to serious accidents. The ultrasonic detection method is commonly used to detect partial discharge (PD) signals in power equipment to discover defects. However, the traditional method to diagnose defects in GIS with ultrasonic PD signals is still based on the experience of testers. In this study, a classification system was proposed to identify insulation defects of GIS, based on voiceprint recognition technology. Twelve coefficients from mel frequency cepstral coefficient (MFCC) and 24 delta MFCC features were extracted as the acoustic features of the system. A support vector machine (SVM) multi-classifier was constructed to perform the classification and the sequential minimal optimization (SMO) algorithm was used to optimize the computational efficiency of the SVM. The experiments were conducted on a 110 kV GIS with different kinds of insulation defects. The results verified that the classification system with SMO-SVM achieved better identification accuracy and efficiency than the system with SVM. Therefore, it reveals the feasibility of the system to realize identification of insulation defects in GIS automatically and accurately.

Keywords: GIS; ultrasonic detection; partial discharge; MFCC; SVM; SMO

1. Introduction

Gas-insulated switchgear (GIS) is a metal switchgear which encloses circuit breakers, isolating switches, earthing switches, transformers, surge arresters, busbars, and other electrical devices [1,2]. Since it was invented, GIS has been one of the most important and widely used types of power equipment in the power grid [3]. However, the occurrence of insulation defects, which are generated in the process of production, transportation, and maintenance, results in potential risks of serious accidents [4]. Various methods such as measurement and evaluation of return voltage, tanδ, partial discharge (PD), insulation resistance, as well as polarization and depolarization current have been studied and applied to condition monitoring on insulations of high voltage equipment in order to avoid serious accidents [5–8]. As partial discharge is the most prominent indicator of insulation degradation in GIS [9,10], researchers have presented a variety of techniques to detect PD signals in GIS for insulation monitoring, such as UHF (ultra-high frequency) detection, ultrasonic detection, optical detection, and chemical detection [11–14]. As ultrasonic detection is a noninvasive and nondestructive measurement method and it processes high sensitivity, as well as strong resistance to electromagnetic interference, it has been increasingly used for defect diagnosis of GIS in normal operation [11,15]. The traditional diagnostic technique for GIS, based on ultrasonic detection, is to analyze the peak value, RMS, 50 Hz correlation, and 100 Hz correlation of the detected PD signals.
according to the experience of testers, resulting in unstable accuracy [15–17]. Otherwise, the methods based on the analysis of waveform features and wavelet transform are also applied for defect diagnosis of power equipment [18–20]. Wang et al. [18] extracted waveform features (rise time, pulse width, amplitude, energy, and ringing) from the first detected PD pulse and used a probabilistic neural network to diagnose the defects of transformers. Tang et al. [19] used wavelet transform and singular value decomposition to extract features from PD signals and adopted artificial neural network to identify the types of insulation defects in XLPE cable. However, as the waveform features cannot discriminate the defects of floating electrode and creeping discharge precisely [18] and the wavelet transform is unable to conduct analysis on the whole frequency of signals [21], these methods still have limitations to obtain high accuracy in defect identification.

This paper presents a classification system based on the technology of voiceprint recognition to automatically and precisely identify the insulation defects of GIS. Voiceprint recognition was invented and originally applied to speaker identification based on the acoustic features of speech signals [22]. Due to its significant advantages including low cost, less complexity, and high accuracy [23,24], the application of voiceprint recognition technology has been extended to the engineering and medical fields and has achieved positive results. Wang et al. [25] adopted voiceprint recognition technology to investigate the characteristics of the transformer noise. Jiang et al. [26] tried to use the technology to diagnose the faults in axial piston pumps and the effect of this method was verified by experience results [26]. The technology has also been applied to emboli detection based on ultrasonic signals, which has achieved great classification accuracy of 83.04% [27]. Acoustic feature extraction and pattern recognition are the key to voiceprint recognition technology [28–30]. The most common acoustic features include mel frequency cepstrum coefficients (MFCC), linear prediction cepstrum coefficients (LPCC), and perceptual linear prediction [30]. Among these acoustic features, the outstanding advantages of MFCC include simple extraction method, high accuracy, and strong resistance to noise [31]. A support vector machine (SVM) is one of the most used pattern recognition classifiers in voiceprint recognition technology because SVM possesses simple theoretical analysis and excellent generalization performance [32]. Moreover, the central minimization task of SVM, stated as convex quadratic programming, guarantees that the training of SVM converges to a single global optimum [33], whereas the neural network tends to a local optimum [34,35]. However, SVM is computationally expensive especially while dealing with a large quantity of training samples [36]. Sequential minimal optimization (SMO) can solve the problem to increase the efficiency and accuracy of the SVM classifiers [37]. Therefore, the classification system constructed for the insulation defect diagnosis of GIS adopts MFCC feature extraction and SVM classifiers optimized by SMO to realize automatic and accurate identification. Experiments were conducted on a 110 kV GIS with four kinds of defects to test the performance of the system and the results indicated that with the optimization of SMO, the accuracy and efficiency of the system were increased effectively.

