Infrared Evaluation Classification Method for Deteriorated Insulator Based on Bayesian Algorithm

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Abstract. The insulation state detection of transmission line insulators in power systems is essential to ensure the reliability of transmission power supply. Aiming at the low accuracy of the infrared diagnostic fault diagnosis method for porcelain insulators in transmission lines, this paper proposes a classification method based on Bayesian algorithm for the classification of infrared map degradation degree of insulators. Bayesian algorithm is used to mine the correspondence between the characteristic parameters of the insulator infrared inspection map and the insulator state represented by the map, so as to improve the Bayesian network structure and finally classify the map. The results show that the method can effectively classify the operating state of insulators. The accuracy of the power insulator state classification model based on Bayesian algorithm reaches 94.2%. A new method of intelligent detection and diagnosis for evaluating the deterioration of insulators is proposed. This method has the advantage of high stability and accuracy.

1. Introduction

Insulator as an important part of the transmission lines, maintaining its security and stable operation is essential. Insulators are widely used in transmission lines and substations, and most of them are exposed to the outdoors. The conventional methods for detecting insulators include spark fork method, ball discharge method, electric field measurement method, and ultraviolet infrared ultrasonic detection. The spark fork method is a traditional detection method. This method requires a lot of manpower and material resources. It is susceptible to electromagnetic interference because the detection method is backward. Even if it is carried out once a year, it's still impossible to eliminate hidden dangers, resulting in missed inspection or false inspection. Infrared temperature measurement technology has the characteristics of no contact, and meets the needs of power maintenance. Up to now, infrared temperature measurement technology has been applied to power detection in many countries around the world, and has played a positive role. Literature [1] proved the feasibility and accuracy of infrared device detection of insulator state by studying the infrared spectrum of low-zero insulators. Document [2] studied the influence of the insulator under different conditions for the infrared detector. Document [3] Insulator strings of different defect types are proposed, and their heating characteristics are different. It is necessary to pay special attention when performing infrared detection. The literature [4] proposes that the infrared detection device can perform effective detection when the emissivity of the device to be tested needs to meet certain conditions. The experimental method used in this paper is
infrared detection. Its basic principle is to detect the deterioration of the insulator in time by monitoring its operation status by infrared detection. Infrared detection method allows long-distance, non-contact measurement of temperature and online monitoring of measured objects, so it is widely applied to power system fault diagnosis.

Bayes' theorem has a lot to do in many computer applications, such as machine learning, recommendation systems, image recognition, and game theory. Bayesian classification method is to subjectively determine the prior probability for some uncertain events under incomplete information, and then modify the prior probability by constructing an effective Bayesian network to achieve the expected value. When the classification decision is made, the corrected probability and the expected value are used to perform effective classification. In literature, a classification method based on Bayesian algorithm for weather phenomena is proposed. Firstly, the traditional features of outdoor images are extracted, and an effective Bayesian network is constructed to learn the images, which is effective for weather images. In literature, the Bayesian algorithm is applied to the medical field. The identifiable particles in the urine sediment image are labeled and segmented to obtain the traditional features of the image. Then the Bayesian network is constructed to classify and identify the image. At present, the development of Bayesian algorithm in the field of image processing technology is relatively mature, but there are few attempts in the field of power transmission and infrared imaging detection.

This paper attempts to combine Bayesian algorithm with infrared detection of deteriorated insulators, and proposes an intelligent classification method based on Bayesian algorithm for infrared map of insulators. The infrared spectrum sample library is obtained by a large number of insulator infrared experiments. The Bayesian algorithm is used to train the insulator infrared spectrum and the traditional features of the monolithic porcelain insulator state to explore the correspondence between the characteristic parameters and the insulator state. Then we modify the model prediction parameters to complete the classification and identification of the insulator.

2. Experimental Method

Since the Bayesian algorithm requires a large number of positive and negative samples of defective insulators, the positive samples are normal insulators and the negative samples are defective insulators. It is necessary to build a sample library with a large number of defects. The positive and negative samples of the Bayesian algorithm determine the convergence and recognition ability of the Bayesian algorithm. Therefore, this chapter will focus on the generation and generation of training sample libraries for Bayesian algorithms.

