Research on excavation and identification method of typical interference signal during transformer partial discharge test

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Abstract—In order to remove interference signal and external discharge signal during partial discharge test and get the effective signal of partial discharge, this paper carries out the research of typical interference signal mining and identification method for transformer partial discharge test. Firstly, based on the experience of previous researchers in partial discharge research, 47 feature parameters including statistical, texture and shape features are extracted, and the original feature space is constructed based on them, which provides the data basis for the optimization of the feature space and signal classification identification later. Next, the random forest algorithm is used to measure and rank the importance of the feature parameters, and the original feature space is optimized according to the ranking results to obtain the optimized feature space. Finally, the optimized feature space is used as the input of linear discriminant analysis algorithm and K-nearest neighbor algorithm to classify and identify the local discharge signal and typical interference signal, and the recognition accuracy of these two classification and identification algorithms is compared and analyzed, and the K-nearest neighbor algorithm is selected as the final classification and identification algorithm.

1. Introduction

As a pivotal device of the power system, the operational reliability of power transformers is directly related to the safety and stability of the power system, so it is of great importance to carry out fault diagnosis studies on transformers and clarify the types of transformer faults [1].

Transformer faults mainly include short-circuit damage faults, overheating faults, and insulation damage faults, of which insulation damage faults account for about 70% to 80% of the total faults. And most of the transformer insulation faults are caused by insulation aging or breakdown due to transformer partial discharge [2]. In the field of transformer insulation condition diagnosis at home and abroad, partial dis-charge measurement is the most direct and effective measurement means and evaluation method for local defects of electrical equipment [3].

There are many studies on transformer partial discharge pattern recognition, but the actual application often shows that the actual measurement data are difficult to analyse. It is mainly because the large amount of existing literature on partial discharge data analysis methods are based on the theory of mathematical methods [4, 5, 6], but lack of practical experience support. As a result, the application often offers an inaccurate state evaluation of the transformer, especially when the measured pulse signal contains only interference signals or discharge signals outside the subject, whose characteristics are similar to the internal partial discharge of the equipment, which are fully compatible with the typical
discharge signal characteristics in the current standards. Therefore, it is especially important to remove the interference signal and external discharge signal from the measured pulse signal in the field to get the effective signal of partial discharge.

To this end, this paper carries out the research on the mining and identification method of typical interference signals of transformer partial discharge test, based on the analysis method of big data, firstly extracts the feature parameters of partial discharge and typical interference signals and constructs the original feature space; on this basis, uses the random forest algorithm to optimize the original feature space and derives the optimized feature space; finally uses the linear discriminant analysis algorithm and K-nearest neighbor algorithm Finally, the linear discriminant analysis algorithm and the K-nearest neighbor algorithm are used for signal classification and identification, and the accuracy of the two algorithms is compared, and the K-nearest neighbor method with higher average recognition accuracy is selected as the classification and identification method for partial discharge and typical interference signals.

2. Extraction of feature parameters of partial discharge and typical interference signal

A library of Q-ϕ maps is constructed for the experimental data of local discharge signals and typical interference signals measured in the laboratory. In order to classify and identify the partial discharge signals and typical interference signals better, feature parameters that can describe the differences between these two types of signals need to be extracted from the plots. In this paper, the statistical features and image features of transformer partial discharge patterns are extracted respectively.

2.1 Statistical feature parameters

The statistical characteristic parameters describe the distribution of the local discharge signal and the typical interference signal, and are often used to describe the difference between the shape of the plot and the positive and negative half-perimeter profiles.

① Skewness $S_k$, which is used to characterize the skew direction and degree of skewness of the spectrum.

② Cliffness $K_u$, which indicates the degree of protrusion of the plots of local discharge signals and typical interference signals.

③ Correlation coefficient $r_c$, which is used to describe the degree of similarity between the positive and negative half-perimeter shape contours of the signal mapping [7].

④ The number of peak points $P_k$, which records the number of local peak points and describes the overall smoothness of the mapping.