2. Algorithms in the Classification System

2.1. Extraction Method of MFCC

The core of MFCC is to simulate the characteristics of human beings’ auditory perception to obtain a set of characteristic parameters of acoustic signals [38]. The sensitivity of the human auditory system is unstable and varies with frequency. MFCC attempts to simulate this kind of nonlinear characteristic of the human ear by converting the actual frequency into the mel frequency domain. The conversion relationship between mel frequency and actual frequency is as follows [39]:

$$f_{mel} = \frac{2952 \times \log \left(1 + \frac{f}{700}\right)}{}$$  \hspace{1cm} (1)

where $f_{mel}$ represents the mel frequency and $f$ is the actual frequency, as shown in Figure 1.
Figure 1. Graph indicating the relationship between mel frequency and actual frequency directly.

MFCC features are extracted through the following steps: FFT transform, mel filtering, logarithmic transform, and discrete cosine transform (DCT) [38]. Mel filtering uses the filter bank composed of several triangle bandpass filters which are distributed evenly on the mel frequency domain to convert the signal to mel frequency and the filter bank [40] is

\[
H_m(k) = \begin{cases} 
0, & f(k) < f(m - 1) \text{ or } f(k) > f(m + 1) \\
\frac{1}{2[k - f(m - 1)]} [f(m + 1) - f(m)], & f(m - 1) \leq f(k) \leq f(m) \\
\frac{1}{2[f(m + 1) - k]} [f(m + 1) - f(m)], & f(m) \leq f(k) \leq f(m + 1) 
\end{cases}
\]

(2)

where \(f(m)\) is the center frequency of the \(m\)-th triangular filter, and \(M\) is the total number of triangular filters, then, calculate as Equation (3) to obtain \(M\) features where \(X(k)\) is the FFT of the signal and \(N\) is the FFT length.

\[
s(m) = \ln \left( \sum_{k=0}^{N-1} |X(k)|^2 H_m(k) \right), \quad 0 < m < M
\]

(3)

Finally, MFCC features are obtained through discrete cosine transform with \(c(i)\) representing the \(i\)-th MFCC feature.

\[
c(i) = \sum_{j=1}^{N^2} m_j \cos \left( j - 0.5 \right) \frac{\pi i}{M}, 1 \leq i, j \leq M
\]

(4)

Since the features extracted above are static MFCC features which cannot reflect the changing trends of the acoustic signal, the delta MFCC features which are composed of the first- and second-order differences of the static MFCC features are proposed to describe dynamic characteristics of the signal. The delta MFCC features are calculated as Equations (5) and (6). In order to obtain the delta MFCC features of the same length as the static MFCC features, the forward difference and the backward difference are used to complement the first frame and the last frame, respectively [40].

\[
\Delta_n = \begin{cases} 
c_n - c_{n+1}, & n \leq K \\
\frac{1}{\sqrt{2 \sum_{k=1}^{N-K} k^2}} \sum_{k=1}^{K} k (c_{n+k} - c_{n-k}), & K + 1 \leq n \leq N - K \\
c_n - c_{n-1}, & n \geq N - K + 1 
\end{cases}
\]

