Classification of partial discharge severities of ceramic insulators based on texture analysis of UV pulses

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Abstract
Inspection of partial discharge before contamination flashover is of great importance for preventing exterior insulation accidents. In this study, a new method for identification of discharge severities is proposed. Specifically, a low-cost ultraviolet (UV) sensor detection system was combined with time–frequency method, texture analysis and support vector machine (SVM) classifier to classify partial discharge severities for ceramic insulators. The visible images and the root-mean-square value of leakage currents detected simultaneously are used to classify the UV signals into different discharge faults. The frequency and amplitude integration of UV pulses are minimum in corona discharge and larger in arc discharge. The images of UV signal spectrograms differ significantly at different discharge stages. The density and brightness of image textures are minimal in corona discharge and larger in arc discharge. Valid and reliable features selected by two texture feature extraction methods with SVM classifier have a reliable classification accuracy of 90.6% for ceramic insulators, and outperform a single time feature or other texture features. SVM outperforms k-Nearest Neighbour, Naive Bayes and Decision Tree. Our new method with computational effectiveness and high practicality can solve the problem of high randomness and low accuracy of UV sensor detection. It can be further applied to the deterioration diagnosis of power facilities.

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1 | INTRODUCTION

Outdoor insulators are equipped in overhead lines to offer high-voltage isolation, and are extensively used in transmission and distribution lines under different voltage levels. The micro-void and micro-cracks of solid dielectrics may cause partial discharge (PD) of these insulators due to changes in temperature, acidity and pressure, which produce local erosion and deterioration that lead to a final dielectric breakdown [1,2]. In actual operation, the overvoltage caused by natural factors (e.g. lightning strike) or human factors may initiate PD. As these insulators are installed in the outside environment, they are affected by various environmental factors such as moisture, acidic components in rain, snow, ultraviolet (UV) radiation and pollutants, which will decrease the insulation performance [3,4]. In summary, the PD of insulators results from the combined effects of climate, insulator contamination, and insulator conditions under the applied voltage, and all these factors affect the monitoring results. Hence, it is crucial to use long-term online detection methods to detect and diagnose the PD of insulators.

Porcelain, glass and polymer insulators are the main facilities of outdoor insulation. Although non-ceramic insulators have better anti-ageing properties, ceramic insulators are widely installed in different countries and often used in special environments such as contaminated environments, where the practical insulation conditions should be urgently assessed [5,6].

The discharge severity of contaminated insulators in transmission lines reflects the state of the external insulation. Dry band discharge of insulators is the main cause of insulator deterioration. Hence, research on different discharge severities of the contaminated insulators is essential. In a high-humidity environment, the contamination layer on the insulator surface is wet, and the mixture of the polluted layer and water is dissolved and ionised under the electric field, resulting in the leakage current on the surface of the pollution layer thereby leading to PD. Because of the inhomogeneous leakage current, enough heat evaporates the moisture in some surface areas and creates dry bands. Subsequently, a voltage stress concentration area is formed around the dry bands, which will break down and cause dry band arcing. The
local arcs are further enlarged with the increasing leakage current, which may cause flashover [7,8].

Many scholars focus on the PD monitoring technologies for non-ceramic or ceramic insulators, such as leakage current detection [9,10], ultrahigh frequency (UHF) [11,12] and UV image recognition [13]. Among them, leakage current detection is the most extensively adopted and includes analysis of the root-mean-square (RMS) value, peak value or frequency features of leakage current. However, leakage current measurement and UV image-based technique, which is commonly used for PD monitoring recently, are challenging for the long-term online monitoring of the operating insulation. UV images are easy-to-operate with UV cameras installed on unmanned aerial vehicles for timed automatic inspection, but sometimes may lead to missed detection and will largely raise the equipment costs.

UV sensor detection is a non-contact, anti-interference, low-cost and long-term online detection method, and has been already studied. Some types of UV detection systems, consisting of a UV sensor and optic lens, have been developed to detect discharge [14]. Most studies focus on analysis of a single UV pulse feature related to electrical parameters [15,16]. Study on UV measurement techniques for fault identification of insulators is of great importance, but has been rarely reported. The only existing study in this field is based on the UV pulse count with a fuzzy inference system to evaluate the discharge intensity [17].

Most of the above UV measurement methods target at the time-domain features, such as the UV pulse count or UV pulse amplitude. Since UV signals are generally random and follow no definite rule, the use of a single time-domain feature of UV pulses is unable to accurately distinguish corona discharge from arc discharge of insulators in real time.