2.2 Image feature parameters

Image features are mainly classified as texture features and shape features, etc. A good description of the basic information of the atlas can be made.

① Texture features

The gray-gradient co-occurrence matrix method based on the statistical type is used. The gray-gradient covariance matrix integrates the joint statistical distribution of gray levels and edge gradients of the pixels of an atlas, reflecting the discrimination pattern of gray levels and gradients of pixel points, and also being able to reflect the spatial relationship between each pixel point and its neighboring pixel points [7].

Fifteen texture features are extracted for each atlas, and each texture feature is calculated and named as shown in Table 1 below.
Table 1 Texture feature of atlas

| ID | Name                          | Expression                                    |
|----|-------------------------------|-----------------------------------------------|
| 1  | Average grayscale             | \[ T_i = \frac{1}{\sum P_i} \]                |
| 2  | Average grayscale             | \[ T_i = \frac{1}{\sum A_i P_i} \]           |
| 3  | Grayscale mean square deviation | \[ T_i = \sqrt{\frac{\sum (i-j)^2 P_i/\sum P_i)}{\sum P_i}} \] |
| 4  | Gradient mean square deviation | \[ T_i = \sqrt{\frac{\sum (jT_i^2 - T_i^2)^2 P_i}{\sum P_i}} \] |
| 5  | Small gradient advantage      | \[ T_i = \frac{P_i}{j^2} \]                  |
| 6  | Large gradient advantage      | \[ T_i = \frac{P_i}{j^2} \]                  |
| 7  | Unevenness of grayscale       | \[ T_i = \frac{\sum H_i}{\sum H_i} \]       |
| 8  | Unevenness of gradient        | \[ T_i = \frac{\sum H_i}{\sum H_i} \]       |
| 9  | Energy                        | \[ T_i = \sum P_i \]                         |
| 10 | Correlation coefficient       | \[ T_i = \sum (i-T_i)(j-T_j) P_i \]          |
| 11 | Grayscale entropy             | \[ T_i = \sum \log(1+P_i) \sum P_i \]       |
| 12 | Gradient entropy              | \[ T_i = \sum P_i \log \sum P_i \]          |
| 13 | Hybrid entropy                | \[ T_i = \sum P_i \log \sum P_i \]          |
| 14 | Inertia                       | \[ T_i = \sum (i-j)^2 P_i \]                 |
| 15 | Inverse moment                | \[ T_i = \sum P_i / (1+(i^2+j^2)) \]        |

(2) shape features

For describing the shape of the object, mainly region features and contour features, the internal shape of the whole shape region is described by region features and the outer boundary of the object is described by contour features [8]. For signal mapping image shape contours, this paper mainly uses Zernike moments and Hu invariant moments for description.

Ten Hu-invariant moment features were extracted for each mapping, and the formula for each feature is shown in Table 2 below.

Table 2 Hu moment invariant feature of atlas

| ID | Expressions                        | ID | Expressions                        |
|----|------------------------------------|----|------------------------------------|
| 1  | \[ R_i = \sqrt{\frac{n_i}{n_i}} \] | 6  | \[ R_i = \sqrt{\frac{n_i}{n_i}} \] |
| 2  | \[ R_i = \frac{n_i + \sqrt{n_i}}{2n_i} \] | 7  | \[ R_i = \sqrt{\frac{n_i}{n_i}} \] |
| 3  | \[ R_i = \sqrt{\frac{n_i}{n_i}} \] | 8  | \[ R_i = \sqrt{\frac{n_i}{n_i}} \] |
| 4  | \[ R_i = \sqrt{\frac{n_i}{n_i}} \] | 9  | \[ R_i = \sqrt{\frac{n_i}{n_i}} \] |
| 5  | \[ R_i = \sqrt{\frac{n_i}{n_i}} \] | 10 | \[ R_i = \sqrt{\frac{n_i}{n_i}} \] |

15 Zernike moments were extracted from the images, denoted as \( A_{11}, A_{21}, A_{12}, A_{31}, A_{32}, A_{33}, A_{41}, A_{42}, A_{43}, A_{44}, A_{51}, A_{52}, A_{53}, A_{54}, A_{55} \).