2.1. Porcelain deteriorated insulator detection principle

Infrared thermal imaging is a non-contact detection method. The infrared imaging device operates through an infrared detector and an optical imaging objective to receive a target infrared radiation energy distribution pattern that is reflected to the infrared detector optical element, then converts the infrared radiation from the detector into an electrical signal and amplifies the electrical signal and conversion. In order to find the temperature distribution on the thermal image, it is necessary to realize the surface temperature measurement function of the object. The schematic diagram of the infrared camera structure is shown in Figure 1:
The normal insulator has good insulation performance, and the leakage current mainly exists in the fouling layer on the surface of the insulator. There is a large amount of pollution of various pollutants and atmospheric humidity on the surface of ordinary insulators, so the leakage current will increase to some extent. Deteriorated insulators typically exhibit porcelain sheets with features such as cracks or surface burns, resulting in reduced insulation properties. Deterioration of the insulator, as well as insulation defects, creates a new leakage current path that causes the flow of the tiles to be exposed to the defect flow of the surface, the final characterization of the porcelain surface being complex. According to its different heating characteristics, infrared detection of insulator failure can be achieved.

2.2. Degraded insulator power generation detection test method

In order to obtain the typical representative of the infrared image degradation of the insulator, the following experiment was carried out: three umbrella-shaped porcelain deteriorated insulators were replaced for the purpose of testing; the insulator defect resistance was 7.5 MΩ, 19 MΩ and 150 MΩ, and the infrared image was taken using the Fluke Ti55TF and the emissivity is 0.9. The experimental platform is shown in Figure 2.

For suspended insulator strings, the insulators are numbered according to the distance from the ground. From top to bottom, #1 is the ground terminal and #7 is the high voltage terminal. We selected different contamination levels #2, #5 and #7 position where the temperature is 7 ℃~25 ℃ and relative humidity is 20% to 95%, deteriorated for the same position, sequentially three different resistance deterioration insulator instead of the normal film, the remaining insulators are normal insulators (the megohmmeter measures its resistance is greater than 1GΩ). After the smearing is completed, the insulator is suspended and allowed to stand after being cooled to room temperature. The follow were the basic steps of the experiment, first we should continuously apply a power frequency voltage of 2 hours to the high voltage end of the insulator. Among this the voltage amplitude was 65.9 kV, and the state of the insulator was photographed every 0.5 hours. End of the experiment, the insulator allowed to cool to ambient temperature and then insert the low-resistance
insulators test. Parametric studies were conducted on the degree of contamination, temperature, humidity, projection angle, deterioration of insulators at different locations, and degree of degradation.

2.3. Production of training samples

718 infrared images were obtained in the infrared insulator strings detection phase. By cutting the insulator string images, 540 negative insulator infrared images (negative samples) and 1236 normal insulator images (positive samples) were obtained as the images to be processed. Due to the large gap between positive and negative samples in the model, it is easy to cause over-fitting in the training process. A new image sample is generated by rotating the negative sample image once. Finally, 2316 positive and negative insulator samples are formed. The ratio of training set to test set is 4:1. First, 1080 of 1236 normal insulator samples are selected as the final positive sample bank, 864 samples are selected as training set in positive sample bank and 216 samples are selected as test set respectively. The training set is used to train Bayesian algorithm structure and the test set is used to validate the model. Figure 3 shows some typical insulator training samples. It can be noted that the infrared radiation emitted by deteriorated insulators is characterized by that the steel cap is heated uniformly and the porcelain is not heated, while in normal insulators, the heat mainly concentrates on the part at the junction of steel and porcelain, or the whole is not heated.

![Partial Sample Bank of Deteriorated Insulator](image1)
![Partial Sample Bank of Normal Insulator](image2)

Figure.3 Schematic diagram of typical insulators training sample library

3. The Structure and Principle of Bayesian Model

3.1. The principle of the naive Bayesian model

Bayesian algorithm is a method to solve statistical problems, which is based on the development of Bayes' theorem. Therefore, its core is Bayes' theorem. Bayes' theorem is a method of finding probability when other probabilities are known. Its core is Bayesian formula, which is expressed as follow:

$$P(\omega | x) = \frac{P(x | \omega) P(\omega)}{P(x)}$$ (1)

The core of the Bayesian algorithm is to continuously revise on the basis of prior probability to obtain a reliable posterior probability. $\omega \in \mathcal{W}$ (W candidate set of assumptions) is the set of the hypothetical event $X$ that is most likely to occur when determining, this hypothesis is also known as the maximal posterior hypothesis, abbreviated as $\omega_{map}$. Its formula is expressed as follows:

$$\omega_{map} = \arg \max \ P(\omega | x_m)$$ (2)

