A Novel Foreign Object Detection Algorithm Based on GMM and K-Means for Power Transmission Line Inspection

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Abstract. The detection of foreign objects on transmission lines is an important research content of intelligent inspection in smart grid. The foreign objects on the transmission line tower will cause adverse effects on the transmission line and other equipment, and even endanger the safe operation of the power grid. In order to accurately identify foreign objects on power transmission lines, this paper proposes an unsupervised foreign object detection algorithm based on GMM (Gaussian Mixture Model) and k-means. Firstly, K-means is used for clustering, and then GMM is used for clustering. Finally, the foreign objects on the power transmission line are identified according to the clustering results. Experimental results show that the proposed algorithm has a high recognition rate. In addition, the more samples, the higher the recognition accuracy.

1. Introduction

The detection of foreign objects on power transmission lines belongs to the field of image classification and target detection, which is the main research direction in the field of computer vision and image processing [1, 2]. In particular, the prevention of bird damage has become a worldwide issue. Substation and transmission system have made great efforts to this issue, and paid a lot of human, material and financial resources [3, 4].

At the same time, many scholars have studied the detection algorithm of foreign objects in power transmission lines [1, 2]. These detection algorithms mainly include infrared, image processing and other related technologies. At present, image processing technology is the best technology to detect foreign objects in power transmission lines. In addition, machine learning can improve the accuracy of foreign object detection. Reference [5] proposed to use the special texture, color and shape of the bird’s nest area to distinguish whether there is a bird’s nest in the image. In [6], the hog features of bird’s nest in the image were extracted and classified by SVM. However, the scheme was not suitable for nest detection in complex environment. Reference [7] proposed its own solution to the problem of bird’s nest detection of transmission lines. Firstly, the image of bird’s nest was preprocessed. Then, the nest feature image was extracted. Finally, machine learning algorithm was used for recognition. In [8], a solution was put forward for the detection of tower nests on both sides of the rail. After image preprocessing such as binarization and morphology, the main and branch parts of the image were extracted. After that, the suspension point detection was used to extract the nest branches. Finally, SVM classifier was used to classify and recognize the branch information.
The rest of this paper is organized as follows. Machine learning algorithms are introduced in Section 2. In Section 3, an unsupervised foreign object detection algorithm based on GMM and K-Means is proposed. In Section 4, the performance is discussed. Finally, conclusion is given in Sections 5.

2. Machine learning algorithm

2.1. K-Means algorithm
K-Means is the simplest clustering algorithm and is widely used in data classification. Firstly, \( k \) objects are randomly selected as the average value or the center of a cluster. The Euclidean distance from \( k \) values to cluster center is calculated. According to the distance, the points close to the corresponding clustering center are divided into this category. Then, the new clustering center is calculated again. This cycle continues until the clustering criterion function converges. The criterion function can be expressed in two forms: the global error function and the last two changes of central error.

For data set \( X \), which contains \( n \) data objects, the initialization clustering center is \( k \), and the algorithm flow is as follows:

Step 1: Randomly select \( k \) data from \( X \) as the initial clustering center;

Step 2: According to the center value of each cluster, calculate the distance from the rest \( n-k \) data to the cluster center. According to the distance, divide the points closest to the cluster center into this category;

Step 3: Update the new cluster center;

Step 4: Calculate criterion function;

Step 5: If the criterion function meets certain threshold conditions, the operation will exit. Otherwise, return to the second step for cycle calculation.

2.2. GMM
GMM is a mixture of multiple Gaussian distributions. The sample set \( X = \{X_1, X_2, \cdots, X_n\} \) contains \( n \) data, each of which is \( d \)-Dimension. Suppose that this group of data is composed of \( M \) single Gaussian model, but which single Gaussian model does a specific data \( x \) belong to, and the proportion \( \alpha \) accounts for in the Gaussian mixture model is not clear. At this time, if all the points are mixed together, a distribution formed will be a mixture Gaussian distribution. The probability density function of all these data can be expressed as:

\[
p(x) = \sum_{j=1}^{M} \alpha_j N_j(x; \mu_j, \Sigma_j), \quad \sum_{j=1}^{M} \alpha_j = 1
\]  

where \( N_j(x; \mu_j, \Sigma_j) = \frac{1}{\sqrt{(2\pi)^d |\Sigma_j|}} \exp \left[ -\frac{1}{2} (x - \mu_j)^T \Sigma_j^{-1} (x - \mu_j) \right] \) is the probability density function of the \( j \)-th single Gaussian model. Suppose that \( \varphi_j = (\alpha_j, \mu_j, \Sigma_j) \). GMM consists of \( M \) single Gaussian models, then all parameters \( \Phi = (\varphi_1, \varphi_2, \cdots, \varphi_M) \) of the GMM are estimated by sample set \( X \). The probability formula of sample \( X \) is as follows:

\[
p(x | \Phi) = \prod_{i=1}^{N} \sum_{j=1}^{M} \alpha_j N_j(x_i; \mu_j, \Sigma_j)
\]  

3. Unsupervised foreign object detection algorithm based on GMM and K-Means
In order to detect the foreign object on the transmission line, this paper proposes an unsupervised foreign matter detection algorithm which is based on GMM and K-Means.
3.1. The overall flow of the proposed detection algorithm

HOSHLS represents a sub-process. A model and B model represent two sub-processes. The overall flow of the proposed detection algorithm is as follows.

