An improved HOG-SVM recognition algorithm of power equipment with infrared images

Yucheng Qian\textsuperscript{1}, Chao Zhen\textsuperscript{1}, Mengjun Wang\textsuperscript{*}, Sheng Han\textsuperscript{2}, Jiaxuan Li\textsuperscript{2},
Changwei Zhao\textsuperscript{1} and Taiyun Zhu\textsuperscript{1}

\textsuperscript{1} State Grid Anhui Electric Power Co. Electric Power Research Institute, Hefei, Anhui, 230601, China
\textsuperscript{2} State Key Laboratory of Power Transmission Equipment & System Security and New Technology, School of Electrical Engineering, Chongqing University, Chongqing, 400044, China
\textsuperscript{*}Corresponding author’s e-mail: mengjun0602@cqu.edu.cn

Abstract. Infrared image recognition of power equipment is a necessary prerequisite and a key step to using the infrared image for equipment defect detection, while one of the difficulties is to solve the problem of low accuracy of equipment recognition, which is caused by the difficulty of extracting equipment feature quantity caused by different rotation Angle and scale of equipment image. In this paper, 12 kinds of common power equipment, such as lightning arresters, current transformers, voltage transformers, circuit breakers, and insulators, are taken as the research objects. An improved HOG-SVM algorithm for infrared image recognition of power equipment with rotation invariance is proposed. Experimental results show that the proposed method can effectively compensate for the shortcoming of the HOG algorithm without rotation invariance, and the average recognition accuracy of 12 types of equipment reaches 92.14\%, which significantly improves the recognition accuracy of infrared images of power equipment, and verifies the effectiveness and practicability of the proposed algorithm.

1. Introduction

Infrared thermal imaging technology has become an advanced detection method widely used in all walks of life.[1-2] Nowadays, the application of infrared image for defect detection of power equipment has been extensive.[3-5] And it is necessary to identify power equipment based on infrared images.

A target recognition algorithm is generally divided into two stages: image feature extraction and target recognition. In the field of image feature extraction, researchers have proposed a large number of image feature descriptors in recent years. Lowe\textsuperscript{[6]} proposed SIFT (Scale-invariant Feature Transform) feature, which has a relatively stable effect. However, its computational complexity is high. Bay\textsuperscript{[7]} et al proposed SUFT (Speeded Up Robust Features), which uses integral graph and Hessian matrix to realize faster calculation. But the computational complexity has increased. Then, Dalal\textsuperscript{[8]} proposed the HOG (Histogram of Oriented Gradient) for pedestrian detection on CVPR, which has better robustness and achieved a very good detection effect. Meanwhile, the classification idea of HOG combined with SVM (Support Vector Machine) has been widely used.[9-11] However, without rotation invariance of HOG, when the target object rotation range, this descriptor detection effectiveness is greatly reduced. In this paper, according to the limitations of HOG and the
characteristics of common power equipment, we proposed a method of HOG extraction with rotation invariance.

2. Improved HOG algorithm

2.1. Equipment image feature analysis
The main purpose of this paper is to recognize the power equipment. The appearance of equipment with different voltage levels is quite different, this paper will subdivide the power equipment according to the voltage level, and the final data set is a total of 12 kinds of power equipment. Infrared images of power equipment are all captured by FLIR T640 equipment, and the image resolution is 640*480. Sample examples of 12 types of equipment are shown in Figure 1.

Figure 1. Samples of electrical equipment.

The main idea of the descriptor is that: dividing an image into several small cell, and then calculating the gradient information (gradient weight and gradient phase) of each pixel in each cell. To improve performance, several cell are formed into a block. Then, the gradient of each cell is normalized in these intervals to obtain the HOG of the whole image. The appearance and shape of power equipment can be well described by HOG. This descriptor extraction schematic diagram is shown in the Figure 2.

Figure 2. HOG descriptor extraction schematic diagram.

2.2. HOG algorithm improvement
In order to solve the problem that the HOG does not have rotation invariance. Chen Derong et al. Experiment has proved that HOG still has descriptive invariance in the case of small-angle difference. By observing Figure 1, common power equipment images have an obvious main
direction, as long as the main direction angle of the device in the infrared image is determined, and the HOG phase is unified to one direction, the HOG change due to image rotation can be reduced. This paper designed a rotation-invariant HOG feature based on electric power equipment according to the characteristics, as shown in Figure 3.

Figure 3. Improved HOG descriptor extraction process.

The steps of the improved HOG main direction feature extraction are as follows:

1) The input image needs to be normalized in color space by the gamma correction method to eliminate the influence of ambient light on the target recognition of power equipment.

   \[ I'(x, y) = I(x, y)^{\gamma_{\text{norm}}} \]  

   Where \( I(x, y) \) and \( I'(x, y) \) are respectively the normalized gray values of the input and output of the image; \( \gamma \) is the correction factor and \( \gamma = 1/2 \).