In this paper, 47 feature parameters are extracted, which are 7 statistical features and 40 image features, of which 40 image features contain 15 texture features, 15 Zernike moments and 10 Hu-invariant moments.

3. Construction of the original feature space of partial discharge signals and typical interference signals

According to the previous section, 47 characteristic parameters were extracted to characterize the differences between the local discharge signal and the typical interference signal. The 47 characteristic parameters and the corresponding symbols of the local discharge signal and typical interference signal are listed and numbered in Table 3.
The characteristic parameters of a total of seven types of partial discharges and typical disturbance signals are extracted: A-phase oil gap discharge, A-phase tip discharge, A-phase discharge along the surface, suspension discharge, grounding disturbance, artificially created disturbances that mimic the periodic discharge of transmission lines, and field noise disturbances. For each signal type, three types of original feature spaces including statistics, texture, and shape can be established. Here, the representation of the original feature space is defined as \( n \times m \), where \( n \) denotes the number of samples and \( m \) denotes the number of feature parameters. The dimension of the primitive feature space constructed in this chapter is \( 500 \times 47 \).

### Table 3 Original feature parameter reference

| ID  | Expressions                                      | Name                      | ID  | Expressions                                      | Name                      | ID  | Expressions                                      | Name                      | ID  | Expressions                                      | Name                      |
|-----|--------------------------------------------------|---------------------------|-----|--------------------------------------------------|---------------------------|-----|--------------------------------------------------|---------------------------|-----|--------------------------------------------------|---------------------------|
| 1   | \( S_k^+ \) Positive half-period skewness        |                           | 13  | \( T_6 \) Large gradient advantage              |                           | 25  | \( R_3 \) Relative moment 3                      |                           | 37  | \( Z_{32} \) Zernike moment 32                   |                           |
| 2   | \( S_k^- \) Negative half-period skewness        |                           | 14  | \( T_7 \) Grayscale Release                      | Unevenness                | 26  | \( R_4 \) Relative moment 4                      |                           | 38  | \( Z_{33} \) Zernike moment 33                   |                           |
| 3   | \( K_k^+ \) Positive half-period cliffness       |                           | 15  | \( T_8 \) Grayscale Release                      | Unevenness of gradient    | 27  | \( R_5 \) Relative moment 5                      |                           | 39  | \( Z_{41} \) Zernike moment 41                   |                           |
| 4   | \( K_k^- \) Negative half-period cliffness       |                           | 16  | \( T_9 \) Energy                                 |                           | 28  | \( R_6 \) Relative moment 6                      |                           | 40  | \( Z_{42} \) Zernike moment 42                   |                           |
| 5   | \( P_K^+ \) Number of positive half-cycle peaks  |                           | 17  | \( T_{10} \) Relevance                          |                           | 29  | \( R_7 \) Relative moment 7                      |                           | 41  | \( Z_{43} \) Zernike moment 43                   |                           |
| 6   | \( P_K^- \) Number of negative half-cycle peaks  |                           | 18  | \( T_{11} \) Grayscale entropy                  |                           | 30  | \( R_8 \) Relative moment 8                      |                           | 42  | \( Z_{44} \) Zernike moment 44                   |                           |
| 7   | \( r_c \) Number of positive and negative       |                           | 19  | \( T_{12} \) Gradient entropy                   |                           | 31  | \( R_9 \) Relative moment 9                      |                           | 43  | \( Z_{51} \) Zernike moment 51                   |                           |
|     | semicircular interrelationships                  |                           |     |                                                  |                           |     |                                                  |                           |     |                                                  |                           |
| 8   | \( T_1 \) Grayscale average                     |                           | 20  | \( T_{13} \) Hybrid entropy                     |                           | 32  | \( R_{10} \) Relative moment 10                 | Zernike moment 10          | 44  | \( Z_{52} \) Zernike moment 52                   |                           |
| 9   | \( T_2 \) Gradient average                      |                           | 21  | \( T_{14} \) Inertia                            |                           | 33  | \( Z_{11} \) Zernike moment 11                  |                           | 45  | \( Z_{53} \) Zernike moment 53                   |                           |
| 10  | \( T_3 \) Grayscale                             |                           | 22  | \( T_{15} \) Inverse moment                     |                           | 34  | \( Z_{21} \) Zernike moment 21                  |                           | 46  | \( Z_{54} \) Zernike moment 54                   |                           |
| 11  | \( T_4 \) Gradient mean square deviation        |                           | 23  | \( R_1 \) Relative moment 1                      |                           | 35  | \( Z_{22} \) Zernike moment 22                  |                           | 47  | \( Z_{55} \) Zernike moment 55                   |                           |
| 12  | \( T_5 \) Small gradient advantage              |                           | 24  | \( R_2 \) Relative moment 2                      |                           | 36  | \( Z_{31} \) Zernike moment 31                  |                           |