(5)

\[
\Delta\Delta_n = \begin{cases} 
\Delta_n - \Delta_{n+1}, & n \leq K \\
\frac{1}{\sqrt{2 \sum_{k=1}^{N-K} k^2}} \sum_{k=1}^{K} k (\Delta_{n+k} - \Delta_{n-k}), & K + 1 \leq n \leq N - K \\
\Delta_n - \Delta_{n-1}, & n \geq N - K + 1 
\end{cases}
\]

(6)
where, respectively, $\Delta_n, \Delta_n^2$ represent the first- and second-order differences of static MFCC features of the $n$-th frame and $K$ is the difference coefficient, generally $K = 2$.

2.2. Classification Algorithm of SVM

The principle of support vector machine (SVM) to classify samples is to obtain a hyperplane that can separate different kinds of samples in a high-dimensional space where the input space has been mapped [41]. The expression of the hyperplane is

$$ w^T X + b = 0, \quad (7) $$

where $X$ represents the training set including $N$ samples $x_i$ ($i = 1, \ldots, N$) and the corresponding class label $y_i \in \{-1,1\}$ so $X = \{(x_i, y_i) | i = 1, \ldots, N\}$; $b$ is the bias term; and $w$ is a vector of tunable weights.

The closest sample to the hyperplane on each side is called support vector (SV). The sum of the distance between the SVs on both sides and the classification hyperplane is the classification interval. To ensure the best classification performance, the classification interval must be the largest. The one-sided distance is approximately $\frac{1}{||w||}$ then for linear separable samples, the optimization problem in SVM is expressed as follows [41]:

$$ \min_{w,b} \frac{1}{2}||w||^2 $$

$$ \text{s.t.} \ y_i (w^T x_i + b) - 1 \geq 0, i = 1, \ldots, N \quad (8) $$

But for nonlinear separable samples, the above constraints cannot be met, which results in no feasible solution to the optimization problem. Therefore, a nonnegative relaxation variable $\zeta_i$ is introduced, and the corresponding penalty term is added to the original objective function. Then, the optimization problem turns to be [42]

$$ \min_{w,b,\zeta} \frac{1}{2}||w||^2 + C \sum_{i=1}^{N} \zeta_i $$

$$ \text{s.t.} \ y_i (w^T x_i + b) \geq 1 - \zeta_i, i = 1, \ldots, N $$

$$ \zeta_i \geq 0, i = 1, \ldots, N \quad (9) $$

where $C$ represents penalty variable.

By introducing the high-dimensional space mapping kernel function $K(x, y)$ and adopting Lagrange multiplier method, the optimization problem is turned into a convex quadratic programming problem to solve ($\alpha$ is a set of Lagrange multipliers) [42]:

$$ \min_{\alpha_i} \Psi(\alpha_i) = \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} y_i y_j K(x_i, x_j) \alpha_i \alpha_j - \sum_{i=1}^{N} \alpha_i $$

$$ \text{s.t.} \ 0 \leq \alpha_i \leq C, i = 1, \ldots, N $$

$$ \sum_{i=1}^{N} y_i \alpha_i = 0 \quad (10) $$

Solve the problem above to obtain the optimal solution of $w, b$ (shown as $w^*, b^*$) and the optimal classification hyperplane $w^T X + b^* = 0$. Finally, the training of SVM is completed and the samples can be recognized through the model.

2.3. Optimization Algorithm of SMO

Sequential minimal optimization (SMO) is a kind of optimization algorithm to increase the efficiency of solving quadratic programming problems [37,43]. The principle of SMO is to decompose the large-scale quadratic programming problem into a series of subproblems with the smallest possible quadratic programming, and then solve them analytically in inner loops to obtain the solution of the original problem [44]. It can be divided into the following three steps for SMO to solve the quadratic programming problem:
First Initialize variables including Lagrange multiplier $\alpha$ and threshold $b$, and set accuracy parameter $\epsilon$.