This study is primarily aimed at the classification of sensor-detected UV signals in three typical discharge severities, including corona discharge, local arc discharge, and long arc discharge with dry-band arcing. Because corona discharge and arc discharge occur randomly and sometimes interfere in short time, the precision of dividing coronas and arcs by using a simple time-domain feature is low. The contribution of this study is a new method based on the texture features of frequency spectrograms of UV signals to classify coronas, local arcs and long arcs.

The texture analysis method was applied into the images obtained by the spectrograms of UV signals and is used to extract the grey level co-occurrence matrix (GLCM) and Tamura features. A support vector machine (SVM) with six features selected by ablation experiments of eight features was performed for each PD fault. The accuracy of this feature analysis method was assessed by comparing UV pulse count, UV pulse amplitude, local binary pattern (LBP), GLCM and Tamura features. The new method was tested and verified with other feature extraction methods and classifiers.

2 EXPERIMENTAL SETUP AND DATA PREPARATION

The Hamamatsu UV sensor R2868, which has an anode and a cathode on the sides, was used to detect UV rays from PD. Figure 1 shows the physical and circuit diagrams of a UV detector. Figure 2 shows the field-of-view of the UV sensor with a vertical view at 120° and a horizontal view at 170°. The UV detector designed by referring to the Hamamatsu manual is composed of a UV sensor and its driving circuit. When UV light hits the sensor, the cathode generates photoelectrons and the sensor is turned on. The recommended operating circuit is used as the driving circuit, and the DC voltage source provides 300–350 V. The working circuit consists of resistors R1, R2 and a capacitor C1, and the UV pulse waveforms are outputted at capacitor C2. The signals are transmitted to the signal acquisition card and then to the computer via the ZigBee system and antenna, and are transferred to the computer for data processing.

Figure 3 schematically illustrates the general setup of leakage current and UV pulse detection. Tests were carried out in an artificial fog chamber (volume 4.0 × 3.5 × 4.0 m3) in a high-voltage laboratory. The UV sensor system was used simultaneously with a leakage current detector and a visible light camera to detect insulation discharge. The sampling frequency of the UV sensor was 5 kHz. Leakage current waveforms were measured by an oscilloscope (Tektronix TDS2000 C) and observed on a data recorder. Visible images were taken by a Sony a550 camera at a maximum resolution of 4592 × 3056 pixels and with a continuous shooting rate of five frames per second. Two types of insulators including three suspension single-disc ceramic insulators and three four-disc ceramic insulators on pillars were selected. On the basis of international standard IEC 60,507 [18], we used three types of pollutants with equivalent salt deposit density (ESDD) 0.1, 0.08 and 0.06 mg/cm2 to manufacture massive, mediate and slight contamination respectively. Since the UV sensor can detect discharge from one side of the insulator, the insulator pollution was prepared by polluting only one side, while the other side of the insulator was guaranteed to be clean. The single UV detector was placed upright in alignment with the insulator axis, and the cathode centre was positioned in a straight line with the insulator centre. An actual test arrangement is illustrated in Figure 4.

In the tests, a constant boost rate of 0.03 kV/s was used to increase the applied voltage until it reached 10 kV. The tests were conducted twice for each of six insulators and each test lasted 5 min. Testing data were obtained by three devices, including the UV sensor detector, the leakage current detector, and the visible camera.

The leakage current waveforms and typical visible images with three discharge severities were used to classify the UV pulse waveforms. The insulator discharge strength can be crucially reflected by studying the variation of the leakage current. Leakage current waveforms can be used to determine discharge intensity [9,10], and the RMSs of leakage currents are frequently used for quantitative diagnosis of the PD. The RMS of the leakage current, Ie, is calculated as follows [19]:

\[
I_e = \sqrt{\frac{1}{T} \int_{0}^{T} i(t^2) dt}
\]

where \(i(t)\) is the instantaneous value of leakage currents in the time domain; \(T\) is the sampling period.
The discharge severities are described in Table 1. The typical waveforms of leakage currents, visible light images and UV pulses in three typical discharge severities (including corona discharge, local arc discharge, and long arc discharge) are presented in Figures 5–7.

Since the changes of leakage current waveforms were consistent with the visible images, we first divided the data into three discharge stages according to the description of visible images in Table 1 and then confirmed the divisions of the discharge stages according to the RMSs of leakage currents (Table 1). If the visible images and the RMSs of leakage currents divided UV pulses to the same discharge stage, the UV pulse samples were kept; if they were divided into different discharge stages, the UV pulse samples were regarded as invalid samples and rejected.