2) Use the horizontal edge operator \([-1, 0, 1] \) and the vertical edge operator \([-1, 0, 1]^T \) to carry out the image convolution operation. Based on this, the gradient of each pixel is calculated. The gradient of each pixel \((x, y) \) \((1 \leq x \leq 640, 1 \leq y \leq 480)\) in a given image is:

   \[ G_x(x, y) = [-1 \ 0 \ 1]\ast I(x, y) \]  

   \[ G_y(x, y) = [-1 \ 0 \ 1]^T \ast I(x, y) \]  

   Then, the gradient amplitude (i.e., gradient weight) of this point is:

   \[ G(x, y) = \sqrt{G_x(x, y)^2 + G_y(x, y)^2} \]  

   The gradient phase (i.e., gradient direction):

   \[ \theta(x, y) = \arctan \left( \frac{G_y(x, y)}{G_x(x, y)} \right) \]  

   The gradient direction is divided into nine parts \((Z_1\sim Z_9)\), \(0^\circ\sim20^\circ, 20^\circ\sim40^\circ \ldots, 160^\circ\sim180^\circ\), as shown in Figure 4, each part represents a direction. When the gradient direction of the pixel is \(0^\circ\sim20^\circ\), the weight of the point is added to the \(Z_1\) interval. And so on, all pixels in the final image can find their corresponding intervals.

3) The range of \(\theta(x, y)\) is \((-\pi, \pi)\), in order to simplify operation, this paper converts the value range of gradient phase of each pixel to \((0, \pi)\) and redefine the pixel gradient direction:

   \[ \theta(x, y) = \begin{cases} \theta(x, y), & \theta(x, y) > 0 \\ \theta(x, y) + \pi, & \theta(x, y) < 0 \end{cases} \]  

   The gradient direction of each pixel after conversion \(\tilde{\theta}(x, y) \in (0, \pi)\).

After getting the HOG of each pixel in the picture, count the phase sum of pixels in each interval:
\[ M_n = \sum G(x,y) \frac{n\pi}{9} < \theta'(x,y) < \frac{(n+1)\pi}{9} \quad n = 0,1,...,9 \]  

(7)

Find the maximum value \( Z_{\text{max}} \) of the pixel weight and its interval \( M_{\text{max}} \) (the corresponding interval number is \( n_{\text{max}} \)). Then the angle of the main direction of the image is:

\[ \theta_{\text{max}} = \frac{n_{\text{max}} \pi}{9} \]  

(8)

After getting the main direction of the whole image, adjust the gradient direction of each pixel:

\[ \theta_r(x,y) = \theta(x,y) - \theta_{\text{max}} \]  

(9)

Where \( \theta_r(x,y) \) is the direction of pixel gradient after adjustment.

The adjusted gradient direction and amplitude are used as the improved HOG descriptor of the pixel.

4) Divide the image into cells, and each cell is 8×8 pixels in size. HOG values of pixels in each cell block are counted to form the HOG descriptor of each cell unit. Construct 2×2 adjacent cells into a block. The descriptors of all cells in a block are concatenated to obtain the HOG descriptor of the block. Slide the block forward with a step size of 8×8 pixels. All the descriptors of blocks in an image are summarized to obtain the HOG descriptor of the whole image.

3. Infrared image recognition algorithm for electrical equipment

The classifier is the key to target recognition. In this paper, the SVM is used for target recognition. The idea of SVM was first proposed by Cortes and Vapnik[13] in 1995. SVM classifier has an outstanding performance in solving the problem of data classification in the nonlinear, and high dimensional space.

3.1. Data set preparation

In order for this algorithm to be suitable for identifying infrared images taken by various devices and improve the computational efficiency, we remove redundant information such as watermarks in the image. The result is shown in Figure 5. Since this experiment involves 12 types of samples, the sample training set and the division of the test set are introduced by taking 220kV arrester as an example.

The first is the training set. 220 images of different directions and colors are selected from the processed image samples as the positive samples. The negative samples are composed of the remaining 11 categories of devices, and the total number of negative samples is 1100 (100 pieces of each category of devices are randomly selected and put into the negative sample set). The ratio of positive and negative samples is 1:5. Prepare test sets for the remaining 11 types of devices in this way.

Figure 4. Gradient direction division.  

Figure 5. Redundant information of infrared thermal mapping is removed.
3.2. HOG-SVM infrared image recognition algorithm for electrical equipment

An improved HOG-SVM infrared image recognition algorithm for power equipment is as follows:

1. Import the prepared test sample of the target device, and extract the HOG of the target device according to the improved method proposed in this paper.

2. Due to the large sample size and the high dimension of the feature vector in this paper, in order to reduce the calculation time and improve the calculation efficiency, PCA is used to reduce the dimension of the HOG descriptor of the power equipment image.

3. The HOG after dimensionality reduction is put into SVM for training, and the initial classifier is obtained. However, the effect of the initial detector is very poor. At this time, the training of SVM has not been completed.