Second According to heuristic rules, select a pair of optimization variables $(\alpha_u, \alpha_v)$ and solve the quadratic subproblems of $(\alpha_u, \alpha_v)$ to obtain the optimal solution and update variables. The heuristic rules are as follows:

- The outer loop is the selection of the first optimization variable $\alpha_u$. Search out and optimize all the samples that violate the KKT condition, and then optimize the others. Traverse and optimize all the unbound samples (the samples that meet the condition $0 < \alpha < C$) until they all meet KKT conditions. To be noticed, the samples that violate KKT conditions are prioritized to take optimization. The outer loop does not stop until all the samples satisfy KKT conditions.

- The inner loop is the selection of the second optimization variable $\alpha_v$. After selecting $(x_u, y_u)$ to take optimization, the sample $(x_v, y_v)$ is chosen according to a certain calculation method to ensure the optimized step is maximum, which determines $\alpha_v$.

Third Check whether the stopping condition of SMO is satisfied within the accuracy $\epsilon$. If the condition is met, the solution is completed and the optimal solution of the original quadratic programming problem (shown as $a^*, b^*$) is obtained. Otherwise, return to the second step.

3. Diagnosis System

3.1. Signal Preprocessing

In order to facilitate feature extraction and recognition of ultrasonic signals, preprocessing needs to be performed on ultrasonic signals at first, which includes denoising, frequency shifting, framing, and windowing.

The collected ultrasonic signals should be denoised to eliminate the negative effect of environmental noises on diagnosis. The wavelet denoising method is adopted to denoise the signals with a posterior median threshold rule.

Frequency shifting is essential for the collected ultrasonic PD signals to make their MFCC features more distinguishable. According to the relationship of the actual frequency and mel frequency, the growth rate of the mel frequency gradually slows down with the increase of the actual frequency, as shown in Figure 1. This indicates that the sensitivity of the signal in the high-frequency domain gradually reduces when they are converted into mel frequency, which will vague the differences of MFCC features. The ultrasonic PD signal of GIS ranges from 20 to 80 kHz [45], obviously located in the high-frequency domain. Therefore, the reduced sensitivity has a significant negative impact on the accuracy of insulation defects diagnosis of GIS. Shifting the ultrasonic spectrum to a lower frequency range with higher sensitivity in mel spectral can solve the problem, and therefore the accuracy of the diagnosis can be enhanced. The collected ultrasonic signal is frequency modulated with a 38.4 kHz sinusoid to downshift it to be centered at 1.6 kHz.

Since short signals are more stable than long signals, signal framing is a method to facilitate signal analysis with MFCC. Take the length of one frame of the ultrasonic signal the same as its period, which is 20 ms. In order to avoid excessive changes between two adjacent frames and ensure the continuity of the framed signal, there should be an overlapping area between two adjacent frames. In this paper, the overlap rate is 50%.

The framed signal being windowed is indispensable for improving the continuity of the ends of each frame. Hamming window (11) is chosen because it can help prevent spectral leakage and reduce attenuation at FFT when MFCC features are extracted.

$$W(n, a) = (1 - a) - a \times \cos \left( \frac{2\pi n}{N - 1} \right), \quad 0 \leq n \leq N - 1 \quad (101)$$

where $N$ is the length of the Hamming window, and $a$ is a specific parameter of the Hamming window because the value of $a$ affects the performance of the Hamming window, generally $a = 0.46$. 
3.2. SMO-SVM Multi-Classifier

The system adopts SMO-SVM classifying to improve the computational problem of SVM while dealing with a lot of training samples. By using SMO to optimize SVM, the objective function of SMO-SVM with two variables \( (\alpha_u, \alpha_v) \) in a single cycle can be rewritten as follows [37]:

\[
\begin{align*}
\min_{\alpha_u, \alpha_v} & \Psi(\alpha_u, \alpha_v) = \frac{1}{2} K_{uu} \alpha_u^2 + \frac{1}{2} K_{vv} \alpha_v^2 + y_u y_v K_{uv} \alpha_u \alpha_v + p_u y_u \alpha_u + p_v y_v \alpha_v - \alpha_u - \alpha_v \\
\text{s.t.} & \quad 0 \leq \alpha_1 \leq C \\
& \quad 0 \leq \alpha_2 \leq C \\
& \quad y_u \alpha_u + y_v \alpha_v = -\sum_{i \in u,v} y_i \alpha_i^0 = y_u \alpha_u^0 + y_v \alpha_v^0
\end{align*}
\]

where \( p_u = \sum_{j=1}^N y_j K_{ij} \) and \( p_v = \sum_{j=1}^N y_j K_{ij} \). With the KKT conditions [43] shown as Equation (13), the first variable \( \alpha_u \) can be selected by the method mentioned in Section 2.3.