The tests were performed under continuous pressure and a total of 12 tests were carried out on six insulators. The parameters of insulator samples and discharge phenomena are shown in Table 2. UV pulse waveforms sampled per 200 ms from the above insulators were prepared and used to classify three PD severities. A total of 900 effective samples were collected, including 300, 290 and 310 samples of corona, local arcs and long arcs, respectively. About 25, 32 and 78 samples were sampled at each corona discharge stage, local arc stage and long arc stage, respectively.

Four fifths of the data were selected randomly as a training set, and the remaining one fifth as a test set. The tests were conducted five times by randomly selecting data as a training set.

Data were processed. First, UV pulse waveforms were acquired and classified into three typical discharge severities based on the RMS of the leakage current and visible images. Then the spectrograms of the UV pulse waveforms were obtained. GLCM and Tamura features of the spectrograms were extracted. Totally six features describing the texture distributions of UV pulses were selected. SVM was used to determine the discharge severities.
3 METHODOLOGY

3.1 Basic principles of spectrogram

Spectrogram based on finite-time window-width Fourier spectral tests is the most basic quadratic time–frequency distribution. Let \( x(t) \) be UV signals and \( \omega(t) \) be a square integrable window, the spectrogram of \( x(t) \) is expressed as

\[
S_x^{(\omega)} = \left| \int_{-\infty}^{\infty} x(\tau) \omega(t-\tau) e^{-i2\pi \omega t} d\tau \right|^2
\]

Here \( \omega \) is the sampling frequency. The \( \omega(t) \) is a Gaussian window [20] and its main lobe of the window spectrum is wide, so the frequency resolution is low. This window was used to cut-off UV signals.

Typical UV pulse waveforms, colour and grayscale spectrograms at three discharge severities are shown in Figures 5–7.

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**TABLE 1** Description of discharge severities

| Severity of PD | Description of discharge |
|----------------|--------------------------|
| Corona discharge | The polluted layer of an insulator is wet with a hissing sound and lilac filamentous discharge. Leakage current waveform distortion is slight. RMS of leakage current is <1.5 mA. |
| Local arc | Small orange arcs with louder corona sound appear occasionally, indicating the formation of dry bands. Leakage current distortion becomes more significant than corona discharge. The RMS of leakage current is 1.5–4.0 mA. |
| Long arc | Long bright orange arcs bridge two discs, and move randomly. Leakage current waveform distortion is significant. RMS of leakage current is > 4.0 mA. |

Abbreviation: RMS, root mean square; PD, partial discharge.
The spectrograms of UV signals reflect time-domain and frequency-domain information. Clear differences of textures in the three discharges can be seen in the grayscale spectrograms.

### 3.2 Feature extraction of spectrograms of UV signals

The GLCM features are objective parameters for describing local texture features and reflect the spatial correlation characteristics of image grey levels. The Tamura features describe global texture features according to the psychology of human visual perception of textures. Since the textures of three spectrograms at three discharge stages (Figures 8–10) vary in global and local denseness, thickness and brightness, the above two texture features were combined.

#### 3.2.1 Feature extraction by GLCM

GLCM characterises the textures of an image according to the joint distribution of the probability of two position pixels. It characterises the position distribution between pixels with equal or close brightness. The distance $d$ between any pixel $(x, y)$ and another pixel $(x + \Delta x, y + \Delta y)$ at an angle $\theta$ is $\sqrt{\Delta x^2 + \Delta y^2}$. These two points form a pair of pixels with grayscale values $(m, n)$. The frequency $P(m, n|d, \theta)$ of each pixel pair in the grayscale image is mathematically expressed as [21]

$$P(m, n|d, \theta) = \frac{(x, y), (x + \Delta x, y + \Delta y)}{f(x, y) \times f(x + \Delta x, y + \Delta y)}$$

$$f(x, y) = m$$

$$f(x + \Delta x, y + \Delta y) = n$$
Haralick et al. used GLCM to extract 14 features. Here we used five typical features [22] to identify discharge stages.

