Dynamic Frequency-selection Clustering of Automatic Multiple Source Separation based on UHF PD Detection

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Abstract: Partial discharge (PD) ultra-high frequency (UHF) on-line monitoring technique is an important resort to evaluate the insulation condition of the high-voltage power equipment. The presence of a large number of on-site interference affects the detection sensitivity and reliability, and the interference generated by discharges are the crucial bottleneck for effective PD detection under complicated electromagnetic environment, because they have similar time-frequency characteristics as real PD. Therefore, in order to solve the problem of mutual existence of multiple discharge and their interference to each other, a method of auto separation of multiple PD is studied in this paper, and the rules and a combined strategy is presented to make accurate multi-PD separation. The technique of dynamic automated separation of multi-PD is developed based on digital RF chip by using these rules, then theoretical and experimental verification is carried out. The results indicate that the clustering technology presented in this paper could realize automated separation of multiple PD and its accuracy can up to 90 %.

1 INTRODUCTION

Partial discharge (PD) detection has become a key technology for the detection of insulation status of high-voltage power equipment such as gas insulated switchgear (GIS), transformer and power cable (Qin, Wang, Shao, 1997; Wang, Li, Gao, 2006). Especially for sudden faults of high-voltage power equipment, partial discharge detection is much more effective than oil chromatography analysis and gas decomposition products detection. However, the serious electromagnetic interference on the site has greatly hindered the promotion and application of the technology of PD on-line monitoring (Guo, Wu, Zhang, 2005; Zhang, 2017; Liu, Wang, Li, 2013). Due to insufficient interference identification performance and anti-interference performance, the effect of the current PD monitoring device in the substation is unsatisfactory, and the misjudgment and missed detection of PD occur from time to time on the site (Tang, Wang, Li, 2009; Dey, Chatterjee, Chakravorti, 2010; Wang, Tang, Chang, 2012).

Based on a large number of field tests, the author found that although the UHF detection technology has good anti-interference ability for low-frequency signals, there are still a lot of interferences in the frequency band of UHF detection in the field (Lu, Li, Tang, 2017; Tang, Jiang, Ye, 2017). The existence of a large number of discharge interferences is still the main cause of misjudgment and missed detection of partial discharge, and the time-domain characteristics and frequency domain characteristics of discharge interferences are similar to that of PD signals of the detected equipment, so conventional filtering methods are ineffective for such interferences. However, differences in signal sources and propagation paths can result in subtle diversity in the time domain waveforms and frequency spectra of different pulse signals. Clustering and separating multi-source signals that are superimposed and similar in characteristics, and then performing separate statistics and feature identification for each type of signal is an effective way to eliminate and reduce the effects of such interference (Tang, Wang, Chang, 2012).

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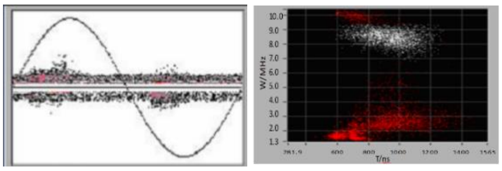
For multi-source partial discharge detection, scholars have proposed a variety of representative methods, such as equivalent time-frequency (T-F) analysis, 3-phase synchronous contrast method, multi-frequency detection and so on(Cavallini and Montanari,2005; Herold, Wenig, Leibfried, 2010). Figure1 is a schematic diagram of multiple-sources PD separation of Italian Techimp Company, which is achieved by T-F clustering for high-frequency current detection. In Figure 1, Figure 1(a) is the PRPD spectrum of multi-sources PD and its T-F spectrum, and (b), (c), (d) are the PRPD spectra and waveform of three types of discharge separated from multi-sources PD. Omicron Company in Austria uses the amplitude relationship and the arrival time of the three-phase synchronous signals to perform multi-sources PD separation, as shown in Figure 2.