### 4. Optimal selection of the original feature space of local letters and typical interference signals

In the initial stage, it is not clear which feature parameters can better describe the differences between local discharge signals and typical interference signals, so extensive feature parameter extraction is done. This results in more extracted feature parameters with higher dimensionality and a large number of redundant feature parameters, which can affect the efficiency and accuracy of classification recognition. Therefore, the redundant feature parameters in the original feature parameters need to be eliminated. In
this chapter, the random forest method is used to optimize the selection of the feature parameters extracted in part 1.

In this paper, the optimally selected feature parameters are called the optimized feature parameters, and the feature space constructed from the optimized feature parameters is called the optimized feature space.

4.1 Optimization process of original feature space selection based on random forest method
In the optimization selection method of feature space, the random forest algorithm is used to measure the importance of the feature parameters and select the feature parameters with higher importance to construct the optimized feature space. The optimized selection process of the original feature space of local discharge signals and typical interference signals based on the random forest algorithm is shown in Figure 1 below.

![Figure 1: Optimal selection process of the original feature space](image)

Figure 1 Optimal selection process of the original feature space

Figure 1 can be divided into two parts, the first part can be expressed as the importance measure of the feature parameters, and the second part is the construction of the optimized feature space.

(1) Importance measure of feature parameters
To calculate the importance of a feature parameter $X$, the corresponding out-of-bag data (OOB) are first selected to calculate the out-of-bag data error for each decision tree, denoted as $e_{r1}, e_{r2}, \ldots, e_{rn}$. The out-of-bag data refers to the data that did not participate in the decision tree building when the new training sample data set was obtained by repeated sampling, and there are about 1/3. The out-of-bag data is used as the test sample data, and the prediction error rate of the random forest is called the out-of-bag data error. Next, the value of the out-of-bag sample data at the feature parameter $X$ is randomly changed, and again the out-of-bag data error is calculated, which is noted as $e_{r11}, e_{r12}, \ldots, e_{r1n}$, and finally, assuming that there are $n$ trees in the forest, the degree of importance of the characteristic parameter $X$ is denoted as $P_X$, and the computational equation is:
If the out-of-bag data error increases substantially after randomly changing the value at the feature parameter \( X \), it indicates that this feature parameter \( X \) has a strong influence on the prediction results of the sample, which in turn indicates that the importance of this feature parameter \( X \) is relatively high.

(2) Construction of optimized feature space

Constructing the optimized feature space means calculating the importance of each feature parameter based on the feature importance measure and sorting them in descending order; then selecting the top \( k \) feature parameters with high importance to construct the optimized feature space.

The \( k \) value is determined by adding 1 to 47, and the data set constructed from the optimized feature space is used as the input of the random forest classification algorithm to calculate the classification recognition accuracy for each \( k \) value. The minimum \( k \) value that corresponds to a stable classification accuracy is the final \( k \) value, which is the number of elements contained in the optimized feature space.