\[
\begin{align*}
\alpha_i &= 0 \Rightarrow y_i d_i \geq 1 \\
0 < \alpha_i < C &\Rightarrow y_i d_i = 1, \\
\alpha_i &= C \Rightarrow y_i d_i \leq 1 \\
\end{align*}
\]

(13)

The second variable \( \alpha_v \) is selected based on the difference between \( y_i \) and \( d_i \) represented by \( E_i \):

\[
E_i = d_i - y_i
\]

where \( d_i = \sum_{j=1}^N y_j a_{ij} + b \) and \( b \) is the threshold. By setting \( |E_u - E_v| \) to approximate the step size, after the sample \( (x_u, y_u) \) is determined in the outer loop, the sample \( (x_v, y_v) \) which makes \( |E_u - E_v| \) maximum is selected to maximize the step size of optimization.

The solution is

\[
\begin{align*}
\alpha_v' &= \alpha_v^0 + \frac{y_v (E_u - E_v)}{\eta} \\
\alpha_v &= \alpha_v^0 + y_v (\alpha_v^0 - \alpha_v')
\end{align*}
\]

(15)

where \( \alpha_v' \) has a range of value \([\alpha_v_{\text{min}}, \alpha_v_{\text{max}}]\). The value of \( \alpha_v_{\text{max}} \) and \( \alpha_v_{\text{min}} \) is calculated as

\[
\begin{align*}
\alpha_v_{\text{max}} &= \left\{ \begin{array}{ll}
\min(C, \alpha_v^0 + \alpha_u^0), & y_u y_v = 1 \\
\min(C, \alpha_v^0 - \alpha_u^0 + C), & y_u y_v = -1
\end{array} \right. \\
\alpha_v_{\text{min}} &= \left\{ \begin{array}{ll}
\max(0, \alpha_v^0 + \alpha_u^0 - C), & y_u y_v = 1 \\
\max(0, \alpha_v^0 - \alpha_u^0), & y_u y_v = -1
\end{array} \right.
\end{align*}
\]

(17)

(18)

If \( \alpha_v' \) calculated by Equation (15) is above \( \alpha_v_{\text{max}} \), \( \alpha_v' = \alpha_v_{\text{max}} \). If it is below \( \alpha_v_{\text{min}} \), \( \alpha_v = \alpha_v_{\text{min}} \). In addition, \( \alpha_u \) needs to be updated along with the change of \( \alpha_u \) and \( \alpha_v \) as Equation (19) to ensure \((x_u, y_u)\) and \((x_v, y_v)\) satisfy KKT conditions and update \( E_i \) as Equation (20):

\[
\begin{align*}
\{ \begin{array}{l}
(\text{if } 0 < \alpha_u < C, b' = -E_u^0 - y_u K_{uu}(\alpha_u' - \alpha_u^0) - y_v K_{uv}(\alpha_v' - \alpha_v^0) + b^0 \\
(\text{if } 0 < \alpha_v < C, b' = -E_v^0 - y_v K_{uv}(\alpha_u - \alpha_u^0) - y_v K_{uv}(\alpha_v - \alpha_v^0) + b^0
\end{array} \}
\end{align*}
\]

(19)

\[
E_i = E_i^0 + y_u K_{uu}(\alpha_u' - \alpha_u^0) + y_v K_{uv}(\alpha_v' - \alpha_v^0) + (b' - b^0)
\]

(20)

Then, continue the loop with new \( \alpha_u', \alpha_v', b' \), and \( E_i \) until the stopping conditions [43] are satisfied.
Furthermore, since the type of common insulation defects is more than two kinds, the multi-classifier is demanded in the system. However, according to the classification principle of SVM, it is originally designed for binary classification [34], therefore, SVM cannot be used directly to recognize multiple types of insulation defects. In order to implement the requirement of the system, it is indispensable to extend SVM to the multi-class scenario. A multi-class problem can be divided into a series of two-class problems. Construct a binary SVM classifier for any two types of samples, thus, for an N-class problem, the number of binary classifiers is \( k = \frac{N(N-1)}{2} \). A sample is identified by all the binary classifiers in turn and get \( k \) results to vote for a final classification result.