(1) Angular Second Moment (ASM): It is the sum of the squares of the GLCM elements, and uncovers the uniformity of texture grey distribution and the texture thickness:

\[ G_{ASM} = \sum m \sum n P(m, n)^2 \]  \hspace{1cm} (6)

(2) Contrast (CON): It is the inertia matrix near the main diagonal of GLCM and reveals the texture sharpness and groove depth:

\[ G_{CON} = \sum m \sum n P(m, n)(m-n)^2 \]  \hspace{1cm} (7)

(3) Correlation (CORRLN): It represents the similarity of the spatial GLCM elements in a row or column and implies the local grey level correlation of the image:

\[ G_{CORRLN} = \frac{\sum m \sum n ((mn)P(m, n) - \mu_m\mu_n)\sigma_m\sigma_n}{\sigma_m^2 \sigma_n^2} \]  \hspace{1cm} (8)

\[ \mu_m = \sum m \sum n P(m, n) \]  \hspace{1cm} (9)

\[ \mu_n = \sum m \sum n P(m, n) \]  \hspace{1cm} (10)

\[ \sigma_m^2 = \sum (m - \mu_m)^2 \sum P(m, n) \]  \hspace{1cm} (11)

\[ \sigma_n^2 = \sum (n - \mu_n)^2 \sum P(m, n) \]  \hspace{1cm} (12)

(4) Entropy (ENT): It reflects the non-uniformity or complexity of the texture (a larger entropy means the texture is more complex):

\[ G_{ENT} = - \sum m \sum n P(m, n) \log P(m, n) \]  \hspace{1cm} (13)

(5) Homogeneity (HOM): It measures the local grey uniformity of the image and reflects the local characteristics of the texture:
\[ G_{\text{HOM}} = \sum_{m} \sum_{n} \frac{P(m,n)}{1 + (m-n)^2} \]  

(14)

3.2.2 | Feature extraction by the Tamura method:

Three common Tamura features [23,24] were selected:

(1) Coarseness (COS): It relates to the size of the primitive elements forming the texture. COS can be calculated by the following steps:

At each pixel \((x,y)\), six average intensities were computed for the windows of \(2^k \times 2^k\), \(k = 0, \ldots, 5\), around the pixel:

\[ A_k(x,y) = \sum_{i=-2^k}^{2^k} \sum_{j=-2^k}^{2^k} f(x+i, y+j) \]  

(15)

\( f(x,y) \) is the grayscale value at \((x,y)\).

At each pixel, the absolute differences \(E_k(x,y)\) between the pairs of nonoverlapping averages in the horizontal and vertical directions were computed:

\[ E_{k,h}(x,y) = |A_k(x + 2^{k-1}, y) - A_k(x - 2^{k-1}, y)| \]  

(16)

\[ E_{k,v}(x,y) = |A_k(x, y + 2^{k-1}) - A_k(x, y - 2^{k-1})| \]  

(17)

The coarseness feature \(T_{\text{COS}}\) was computed by averaging \(S_{\text{best}}(x,y) = 2^k\) over the entire image:

\[ T_{\text{COS}} = \frac{1}{mn} \sum_{i=1}^{m} \sum_{j=1}^{n} S_{\text{best}}(m,n) \]  

(18)

where \(m\) and \(n\) are the number of primitives in the horizontal and vertical coordinates of the image, respectively.

(2) Contrast (CON): It statistically analyses pixel intensity distribution in the entire image:

\[ T_{\text{CON}} = \frac{\sigma^2}{\mu^4} \]  

(19)

where \(\mu = \mu_4/\sigma^4\), \(\mu^4\) is the fourth moment and \(\sigma^2\) is the variance.

(3) Direction (DIR): The module and direction of the gradient vector \(\Delta G\) at each pixel is expressed as:

\[ |\Delta G| = \frac{|\Delta H| + |\Delta V|}{2} \]  

(20)

\[ \gamma = \arctan(\Delta V/\Delta H) + \pi/2 \]  

(21)

where \(\Delta H\) and \(\Delta V\) are the horizontal and vertical changes, respectively.

3.3 | Classifier design

SVM with a quadratic polynomial kernel function [25,26] that uses Bayesian optimization [27] for automatic parameterisation is more accurate than other classifiers for this problem. The weighted kNN [28], the Naïve Bayesian classifier with Gaussian kernel [29], and a decision tree with 20 split numbers by Gini diversity index [30] were also used for this classification problem.