Apply the Bayesian formula to get the formula (3):
\[ \omega_{\text{map}} = \arg \max \frac{P(x_m | \omega_n) P(\omega_n)}{P(x_m)} \]  

Because \( P(x_m) \) is not dependent on \( \omega_n \), remove it to get the formula (4):

\[ \omega_{\text{map}} = \arg \max P(x_m | \omega_n) P(\omega_n) \]  

### 3.2. Establishment of Bayesian model

In order to achieve effective insulator infrared image classification and recognition, it is necessary to combine the Bayesian model with the actual insulator image problem. When identifying a given image, firstly we need to extract the features of the image to obtain some basic feature quantities. Through the relationship between the image and the extracted feature quantities, the Bayesian network is optimized and perfected. Then we can get the posterior probability and finally complete the identification process. In this paper, using the Bayesian algorithm in machine learning, it is not necessary to manually extract the image features, only the image is subjected to dimensionality reduction processing and then input into the Bayesian network algorithm, and the computer is adjusted by prior parameters such as prior probability. Learn automatically to get the results we need. The flow chart of Bayesian algorithm is shown in Figure 4.

![Bayesian Algorithm Flow Chart](image)

Figure 4. Bayesian algorithm flow chart

In this paper, the infrared image recognition of insulators is combined with the naive Bayesian classifier structure to construct a least risk Bayesian network [11] to classify images. The most commonly used a posteriori hypothesis for image classification and recognition problems is the MAP hypothesis. This paper applies the MAP hypothesis classification. The formula is expressed as follows:

\[ \omega(x)_{\text{map}} = \arg \max P(x_1, x_2, x_3, x_4, \cdots | \omega_n) P(\omega_n) \]  

In the above equation, two probability values are estimated in the case where the total set is determined. Which for the estimate \( P(\omega_n) \) is relatively simple. In this paper, in order to obtain a more reasonable probability value estimate, a naive Bayesian network classifier is used. The assumption of this structure is that the given actual attribute values of the classification are independent of each other. When \( x \) is given, under the premise, the joint probability of the two attribute values observed is equal to the product of the probability of their respective individual attribute values. The mathematical expression is as follows:
\[ P(x_1, x_2, x_3, \cdots, x_n \mid \omega_k) = \prod_{j=1}^{m} P(x_j \mid \omega_k) \]  

Classification Equation (7) into which the formula (5) obtained naive Bayes classifier [12]:

\[ \omega(x)_{\text{map}} = \arg \max P(\omega_k) \prod_{j=1}^{m} P(x_j \mid \omega_k) \] 

By calculating, the following formulas can be obtained:

\[ P(\omega_n) = \frac{\sum_{i=1}^{n} \delta(\omega_i, \omega_n)}{n} \] \hspace{1cm} (8)

\[ P(x_j \mid \omega_n) = \frac{\sum_{i=1}^{n} \delta(x_i, x_j) \delta(\omega_i, \omega_n)}{\sum_{i=1}^{n} \delta(\omega_i, \omega_n)} \] \hspace{1cm} (9)

In practical problems, the above method of calculating the frequency to obtain the probability is acceptable in most cases. However, when an attribute value with a frequency close to zero occurs, the frequency value obtained by combining with the attribute is caused to be low or even close to zero. More serious cases, when the property value of the frequency of occurrence of zero, its frequency value obtained by the combination calculation is zero, in order to avoid the above problems, is often used to smooth the estimated Laplacian probability obtained above to thus the mathematical expression (7) and (8) to be revised, to give formula (10) and (11):

\[ P(\omega_n) = \frac{\sum_{i=1}^{n} \delta(\omega_i, \omega_n) + 1}{n + n_{\omega}} \] \hspace{1cm} (10)

\[ P(x_j \mid \omega_n) = \frac{\sum_{i=1}^{n} \delta(x_i, x_j) \delta(\omega_i, \omega_n) + 1}{\sum_{i=1}^{n} \delta(\omega_i, \omega_n) + n_j} \] \hspace{1cm} (11)

The minimum risk Bayesian classifier is designed. After assigning the prior probability, the training set is used to optimize the Bayesian network [13] to obtain better classification effect. The design decision function is used to judge the test set. got the answer.

4. The Experimental Results and Analysis

4.1. Establishment of Bayesian model

In the data processing process, the infrared spectrum is grayscaled firstly, and the features of the spectrum are extracted. The principal component analysis method is used to convert the characteristics of the infrared spectrum into matrix of 1 × 64. The Bayesian network is designed, and the training set is used to optimize the structure of the network, and the classification result is obtained by changing the value of the prior probability.