4.2 Optimization results of the original feature space selection for the discharge signal and typical interference signal

(1) Ranking results of feature parameters based on random forest algorithm

The importance of the characteristic parameters of typical interference signals and local discharge signals based on random forest for partial discharge experiments are shown in Fig. 2, where the top 10 characteristic parameters are negative semicircular cliffness, inverse moment, Zernike moment3, number of positive and negative semicircular interrelationships, gradient distribution inhomogeneity, gray scale distribution inhomogeneity, small gradient dominance, Zernike moment8, number of positive semicircular peaks, and Zernike moment 1.

![Figure 2 Importance of feature parameters](image)

(2) Construction of optimization feature space

According to the random forest algorithm, the importance of the feature parameters is measured and ranked, and the confirmation of the \( k \) value is derived from the way that the classification recognition accuracy of the random forest algorithm tends to be stable when \( k \) is 10, so the number of elements of the optimized feature space is 10. The optimized feature space constructed according to the ranking results is shown in Table 4 below.
Table 4 Optimized feature space

| ID | ID of feature parameters | Expressions | Name of feature parameters | Importance of feature parameters |
|----|-------------------------|-------------|----------------------------|----------------------------------|
| 1  | 4                       | $K_u$       | Negative half-periodic cliffness | 0.5908                           |
| 2  | 22                      | $T_{15}$    | inverse moment              | 0.5771                           |
| 3  | 35                      | $T_{22}$    | Zernike moment 3            | 0.5168                           |
| 4  | 7                       | $r_c$       | Positive and negative semicircular interrelationships | 0.5143                           |
| 5  | 15                      | $T_8$       | Unevenness of gradient distribution | 0.5085                           |
| 6  | 14                      | $T_7$       | Unevenness of grayscale distribution | 0.4914                           |
| 7  | 12                      | $T_5$       | Small gradient advantage    | 0.4789                           |
| 8  | 40                      | $Z_{42}$    | Zernike moment 8            | 0.4751                           |
| 9  | 5                       | $P_k^c$     | Number of positive half-cycle peaks | 0.4747                           |
| 10 | 33                      | $Z_{11}$    | Zernike moment 1            | 0.4702                           |

5. Classification and identification partial discharge signal and typical interference signal
Realizing efficient and fast identification of transformer partial discharge signal and typical interference signal can eliminate a large amount of interference data for later doing partial discharge pattern identification and improve the identification effect. The algorithms that are generally used for the identification of partial discharge signals and typical interference signals in partial discharge experiments are minimum distance classification algorithm, nearest neighbor classification algorithm, linear discriminant analysis algorithm, etc. In this paper, the linear discriminant analysis algorithm and the K-nearest neighbor algorithm are used to compare the classification recognition accuracy of these two classification methods and select the classification method with better recognition accuracy.

5.1 Introduction to the algorithm
(1) Linear Discriminant Analysis, LDA
Linear Discriminant Analysis (LDA) algorithm is one of the most classical and widely used supervised learning methods, which aims to find the optimal discriminant vector to minimize intra-class dispersion and maximize inter-class dispersion with the goal of pattern data differentiability. The linear discriminant analysis with Fisher's criterion function as the kernel function is one of the most classic algorithms, which is also called Fisher LDA (FDA) algorithm based on Fisher's discriminant criterion.

When using linear discriminant analysis algorithm to identify and classify local discharge signals and typical interference signals, firstly, the best projection matrix is required, secondly, the projected data of the training sample data set and the test data set are calculated after the best projection matrix, and the probability density function of each category is calculated according to the data obtained after the projection of the training sample data set, and then the data obtained after the projection of the test sample data are substituted into the probability density function of each category to find the probability of the test sample data belonging to each category. The probability of the test sample data belonging to each category is obtained by substituting the data obtained from the projection of the test sample data into the probability density function of each category, and finally, the category with the maximum probability is output as the prediction category by maximum likelihood estimation.