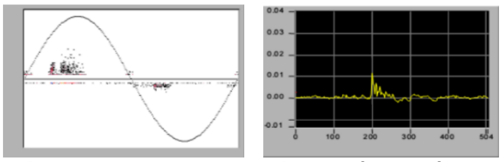
In China, Si Wenrong et al. of Xi'an Jiaotong University used the least squares support vector machine (LS-SVM) to detect and identify multi-sources PD in GIS, which is based on time-frequency feature extraction for PD pulses and competitive learning network unsupervisory clustering to realize rapid classification of pulse groups, and the simulation and experimental results verify the feasibility and practicability of the technique (Si, Li, Li, 2009). Yang Lijun et al. used fuzzy C-mean (FCM) clustering method to obtain the pulse classification on the T-F map and chose the membership degree as the index to separate signals and to realize the separation and recognition of multiple PD sources(Yang, Sun, Liao,2010). Xiao Yan et al. of Shanghai Jiaotong University used the Laplace wavelet-based matching pursuit algorithm to extract the starting time, oscillation frequency and attenuation coefficient of a single PD signal to determine whether the PD pulse is from the same source as other pulses (Xiao, Huang, Yu, 2005).

At present, the separation method of multi-source PD pulses is mostly applicable to the PD signals detected by high-frequency (HF) detection method, and is a manual selection method, so it is complicated to realize on site.

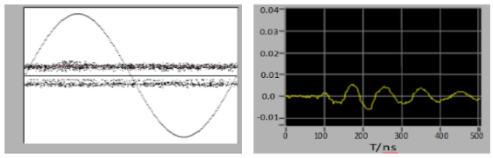
The cluster analysis of the existing multi-discharge power supply is mostly only applicable to the high-frequency current detection mode, and the manual selection method is adopted, which has the disadvantage of complicated operation. Therefore, under complex electromagnetic interference environment, it is of great engineering and practical value to explore the automatic multi-source discharge separation method based on UHF partial discharge detection technology.



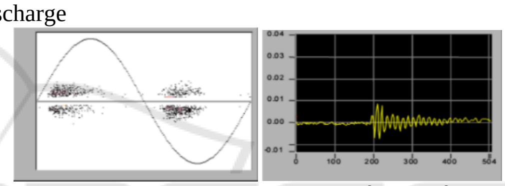
(a) The PRPD spectrum of multi-sources PD and its T-F spectrum



(b) The PRPD spectrum and waveform of A type discharge



(c) The PRPD spectrum and waveform of B type discharge



(d) The PRPD spectrum and waveform of C type discharge

Figure 1. TF Clustering of TechImp PD detection.

2 CLUSTERING ANALYSIS METHOD

Clustering analysis is a kind of multivariate statistical analysis and an important branch of unsupervised pattern recognition. It is the most widely used in many fields such as pattern classification, image processing and fuzzy rule. The cluster analysis method divides samples in a sample set without category marks into several classes according to a certain criterion, so that similar samples are classified into one class. Therefore, cluster analysis can be used to realize automatic separation of multi-source discharge signals.

2.1 Fuzzy C-means Clustering Algorithm

The fuzzy c-means clustering (FCM) algorithm is a clustering algorithm that uses membership degree to determine the extent to which each sample point belongs to a certain class. In order to optimize the