The prior probability of five positive samples is selected to determine the trend of the recognition accuracy curve. Figure 5 is a schematic diagram of the recognition accuracy and prior probability. From the figure, the prior probability of the positive sample is from 0.5-0.7. In the range, the recognition accuracy does not always show an upward trend. When the posterior probability of change in the range of 0.5-0.6, recognition accuracy increases with the increase of the positive probability. When the posterior probability of change in the range of 0.6-0.7, recognition accuracy increases as the sample timing prior probability decreases, so when a positive sample prior probability of 0.6, the recognition accuracy in the vicinity of the highest value. After that, we continuously search for the
positive probability of the positive sample in the range of 0.5-0.7. Finally, we can get the average recognition accuracy of 94.2%, and the positive probability of the positive sample is 0.63.

![Figure 5: A priori probability and accuracy chart](image)

**Figure 5** A priori probability and accuracy chart

Figure 6 shows the relationship between the number of training and the loss rate. Figure 6 (a) shows the relationship between the loss rate of 300 training times and the number of training times when the prior probability is 0.6. Figure 6 (b) shows the relationship between the loss rate of 300 training times and the number of training times when the prior probability is 0.5. It can be concluded from the figure that when the prior probability is determined, the training loss rate does not fluctuate greatly with the change of the training times. When the prior probability is different, the average value of the loss rate is obviously different, so the training loss rate and the prior test can be obtained. The relationship between the probabilities is relatively large, and when the prior probability is determined, the loss rate also changes to some extent with the change of the training times, but the change is not obvious.

![Figure 6: Training times and loss rate](image)

(a) The relationship between training times and loss rates when the a priori probability 0.6

(b) The relationship between training times and loss rates when the a priori probability 0.5

**Figure 6** Training times and loss rate
4.2. Bayesian algorithm compared with BP neural network

As shown in Figure.7, the Bayesian algorithm [15] and the BP neural network algorithm [14,16] change with the number of training samples, and the accuracy of both types of algorithms increases with the increase of the training data set. Among them, the accuracy of the Bayesian algorithm in the early stage of training is low, because the feature sample library in the training process is insufficient at this time, so the accuracy rate shows a low level. As the sample library expands, the accuracy rate [23] also rises rapidly. When the number of training samples is expanded to around 450, the accuracy rate is maintained at a high level. The accuracy of BP neural network model, although with a higher starting point, but lifting slowly and accompanying by a large float, is difficult to stabilize at a higher level. Therefore, the Bayesian algorithm has better model stability.

Figure.7 The accuracy rate varies with the number of training samples under different algorithms.

Under the 560 training samples, the performance comparison between Bayesian algorithm [17] and BP neural network algorithm for evaluating the degree of insulator deterioration is shown in Table 1. In the table, training on behalf of the accuracy of the algorithm in the optimal parameters, the training time [18] represents the time required for each parameter optimization and model construction, and the test time is the classification time. As can be seen from the table, when the training samples reach a certain number, the Bayesian algorithm can learn by training samples to achieve higher accuracy.

Tab.1 Performance comparison between Bias algorithm and BP neural network algorithm

| Diagnosis method       | Training accuracy (%) | Training Time(s) | Test Time(s) |
|------------------------|-----------------------|------------------|--------------|
| Bayesian network       | 94.2                  | 120.0572         | 0.0010       |
| Bp network             | 93.6                  | 630.1204         | 0.0025       |

5. Conclusion

The infrared thermal imager is used to obtain infrared spectra of insulators with different degrees of deterioration and different environments, then a sample database is established. The classification and evaluation of the infrared map [19] of porcelain insulators by Bayesian algorithm is completed, at the same time the classification and evaluation of the high accuracy and high stability of the infrared spectrum of deteriorated insulators are realized.

The Bayesian algorithm used in this paper is compared with the BP neural network [20] model which is currently used more. The research shows that the Bayesian algorithm used in this paper has the advantages of higher accuracy and shorter training time.

The method proposed in this paper is combined with the infrared thermal imager for handheld and online monitoring [21], which can better monitor and diagnose the operating state of the insulator. The infrared spectrum is collected on site [22], and the Bayesian algorithm is used to classify to obtain the
insulator state [21]. At the same time, the deteriorated insulator monitoring and warning system [24] is realized, which has high engineering value and significance.

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