(2) K-nearest neighbor method
The K-NN algorithm mainly consists of two parts: distance calculation and the selection of K values.
Firstly, the distances \(L(x_1,x), L(x_2,x), \ldots L(x_n,x)\) are calculated for each sample in the test sample data and the training sample data set, secondly, the distances obtained are arranged in ascending order, the smaller the distance means the more similar, then the \(k\)-value is gradually increased from 1, then the optimal \(k\)-value is selected by cross-validation, and the optimal \(k\)-value is assumed to be \(K\). Finally, the category corresponding to the training sample data with the smallest \(K\) distances is selected and solved for which of the \(K\) data categories has the most occurrences, and the category is used as the prediction category for the test sample data.

5.2 Classification algorithm selection based on recognition accuracy

Based on the optimized feature space selected in Section 2 and 500 sample data, an \(11 \times 500\)-dimensional data set is constructed, where the first row is the category to which each signal belongs, and the next 10 rows are the extracted optimized feature parameters. The \(11 \times 100\) dimensions are randomly extracted as the sample test set, and the remaining \(11 \times 400\) dimensions are used as the sample training set, and the linear discriminant analysis algorithm and K-nearest neighbor algorithm are applied to classify and identify the signals respectively. The above process was repeated 10 times, and the recognition accuracy of the two algorithms is listed in Table 5. Because the sample test set and the sample training set are randomized, the sample test set and the sample training set are different for the 10 times of classification and recognition process.

Define the recognition accuracy \(P\) as:

\[
P = \frac{S_T}{S_{All}}
\]

where \(S_T\) is the number of correct prediction categories and \(S_{All}\) is the total number of samples in the test set.

| Order of recognition | LDA   | K-NN  | Order of recognition | LDA   | K-NN  |
|----------------------|-------|-------|----------------------|-------|-------|
| 1st                  | 0.93  | 0.96  | 6th                  | 0.93  | 0.93  |
| 2nd                  | 0.86  | 0.88  | 7th                  | 0.90  | 0.93  |
| 3rd                  | 0.83  | 1.00  | 8th                  | 0.86  | 0.96  |
| 4th                  | 0.85  | 0.90  | 9th                  | 0.93  | 0.93  |
| 5th                  | 0.94  | 0.93  | 10th                 | 0.92  | 0.83  |

Shown as in Table 5, it can be calculated that the average recognition accuracy of linear discriminant analysis algorithm (LDA) and K-nearest collar algorithm (K-NN) for these 10 times are 0.895 and 0.925, respectively, so the K-nearest collar algorithm is chosen as the final classification recognition algorithm.

6. Conclusion

In this paper, the typical interference signal mining and identification method research of transformer partial discharge test is studied, and the main work and results are as follows.

(1) In the extraction of characteristic parameters of local discharge signals and typical interference signals, this paper adopts pulse current detection method for 10kV test transformers in the laboratory to collect seven kinds of local discharge signals including A-phase oil gap discharge, A-phase tip discharge, A-phase along-face discharge, suspension discharge, grounding interference, artificially created imitation transmission line periodic discharge interference and field noise interference of power transformers. 500 sets of partial discharge signal and typical interference signal data are used to construct a library of partial discharge signal and typical interference signal in transformer partial discharge experiments. Forty-seven feature parameters including statistics, texture and shape were extracted from them. The 500 47-dimensional original feature space is constructed based on the extracted feature parameters, which provides the data basis for the subsequent optimization of feature space selection and signal classification identification.
(2) In the feature space optimization selection, the random forest algorithm is used to rank the importance of the extracted feature parameters of partial discharge signals and typical interference signals in transformer partial discharge experiments, and the top 10 feature parameters of importance are selected to construct the optimized feature space, which reduces the data redundancy of the feature parameters of partial discharge signals and typical interference signals.

(3) In the classification and identification of local discharge signal and typical interference signal, this paper uses multi-class linear discriminant analysis algorithm and K-nearest neighbor algorithm to classify and identify the sample data, and the accurate recognition rate of these two classification and identification algorithms are compared and analyzed, and K-nearest neighbor algorithm is chosen as the final classification and identification algorithm.

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