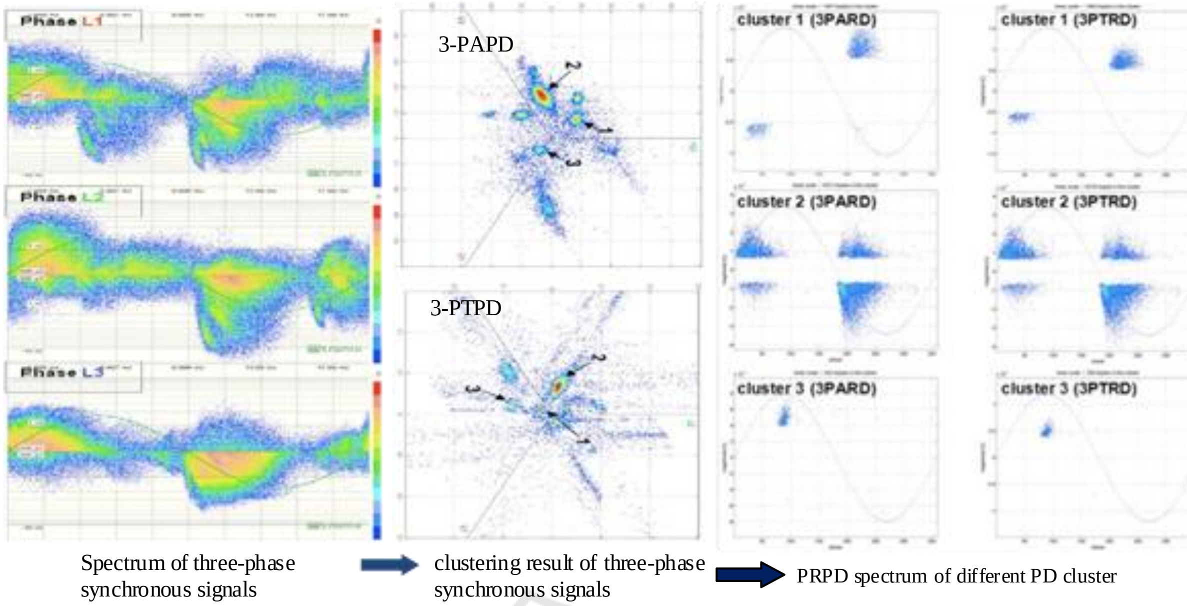


Figure 2. Multi-PD Clustering of Omicron.

classification results, FCM divides n vectors xi (i=1, 2, ..., n) into c fuzzy groups, finds the cluster center of each group, and minimizes the value function of the non-similarity index. The value function (or objective function) of FCM is shown as (1).

$$J(U,c_1,\ldots,c_c)=\sum_{i=1}^{c}J_i=\sum_{i=1}^{c}\sum_{j}^{n}u_{ij}^{m}d_{ij}^{2} \tag{1}$$

Where uij is between 0 and 1; ci is the cluster center of fuzzy group I, and dij=||ci-xj|| is the Euclidean distance between the ith cluster center and the jth data point; m∈[1, ∞)is weighted index, and m is 2 in this paper.

$$u_{ik}=\frac{1}{\sum_{j=1}^{c}\left(\frac{d_{ik}}{d_{jk}}\right)^{\frac{2}{m-1}}} \tag{2}$$

$$c_i=\frac{1}{\sum_{k=1}^{n}(u_{ik})^m}\sum_{k=1}^{n}(u_{ik})^{m}x \tag{3}$$

After the clustering number c is given and the clustering prototype C is initialized , using (2) and (3) , the optimal fuzzy classification matrix and cluster center can be obtained by iterative calculation, according to that, the signal is divided into c classes(Kuo, Lin, Zulvia,2018).

2.2 Gauss Mixture Model Clustering Algorithm

The principle of the Gauss mixture model clustering (GMM) algorithm is to assume that the distribution of the sample conforms to the Gaussian mixture model, and by fitting the sample data, to determine the parameters of each Gaussian component. Each Gaussian component is equivalent to a fuzzy cluster, by calculating the probability that each sample agree with the distribution of each Gaussian component to determine the classification of the sample (Ma, Jie, Hu, 2017).

The Gaussian mixture model is defined as a linear combination of M Gaussian density functions, as (4).

$$P(x)=\sum_{i=1}^{M}\pi_i N_i(x;\mu_i,\Sigma_i) \tag{4}$$

Where Ni(x, μi, ∑i) is a Gaussian distribution with a mean of μi and a covariance of ∑i. πi is a mixed parameter, which is regarded as the weight of the i-th Gaussian distribution and represents the prior probability, as (5).

$$\sum_{i=1}^{M}\pi_i=1,\ 0\le\pi_i\le1 \tag{5}$$

The probability density function of Ni(x, μi, ∑i) is as (6).

$$N_i(x) = \frac{1}{(2\pi)^{d/2}|\Sigma_i|^{1/2}} \exp\left\{-\frac{1}{2}(x-\mu_i)^T \Sigma_i^{-1}(x-\mu_i)\right\} \quad (6)$$