3.3. System Construction

The voiceprint recognition system to diagnose insulation defects of GIS based on ultrasonic PD signals is composed of the following three main parts: signal preprocessing, feature extraction and defect recognition. Four kinds of common defects of GIS are designed in the system, i.e., free metal particles, floating electrode, metal protrusions, and creeping discharge. Therefore, six binary classifiers are demanded to constitute the four-class classifier in the system. The whole flow chart of diagnosis is shown in Figure 2.

![Figure 2](image-url)
The whole process of diagnosing the type of insulation defects of GIS based on the ultrasonic PD signals can be divided into three steps. Firstly, the collected signals go through denoising, frequency shifting, framing, and windowing to make the features extracted from them more distinguishable. Secondly, MFCC feature extraction method is conducted to the preprocessed signals to acquire the static MFCC features and calculate the delta MFCC features. Both constitute the acoustic features of GIS. Finally, the SMO-SVM multi-classifier recognizes the type of the insulation defects according to the acoustic features.

4. Experiments and Result Analysis

4.1. Experimental Setup

The experiment was conducted on a 110 kV GIS (Sieyuan ZF28A-145, rated voltage 145 kV, rated frequency 50 Hz) in the laboratory. Figure 3 shows the detection system of the experiment. The AE sensor used to detect ultrasonic PD signals were mounted on the surface of the GIS with a thin layer of acoustic couplant to assure great sensitivity and fixed by tape. The signals detected by the sensor were amplified by the preamplifier and transmitted to the LeCroy storage oscilloscope. The AC free-halo test transformer (YDTW-25/100) was adopted as a power supply. The average temperature of the test environment was 25 °C. The sampling frequency of the oscilloscope was set to 50 Ms/s.

Figure 3. The detection system of insulation defects of GIS.

Four typical insulation defect models of GIS were designed, as shown in Figure 4.
Figure 4. The designs of four typical kinds of insulation defects. (a) Metal protrusion; (b) Floating electrode; (c) Free metal particles; (d) Creeping discharge.

The steps of the experiment are as follows:

1. Test air tightness for safety. Pump the chamber of the GIS to vacuum, and 24 hours later, measure the pressure in the device. The GIS can be used for experiments only if the air leakage is less than 0.001 MPa/h.
2. Place the defect model into the chamber of the GIS shown as Figure 5.
3. Evacuate the chamber, and then charge with SF6 gas of about 0.5 MPa.
4. Connect the experimental devices according to the wiring in Figure 3.
5. Apply voltage to the device and increase the voltage slowly and observe the screen of partial discharge detector (DDX9101) and the waveform on the oscilloscope.
6. When a partial discharge occurs, stop increasing the voltage and collect several sets of signals with the storage oscilloscope.
7. Before replacing another defect model in the tank of the GIS, slowly decrease the voltage applied to the device to 0, turn off the high-voltage power supply, and remove the wiring.
8. Repeat Steps 2–7 until all the defect models have been tested.

Figure 5. The experimental site. (a) Photo of the GIS; (b) A defect model placed in the GIS.

4.2. Result Analysis

Totally, 160 pieces of signals were collected by sensors, 40 for each kind of defect. To make a comparison with the common method for defect diagnosis of GIS, the peak value, RMS, 50 Hz correlation, and 100 Hz correlation were also extracted for identification. With these features, it was easy to discover the existence of insulation defects, but it was time-consuming and difficult to recognize the type of defects based on the experience of testers, which has verified the inefficiency of the traditional method.