Step 1: read in an original picture $X$;
Step 2: pre-process $X$, that is, gray-scale processing and unifying the image size as $M \times N$, and record it as $P$;
Step 3: set the size $m \times n$ of the sliding window, mark the window as $p$, and the sliding step $d$. By sliding on the gray-scale image $P$ and saving the gray-scale image of each sliding window, $num$ small-scale images $p$ are obtained;
Step 4: enter the circulatory body. Enter HOSHLS sub-process and obtain the characteristic data, length histogram (12 dimensions), gray histogram (18 dimensions) and non-normalized data information of the small graphs of this graph. Therefore, a total of $num$ 60 dimensions of data are obtained.
Step 5: set $i$ from 0 to judge whether it is less than $num$. If $i$ is less than $num$, perform step 6. Otherwise, perform step 10;
Step 6: enter two GMMs;
Case 1: bring the data into the model composed of class A samples, and get the data $X_A$ after three dimensionality reduction. Finally, the probability $P_{xa}$ of unknown samples belonging to a model is obtained;
Case 2: bring the data into the model composed of class B samples, and get the data $X_B$ after three dimensionality reduction. Finally, the probability $P_{xb}$ of unknown samples belonging to a model is obtained;
Step 7: judge the probability of $P_{xa}$ and $P_{xb}$;
Step8: if $P_{xa} > P_{xb}$ is not satisfied, the output “belongs to class B”, and the cycle ends;
Step 9: otherwise, perform the operation of adding 1 to $i$, and judge whether step 5 is satisfied;
Step 10: output the judgment result. This sample is classified as class A, and the cycle ends.

The execution process of HOSHLS is as follows:
Step 1: input unknown $num$ small graphs;
Step 2: first determine whether $i \leq num$. If $i \leq num$, perform step 3. If not, skip to step 7;
Step 3: preprocess the small graph $p$. After binary processing, morphological operation is used to get $openf$. at this time, $openf$ is mostly the tower frame and the main area of foreign object;
Step4: subtraction operation. Compared with the pixels of $f$ and $openf$, the same position is recorded as 1 (white pixels), and the different positions are recorded as 0 (black pixels). The result is the original drawing minus the operation calculation, which is generally the thin branch or high-voltage transmission line or the edge contour part of the insulating piece, and it is recorded as $subf$;
Step 5: reverse $subf$, PPHT (Progressive Probability Hough Transform) test the straight line, and record the starting point and end point coordinates of the straight line;
Step 6: use the coordinates recorded above to calculate the branch length, and draw the normalized line length distribution histogram $HLS$ and the non-normalized length distribution histogram $HLS\_sum$, both of which are 12 dimensions. Similarly, using the coordinates recorded above to calculate the branch slope, and draw the normalized branch direction histogram $HOS$ and the non-normalized direction histogram $HOS\_sum$, both of which are 18 dimensions. Unify the above data to $HOSHLS\_sum = [HLS, HOS, HLS\_sum, HOS\_sum]$, i.e. 60 dimensional data;
Step 7: end this cycle, and finally get the data information of 60 dimensions in row $num$.
The procedure of A and B models are as follows:
Step 1: take 150 samples with nests, but do not label them. 75 images with and without nests are selected respectively, and their features are extracted by the process of $HOSHLS\_sum$. 
Step 2: cluster analysis with K-Means and generate labeled samples;
Step 3: if the label is 1, go to step 4. If the label is 2, perform step 5;
Step 4: if the label is 1, it will be judged as class A sample, totaling $m$ samples. PCA (principal components analysis) is used to reduce the dimension, and the principal component with the largest contribution rate in 60 dimensions is selected to retain, and finally it is reduced to 8 dimensions, which also ensures the contribution rate to maintain more than 90%. After dimensionality reduction, $m \times 8$ matrix is formed, which is brought into GMM to get the return value, i.e. GMM model A formed by $m$ samples and reduced dimension matrix $ncoef1Y$, $ncoef2Y$ and $ncoef3Y$;
Step 5: if the label is 2, it is determined as class B sample, $n$ samples in total. Using PCA to reduce dimensions, the $n \times 8$ matrix formed after dimension reduction is brought into GMM mixed Gaussian model, and GMM model B formed by $n$ samples and reduced dimension matrix $coef1N$, $coef2N$ and $coef3N$ are returned.