Let all the parameters to be determined in the Gaussian mixture density function be c, then the likelihood function is as (7).

$$P(X \mid \theta) = \prod_{i=1}^{N} P(x_i \mid \theta) \Rightarrow \theta^* = \arg\max_{\theta} P(X \mid \theta) \quad (7)$$

In order to simplify the problem, the maximum value of (8) can be calculated.

$$\log(p(X \mid \theta)) = \sum_{i=1}^{N} \log p(x_i \mid \theta) = \sum_{i=1}^{N} \log(\sum_{k=1}^{K} \pi_k N(x_i; \mu_k, \Sigma_k)) \quad (8)$$

2.3 GK Fuzzy Clustering Algorithm

Let the element xk(1≤k≤N) in the set X={x1, x2,……,xN} have n features, that is xk={xk1, xk2,……,xkN }. If the set is classified into c(1≤c≤N) classes, let V={v1, v2,……,vc}to be cluster centers, let U=[uik]c×N to be the membership matrix, where the element uik (0 ≤ uik ≤ 1) indicates membership that the kth element belongs to the ith class(0≤ I ≤ c), and uik satisfies the condition of (9) and (10). The criteria of GK fuzzy clustering (GKFC) is iteratively adjusted to minimize the objective function, and objective function is (11).

$$0 < \sum_{k=1}^{N} u_{ik} < N \quad (9)$$

$$\sum_{k=1}^{N} u_{ik} = 1 \quad (10)$$

$$J_m(U,V,A:X) = \sum_{i=1}^{c}\sum_{k=1}^{N}(u_{ik})^m D_{ik}^2 \quad (11)$$

Distance norm is:

$$D_{ik}^2 = (x_k - v_i)^T A_i (x_k - v_i) \quad (12)$$

Where Ai is an positive definite matrix and determined by the cluster covariance matrix Fi, and Ai and Fi, are as (13) and (14).

$$A_i = [\rho_i \det(F_i)]^{\frac{1}{p}} F_i^{-1} \quad (13)$$

$$F_i = \frac{\sum_{k=1}^{N}(u_{ik})^m (x_k - v_i)(x_k - v_i)^T}{\sum_{k=1}^{N}(u_{ik})^m} \quad (14)$$

Where, ρi is a constant and m (m≥1) is a fuzzy index. The eigenvalues and eigenvectors of the covariance matrix represent information about the shape of the cluster.

The Lagrange multiplication is used to optimize the objective function, and obtain the (U, V) that lead objective function has a minimum point.

2.4 Fuzzy Maximum Likelihood Clustering Algorithm

Pre-processing steps of fuzzy maximum likelihood clustering algorithm (GKL) are similar to the FCM, and the following steps are the following five steps (Savchenko, 2017).

(1) Compute the center of cluster

$$v_i^{(l)} = \frac{\sum_{k-1}^{N}\left(u_{ik}^{(l-1)}\right)^w x_k}{\sum_{k=1}^{N}\left(u_{ik}^{(l-1)}\right)^w}, 1 \leqslant i \leqslant c \quad (15)$$

(2) Compute fuzzy covariance matrix

$$F_i = \frac{\sum_{k-1}^{N}\left(u_{ik}^{(l-1)}\right)^w \left(x_k - v_i^{(l)}\right)\left(x_k - v_i^{(l)}\right)^{\mathrm{T}}}{\sum_{k=1}^{N}\left(u_{ik}^{(l-1)}\right)^w}, 1 \leqslant i \leqslant c \quad (16)$$

(3) Calculated distance

$$D_{ik}^2\left(x_k, v_i\right) = \frac{\sqrt{\det\left(F_{wi}\right)}}{\alpha_i} \exp\left(\frac{1}{2}\left(x_k - v_i^{(l)}\right)^{\mathrm{T}} F_{wi}^{-1}\left(x_k - v_i^{(l)}\right)\right) \quad (17)$$

Where 1 ≤ i ≤ c, 1 ≤ k≤ N.