With the classification system, the detected signals were processed according to the steps in Figure 2. The denoised signals of different kinds of insulation defects are shown in Figure 6. The length of the ultrasonic signal was 500 ms. The frame length was 20 ms and the overlap rate was set as 50%. Consequently, one piece of collected signals could be divided into 49 frames. Static MFCC features and delta MFCC features were extracted from signals. The static MFCC features owned 12 dimensions. Because delta MFCC features contained the first- and second-order differences of the static features and each maintained the same dimensions of the static ones, the dimensions of delta features were 24. The static and delta MFCC features of different kinds of insulation defects are presented in Figures 7 and 8, respectively. Since the features under different dimensions have a large gap, normalization was applied to static MFCC features and delta MFCC features separately to reduce the negative effect of the large gap on defect recognition.
Figure 6. Collected and denoised ultrasonic partial discharge (PD) signals of GIS with different defects. (a) Free metal particles; (b) Floating electrode; (c) Creeping discharge; (d) Metal protrusions.

Figure 7. Static mel frequency cepstral coefficient (MFCC) features extracted from ultrasonic PD signals of GIS under different kind of insulation defects. (a) Free metal particles; (b) Floating electrode; (c) Creeping discharge; (d) Metal protrusions.
For each kind of defect, 20 samples were selected randomly into the training set and the rest were the test set. The construction of SMO-SVM and SVM multi-classifiers was realized on MATLAB R2019b and the convex programming solver CVX was used. Both of them were trained by the training set, and then used to recognize the samples in the test set to test the recognition accuracy of the system in order to compare the performance in defect identification. The recognition system was evaluated from two perspectives, i.e., accuracy and sensitivity. Accuracy is the proportion of samples which are correctly classified. Sensitivity is the proportion of samples correctly classified into a certain type of defect. The results of the insulation defects identified by different classifiers are listed in Table 1.

Table 1. The results of insulation defect identification based on ultrasonic signals of GIS.

| Pattern Recognition Model | Defect Type \(^1\) | Classified Numbers | Correctly Classified Numbers | Accuracy | Sensitivity |
|---------------------------|---------------------|--------------------|-------------------------------|----------|-------------|
| SMO-SVM                   | P                   | 20                 | 20                            | 93.75%   | 94.14%      |
|                           | F                   | 22                 | 18                            |          |             |
|                           | C                   | 19                 | 19                            |          |             |
|                           | M                   | 19                 | 18                            |          |             |
| SVM                       | P                   | 18                 | 18                            | 82.50%   | 83.18%      |
|                           | F                   | 20                 | 15                            |          |             |
|                           | C                   | 20                 | 17                            |          |             |
|                           | M                   | 22                 | 16                            |          |             |

\(^1\) Defect types are shortened as P, free metal particles; F, floating electrode; C, creeping discharge; and M, metal protrusions.

It is obvious that SMO-SVM has achieved better performance of defect diagnosis than SVM, with an accuracy value of 93.75% and sensitivity value of 94.14%. To verify the computational improvement, the operation time of classifiers was recorded as follows: the SMO-SVM multi-classifier took 4.65 s to train and test samples, whereas the SVM multi-classifier took 13.78 s. The comparison indicates that the classification system with SMO-SVM is more efficient to diagnose insulation defects.

5. Conclusions

In order to automatically identify the defects of GIS and help avoid serious accidents resulting from insulation defects, the classification system using MFCC features and SMO-SVM multi-classifiers based on ultrasonic PD signals was proposed. The acoustic feature extraction of the system contains 12 static MFCC features and 24 delta MFCC features. The classification of the system is
performed by SMO-SVM. Through the experiments conducted on a 110 kV GIS with four kinds of insulation defects, it is verified that the system has excellent performance in the defect identification of GIS. With the optimization of SMO, the multi-classifier improves the accuracy from 82.5% to 93.75% and sensitivity from 83.18% to 94.14%. Furthermore, SMO-SVM is more efficient in training and testing samples than SVM. It is confirmed that the classification system with MFCC and SMO-SVM can be used to accurately and efficiently identify the defects of GIS.

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