4 | RESULTS AND DISCUSSION

4.1 | Texture feature analysis of images of UV spectrograms

The five GLCM features and three Tamura texture features were extracted using the method described in Section 3.2. To identify
the three most important features to the SVM classifier, we performed ablation experiments on the most importance five features, including Tamura COS, Tamura CON, Tamura DIR, GLCM ENT and GLCM ASM with the SVM classifier proposed in this study as shown in Figure 11. The ablation experiments were aimed to compare the classification accuracy by varying the type and number of features in the SVM classifier. For SVM, the three most important features are Tamura COS, Tamura CON and GLCM ASM (Table 3). To filter out invalid features, we performed ablation experiments on the last three-dimensional features, including GLCM CON, GLCM COR and GLCM HOM. Specifically, the types and number of the last three dimensions were changed, while the top five dimensions were preserved to compare the accuracy of the SVM.

To further identify the accurate feature order to the SVM classifier, the ablation experiments were combined with the new SVM (Table 4). Since the expected accuracy of discharge fault detection is higher than 90%, the last two-dimensional features (GLCM COR and GLCM HOM) have little effect on the accuracy of the classification problem and are thus filtered as invalid features. Since the SVM classifier has higher accuracy than other classifiers for this classification problem (Table 5), the final method proposed in this article is the SVM classifier with six features (Tamura COS, Tamura CON, GLCM ASM, Tamura DIR, GLCM ENT and GLCM CON) and the three most important features are Tamura COS, Tamura CON, and GLCM ASM.

4.2 Analysis of the effect of training sample size

The classification learning curve of the new method trained using the samples is illustrated in Figure 11. The recognition accuracy of the model on the test set was calculated as follows:

\[ \eta = \frac{y_t}{y_r} \]  \hspace{1cm} (22)

where \( y_t \) is the number of samples in the test set and \( y_r \) is the number of samples with the same predicted and actual values. The effect of training sample size was analysed. Since \( k \)-fold cross-validation \((k=5)\) was adopted, the new SVM trained with all the training samples \((St=550)\) yielded an accuracy of 91.2% for the training set and 90.6% for the testing set. When the training sample size is more than 550, the accuracy is stable.

4.3 Classification of ceramic insulators

Figure 12 shows the average accuracy of the five tests performed on the three pollution classes of single-disc and

![Image](image.png)

**FIGURE 11** Classification learning curves

| No. | Tamura COS | Tamura CON | Tamura DIR | GLCM ASM | GLCM ENT | Accu-racy, % |
|-----|------------|------------|------------|----------|----------|-------------|
| 1   | \( \checkmark \) | \( \checkmark \) |          |          |          | 79.70       |
| 2   | \( \checkmark \) | \( \checkmark \) | \( \checkmark \) |          |          | 82.40       |
| 3   | \( \checkmark \) | \( \checkmark \) |          | \( \checkmark \) |          | 86.50       |
| 4   | \( \checkmark \) | \( \checkmark \) |          |          | \( \checkmark \) | 85.50       |

Abbreviations: ASM, angular second moment; CON, contrast; COS, coarseness; DIR, direction; ENT, entropy; GLSM, grey level co-occurrence matrix.

| No. | The top Five Features | GLCM CON | GLCM COR | GLCM HOM | Accu-racy, % |
|-----|-----------------------|----------|----------|----------|-------------|
| 1   | \( \checkmark \) |          |          |          | 88.20       |
| 2   | \( \checkmark \) |          |          | \( \checkmark \) | 90.60       |
| 3   | \( \checkmark \) |          | \( \checkmark \) |          | 89.90       |
| 4   | \( \checkmark \) |          |          | \( \checkmark \) | 88.30       |
| 5   | \( \checkmark \) |          | \( \checkmark \) | \( \checkmark \) | 88.40       |

Abbreviations: ASM, angular second moment; CON, contrast; COR, correlation; HOM, homogeneity; GLSM, grey level co-occurrence matrix.
four-disc insulators in three faults (corona, local arc and long arc) separately. Clearly, long arc discharge was perfectly recognized. Furthermore, the identification rate for the faults exceeded 80%. The accuracy rates for single-disk insulators and four-disc insulators with three types of discharge were 91.3% and 89.5%, respectively.

The insulator discharge severity reflects the changes of the external insulation state, and is highly related to the environment. In practice, UV pulse waveforms detected by the UV sensor were processed by this new method. Six texture characteristics selected from the images of the UV pulse spectroscopy were combined with SVM to identify the insulator discharge stage. When the insulation is identified as corona or local arc discharge, it should be cleaned. If the fault of the insulation is detected as a long arc discharge, it is recommended to check its deterioration degree and partial damage. Once the fault is serious, replacement is recommended.