(4) Update fuzzy partition matrix

$$\mu_{ik}^{(l)} = \frac{1}{\sum_{j=1}^{c}\left(D_{ik}/D_{jk}\right)^{2(m-1)}} \quad (18)$$

The iteration is terminated until ||U (l)- U(l-1)|| <ε.

The above several clustering methods have different adaptability to different problems. In practice, there are some problems such as the number of clusters need to be determined manually, the selection of the initial cluster center has too much influence on the results ,and it is difficult to achieve the clustering of the data with arbitrary types and so on, which often lead to incorrect classification results. Therefore, it is still unable to meet the requirements of the technology of automatic multi-source PD separation.

3 INTELLIGENT DYNAMIC CLUSTERING SEPARATION OF MULTI-SOURCE DISCHARGE SIGNALS

3.1 Intelligent Dynamic Clustering Strategy

An intelligent dynamic clustering strategy is proposed in this paper to achieve automatic optimization of clustering methods and cluster numbers, as shown in Figure 3.

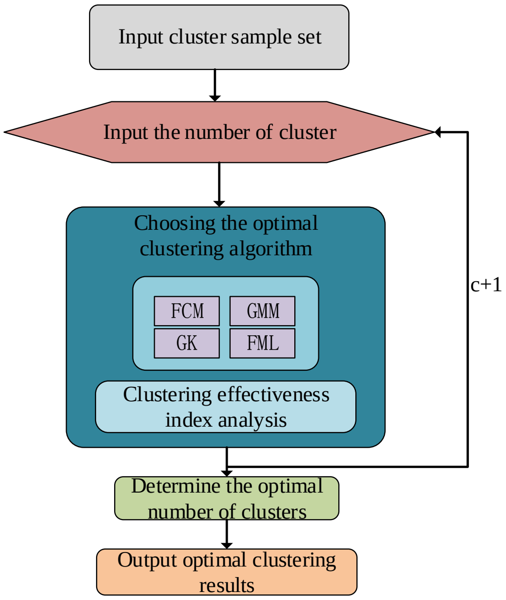


Figure 3. Flowchart of smart dynamic clustering.

3.2 New condition Based on Dynamic Frequency-selection Detection

The conditioner includes three independent local oscillator sources, and realizes scanning the full-band of UHF in a 10MHz step by serial control to find a frequency center with high signal-to-noise ratio (SNR), which is equivalent to three programmable adjustable bandpass filter amplifier. The conditioner has the hardware foundation for dynamic frequency-selection clustering according to signal frequency distribution difference, which avoids many kinds of complicated interferences on the scene.

The dynamic range of the conditioner is -70dBm~10dBm and the maximum sensitivity is -73dBm. The preamplifier has an analog bandwidth of 300M to 2GHz, and the center frequency is continuously adjustable from 300MHz to 1.8GHz. The intermediate frequency signal is amplified by 100MHz low-pass filtering. The schematics of the structure of the partial discharge UHF conditioner is shown in Figure 4.

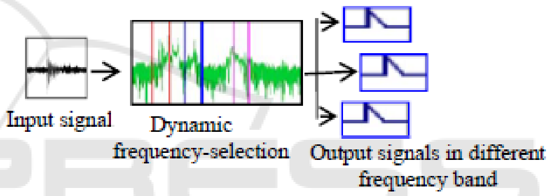


Figure 4. Schematic diagram of the UHF PD signal conditioner.

3.3 Feature Quantities and Validity Index of Clustering

The normalized energy fractions for the low frequency band, medium frequency band, and high frequency band are defined respectively as E1=V1/(V1+V2+V3), E2=V2/(V1+V2+V3) and E3=V3/(V1+V2+V3).

The three-dimensional vector E (E1, E2, E3) is mapped to the two-dimensional data space to obtain a two-dimensional vector J (J1, J2), which is used as a feature quantity of clustering.