4. After that, the initial detector is used to detect the negative sample. DetectMultiscale method of cvHOG is used for detection, and these detected regions are hard examples.

5. The HOG of the hard example in step 4 is extracted and dimensionality reduction is carried out.

6. Integrate the HOG descriptor of the hard example and training set samples, and then the SVM classifier is trained, so that the final classifier is obtained.

7. HOG of test set samples were extracted and PCA dimension reduction was performed.

8. SVM classifier is used for classification and recognition, and the recognition results are obtained.

The algorithm flow is shown in the Figure 6.

Figure 6. An improved HOG-SVM infrared image recognition algorithm flow of power equipment

4. Infrared image recognition experiment and result analysis of electrical equipment

Design four sets of experiments to compare and verify the effect of algorithm in this paper.

| Equipment type     | Improved HOG-SVM | Original HOG-SVM | LBP-SVM | Zernike-SVM |
|--------------------|------------------|------------------|---------|-------------|
| 110kV arrester     | 90.1%            | 86.3%            | 81.0%   | 91.2%       |
| 220kV arrester     | 92.5%            | 89.1%            | 84.5%   | 89.9%       |
| 110kV ct           | 94.6%            | 86.4%            | 83.6%   | 91.3%       |
| 220kV ct           | 94.4%            | 87.4%            | 82.4%   | 92.6%       |
| 500kV ct           | 95.1%            | 89.6%            | 78.6%   | 93.8%       |
| 110kV pt           | 92.1%            | 79.9%            | 79.4%   | 88.4%       |
| 220kV pt           | 93.2%            | 80.0%            | 77.6%   | 89.7%       |
| 500kV pt           | 93.9%            | 82.4%            | 79.4%   | 92.4%       |
| 110kV breaker      | 94.6%            | 81.6%            | 81.6%   | 87.9%       |
| 220kV breaker      | 92.5%            | 83.4%            | 82.5%   | 87.6%       |
| 500kV breaker      | 93.8%            | 88.2%            | 83.2%   | 92.1%       |
| Insulator          | 92.7%            | 82.2%            | 78.8%   | 89.2%       |
1) The improved HOG-SVM algorithm is used to identify the 12 types of power equipment.
2) The original HOG is sent into the SVM classifier to identify the 12 types of power equipment.
3) The LBP-SVM algorithm is used to recognize the 12 types of power equipment in this paper.
4) The Zernike-SVM algorithm is used to identify 12 types of power equipment in this paper.

The recognition accuracy of the four methods obtained from the experiment is shown in the Table 1.

In order to represent the recognition effect of the algorithm in this paper more directly, the accuracy of the four methods is shown by the histogram. The results are shown in Figure 7.

Experimental results show that the average recognition accuracy of the improved algorithm reaches 92.14%, which meets the requirements of equipment identification accuracy in practical applications. The average accuracy of the improved algorithm is nearly 8% higher than the original HOG-SVM, which indicating that the proposed algorithm can effectively avoid the problem of low recognition accuracy caused by different shooting angles of power equipment in infrared images.

In addition, compared with other two target recognition algorithms, this algorithm also shows a greater recognition advantage. The average recognition accuracy based on LBP-SVM algorithm with the value of 81.05% is the lowest among the four algorithms. Due to the calculate limit belonging to algorithm itself, its more suited to describe the local texture feature. The advantages of the proposed algorithm cannot get reflected in power equipment. The recognition effect of Zernike-SVM algorithm is second only to the improved algorithm in this paper, with an average recognition accuracy of 90.79%. However, the calculation process of this algorithm is relatively complex, and high order moments of more than 5 order are generally required to achieve better recognition accuracy, which greatly increases the computational complexity.

The device with the lowest recognition accuracy of the algorithm in this paper is insulator. Analyzation of the experimental samples (as shown in Figure 8) shows that since insulators do not exist alone, the infrared image background of the device is generally complex, so it will have a relatively large impact on the device recognition.
5. Conclusions
This paper mainly focuses on the automatic recognition of infrared image of power equipment. Owing to the fact that when taking photos of the equipment on site, the objects have different rotation angles, illumination, backgrounds and sizes, which greatly influence the target recognition. In this paper, 12 kinds of common power equipment are selected for recognition. According to the appearance characteristics of common power equipment, an improved HOG-SVM power equipment infrared image recognition algorithm with rotation invariance is proposed, and the algorithm is designed and implemented. The experimental results show that the identification method proposed in this paper has a high identification accuracy, with 92.14% average identification accuracy of 12 types of equipment, which can meet the precision requirements of daily power equipment identification, and is conducive to the application of this method in real life. However, the method in this paper still has some imperfections. For example, the number of classifiers used in this paper is a little too large, which increases the computational amount and thus reduces the computational efficiency. Therefore, the selection of classifiers can be improved to improve the speed of training and recognition. Further research on these aspects will be carried out in the following work.

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