4.4 Effect of classifiers on the classification accuracy

Four classifiers including k-nearest neighbour (kNN), Naive Bayes, Decision Tree and SVM were used to classify the partial discharge severities of insulators. The training and testing classification results of different classifiers are listed in Table 5. The accuracy value of the SVM classifier can reach 90.6%, which is the highest among the four classifiers. Figure 13 shows the classification results for the three discharge faults, corona, local arc and long arc.

5 EFFECT OF UV SIGNAL FEATURE EXTRACTION METHODS ON THE CLASSIFICATION ACCURACY

In the comparative experiments, the SVM quadratic function classifier and different feature extraction methods were used to process the UV pulse waveforms. Table 6 shows the classification results with different features by the four classifiers. The UV pulse count method [17] and the UV pulse amplitude method use the number of UV pulses per second, and the integral of pulse amplitude of UV pulses per second as single UV pulse features respectively to classify the three discharge severities. The uniform pattern LBP [31] is used to characterise the local textures of images, which means that the spectrum is split into a 3×3 operator and 59 dimensional features. Results show that the accuracy values of the UV pulse count and UV pulse amplitude feature are only 79.5% and 79.4%, respectively, by regularised linear discriminant analysis, which perform the worst among the eight feature extraction methods. Our feature extraction method has higher accuracy (up to 90.6% with SVM) than other methods.

The accuracy degrees of different feature extraction methods in the three discharge severities are shown in Figure 14. The new method for corona discharge and local arc detection has higher accuracy than other feature extraction methods. Each feature extraction method performs well for the fault of long arc.

The feature distributions of UV pulse count and the three main features (Tamura COS, Tamura CON, GLCM ASM) in Table 3 selected from the top five features with the three discharge severities are shown in Figures 15 and 16. Clearly, in the two methods, the features of long arc fault were completely

| Classifier | Classification, % | Computational time, s |
|------------|-------------------|----------------------|
|            | Training | Testing | Training |          |
| kNN        | 90.5     | 83.1     | 1.202    |          |
| Naive Bayes| 85.1     | 83.9     | 2.816    |          |
| Decision tree | 93.3   | 86.1     | 1.311    |          |
| SVM (new)  | 91.2     | 90.6     | 1.626    |          |

Abbreviation: SVM, support vector machine.
TABLE 6 Recognition accuracy of different feature extraction methods

| Feature extraction method | SVM | kNN | Naive Bayes | Decision Tree |
|---------------------------|-----|-----|-------------|---------------|
| LBP                       | 59  | 83.1| 81.3        | 0.396         | 79.9          |
| GLCM                      | 5   | 81.9| 80.6        | 1.231         | 79.0          |
| Tamura                    | 3   | 82.4| 74.5        | 1.117         | 82.5          |
| GLCM + Tamura             | 8   | 88.4| 80.9        | 1.081         | 82.3          |
| Filtered GLCM + Tamura    | 6   | 90.6| 81.1        | 1.202         | 83.9          |
| (proposed)                |     |     |             |               |               |

Accuracy %, Computing time, s

Abbreviations: GLSM, grey level co-occurrence matrix; kNN, k-nearest neighbour; LBP, local binary pattern; SVM, support vector machine.

FIGURE 14 Classification accuracy of different feature extraction methods with three discharge severities

FIGURE 15 Characteristic distribution of the ultraviolet pulse count with three discharge severities

FIGURE 16 Characteristic distribution of Tamura contrast, Tamura coarseness and GLCM ASM with three discharge severities. ASM, grey level co-occurrence matrix; GLCM, grey level co-occurrence matrix

(Figure 16) selected from filtered GLCM + Tamura features in these two faults were separated evidently, which explains the higher recognition rate of the new method.

6 | CONCLUSIONS

A UV detector system that can diagnose faults in the exterior insulation of the insulator was combined with machine learning. GLCM and Tamura texture features were extracted from the spectrograms of UV signals detected by the UV sensor. Six valid features were selected by ablation experiments and were used to yield a significant accuracy. The accuracy of the new method is up to 90.6% compared with the single UV feature extraction method (79.2%). It is a robust extraction method for PD classification of the insulators.
Compared with kNN and Naïve Bayesian classifier, SVM has the best performance and a recognition rate of over 90%. It is effective for classifying each intensity of PD. Furthermore, the recognition rate is over 89% in both four-disc insulators and single-disc insulators. The new method can save workforce and has prospects in identifying the insulation state of the transformer substations and transmission lines.

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