The partition coefficient (PC) and classification entropy (CE) are selected to evaluate the clustering results in this paper. The PC is used to judge the degree of separation between the clusters and the CE is used to calculate the ambiguity of the classification cluster. In the case where the number of clusters is the same, the larger the PC, the better the classification effect and the smaller the CE, the better the classification effect. The formula of PC and CE are as (19) and (20).

$$PC(c) = \frac{1}{N}\sum_{i=1}^{c}\sum_{j=1}^{N}(\mu_{ij})^2 \qquad (19)$$

$$CE(c) = -\frac{1}{N}\sum_{i=1}^{c}\sum_{j=1}^{N}\mu_{ij}\log(\mu_{ij}) \qquad (20)$$

3.4 Software Design

Based on the LabVIEW platform, a software for intelligent clustering of multi-source discharge signals is programmed, and the interface of multi-source signals separation program as shown in Figure 5. The main functions of the program includes dimension reduction of three-dimensional feature vector, normalization of clustering feature quantities, dynamic and automatic clustering of multi-source discharge signals, automatic separation of PD spectra which overlap with each other.

4 VERIFICATION EXPERIMENT

4.1 Experiment Method

A platform is built in this paper to verify the technology for multi-source PD separation and the structure of the experimental platform is shown in Figure 7, where TC1 and TC2 are two chamber of GIS and S1, S2, S3 and S4 are four UHF sensors. Three kinds of discharge defects are set in the GIS cavity to simulate the multi-source discharge which are floating discharge defect, surface discharge defect, and metal particle discharge defect and the floating discharge defect and the surface discharge defect are set in the chamber TC1, and the metal particle discharge defect is set in the chamber TC2. The initial discharge voltages of floating discharge, surface discharge and metal particle discharge were determined to be 50, 45, 31kV by preliminary tests, so the test voltage was 52kV, which ensured stable discharge of each discharge defect.

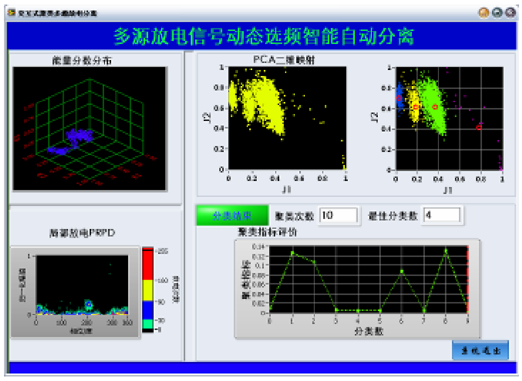
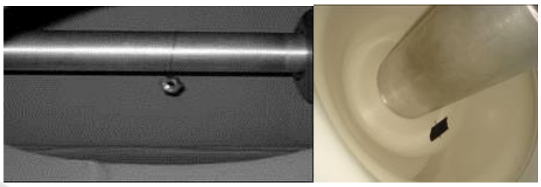


Figure 5.Interface of multi-source signals separation program.



(a) Floating discharge defect (b) Surface discharge defect

(c) Metal particle discharge defect

Figure 6.The mixed discharge defect model.

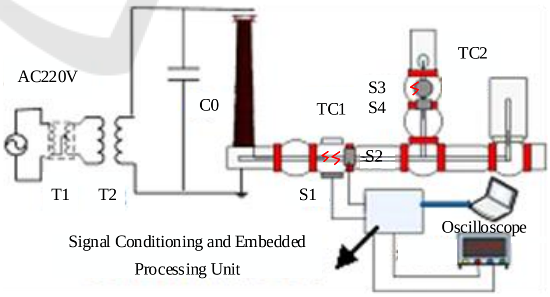
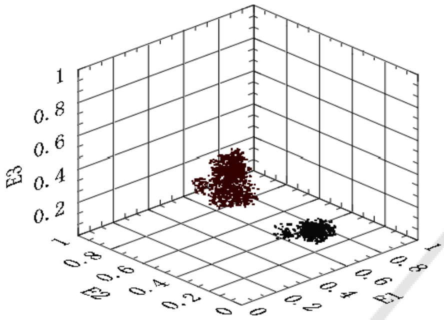


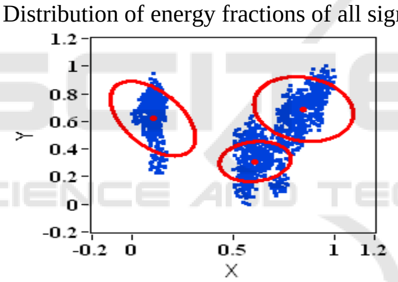
Figure 7.Experiment platform.