3.2. Image preprocessing

3.2.1. Binarization
Because the original image is not suitable for feature extraction directly, it needs to be binarized. The image after binarization is shown in Figure 1.

![Binarization](image)

(1) The original image  (2) Binarization image

Figure 1. Binarization

3.2.2. Morphological open operation
Finally, the tower can be removed by morphological operation. As shown in Figure 2, the twigs of the nest will be removed by morphological opening operation. Therefore, the image after the original image and morphological operation is used for subtraction, so that the remaining part of the image is the twig of bird's nest and the transmission line part

![Open operation](image)

(1) Open operation  (2) Subtraction effect

Figure 2. The example of morphological open operation
3.3. Image feature extraction

3.3.1. Progressive probability hough transform (PPHT)
In this paper, PPHT is used to detect foreign bodies. The input image must be the binary image when the line is detected by PPHT. After the morphological open operation, the line is detected directly by PPHT, and the starting point, end point coordinates and the number of lines in each image are saved.

3.3.2. Design of sliding window
The size of sliding window directly affects the effect of feature extraction. Too large or too small will affect the integrity of the bird's nest area in the image. Here, the sliding window size is set to 250*300, the sliding step is 150, and the original image is processed to 700*500. Figure 3 is the saved sliding window image. From the sliding window, 12 small graphs can be obtained, as shown in Figure 4.

![Figure 3. Saved sliding window image](image1)

![Figure 4. Batch processing of PPHT](image2)

3.3.3. Data normalization
From the above, we can get the branch information obtained by PPHT in each small graph, that is, the coordinates of the starting point \((x_1, y_1)\) and the ending point \((x_2, y_2)\). Furthermore, the length \(l\) and angle \(\theta\) of branches can be counted.

\[ l = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \quad (3) \]

\[ \theta = \arctan \frac{y_1 - y_2}{x_1 - x_2} \quad (4) \]

3.3.4. Feature dimension reduction
In this paper, PCA dimension reduction technology is used. In the selection of dimensionality reduction, the project uses Parto graph to draw. Then, we can get the degree of the original space which can be represented by the reduced dimension space, and finally determine the choice of the reduced dimension. That is to say, the dimension with contribution rate of more than 90% can be selected as dimension selection for dimension reduction, and the latter dimension will not be considered.

4. Performance analysis
Bird’s nest is a common dangerous object in power transmission line. This paper takes bird’s nest as an experiment. The UAV camera collects data to determine whether there is a nest on the power transmission line. Some video images of the experiment are shown in Figure 5. The experimental sample data of K-Means is shown in Table 1. Statistical results of GMM model is shown in Table 2. In this experiment, firstly, K-Means algorithm performs a clustering. Then, the clustering results are used as the input of GMM. Finally, the clustering result of GMM is the recognition result. In this experiment, class A is the image sample without nest, class B is the image sample with nest.
In Table 2, a total of 50 test samples are counted. For the convenience of statistics, class A samples are equal to class B samples, all of which are 25 test sets.

From Table 2, when the number of samples is 80, the overall accuracy of classification is 0.68. When the number of samples is 150, the overall accuracy of classification is 0.78. It can be seen that the increase of the number of samples will improve the overall accuracy of classification. At the same time, it can be seen that the algorithm proposed in this paper has a good classification effect, so as to correctly identify foreign objects in power transmission lines.

Table 1. Sample data of K-Means.

| Total number of samples | Dimensions of samples | Number of A or B samples |
|------------------------|----------------------|--------------------------|
| 80                     | 30                   | 40                       |
| 150                    | 30                   | 75                       |
| 80                     | 60                   | 40                       |
| 150                    | 60                   | 75                       |

Table 2. Statistical results of GMM model.

| Number of samples for k-means clustering | Clustering accuracy | GMM test [A]=[B] 50 test samples | Accuracy for A | Accuracy for B | Overall accuracy |
|------------------------------------------|---------------------|----------------------------------|----------------|----------------|------------------|
| 80 (|A|=|B|)                                  | A:40/40             | 18/25=0.72                      | 16/25=0.64     | 0.68            |
|                                           | B:35/40             |                                 |                |                |                  |
| 150 (|A|=|B|)                                | A:72/75             | 20/25=0.80                      | 19/25=0.76     | 0.78            |
|                                           | B:70/75             |                                 |                |                |                  |

5. Conclusion
In this paper, an unsupervised foreign object detection algorithm based on K-Means and GMM is proposed and verified on the first kind of image. In this paper, bird’s nest is used as a foreign object. For the first kind of image, the preprocessing is carried out firstly, that is to remove the interference and leave the nest branches. Then, the line is extracted by the Progressive Hough transform. Aiming at the specific goal of bird’s nest, the length histogram and direction histogram of bird’s nest branches are designed. Finally, the purpose of unsupervised bird’s nest recognition is realized by PCA. Experimental results show that the proposed algorithm can achieve good recognition effect.

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