4.2 Experimental Results and Analysis

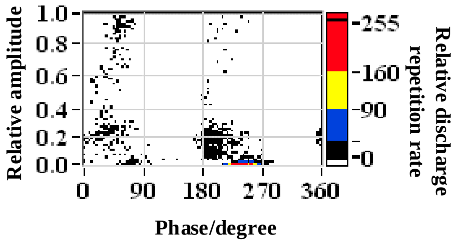
Through the program control, the three channels of the signal conditioner are synchronously detected, and the center frequencies of the three channels are 300M, 700M and 1.2GHz respectively. The energy fractions of the signals in the three frequency bands are calculated using the amplitudes of the pulse signals detected synchronously through the three channels, and are plotted in the three-dimensional view. In order to improve the operation speed, the PCA method is used to convert the three-dimensional view into a two-dimensional view, and then the multi-source PD separation software mentioned above is used for three PD signals. Figure 8(a) shows the distribution of energy fractions of all signals, (b) is a two-dimensional view of energy fractions, (c) is a superimposed discharge spectrum that contains three discharge spectra, and (d)-(g) are three discharge spectra separated from superimposed discharge spectrum.



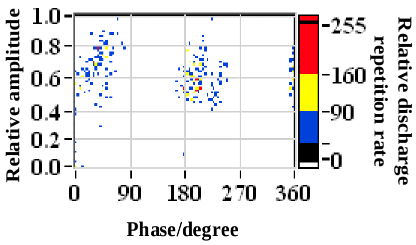
(a) Distribution of energy fractions of all signals



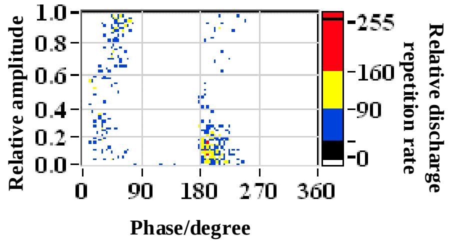
(b) Two-dimensional view of energy fractions



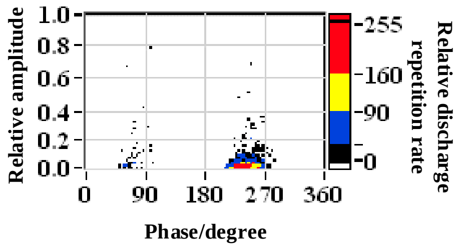
(c) Superimposed discharge spectrum



(d) Spectrum of floating discharge separated from superimposed discharge



(e) Spectrum of metal particle discharge separated from superimposed discharge



(f) Spectrum of surface discharge separated from superimposed discharge

Figure 8. Minimum classification accuracy of any two type of PD signal.

5 CONCLUSIONS

By analyzing the main causes of missed detection and false alarm caused by multi-source discharge in complex electromagnetic environment in substation, the current status of multi-source discharge separation technology in the world and main clustering algorithms are summarized. In addition, a dynamic frequency-selection clustering method based on UHF partial discharge detection is proposed for the problem of automatic separation of multi-source partial discharge and interference signals. A 3-channel dynamic frequency selective UHF conditioner is designed, the normalized energy fraction is selected as the clustering feature quantity, the optimal clustering method is selected from the four clustering algorithms of FCM, GMM, GK and FML according to the clustering index. So that the automatic clustering and intelligent separation technology of multi-source discharge is realized. Moreover, an experiment with three kinds of discharge sources was designed in the laboratory and the result of the experiment verifies the effectiveness of the method. The research results also show that the method can automatically judge the number of discharge sources and separate the multi-source discharge pulses according to the characteristics of the multi-source discharge signals, which does require human intervention and its accuracy is high.

ACKNOWLEDGEMENTS

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