State Detection of Electrical Equipment Based on Infrared Thermal Imaging Technology

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Abstract. With the increasing demand of power supply reliability for electrical equipment in power grid and the continuous development of infrared thermal imaging technology, infrared thermal imaging technology has been widely used in electrical equipment detection. Using infrared instruments to detect and diagnose thermal fault of electrical equipment has become one of the mainstream methods of electric equipment inspection. However, at present, fault detection relies heavily on personnel's experience and has low detection efficiency. In order to improve the intelligent level of power system and solve the problem of accurate detection of thermal faults of electrical equipment in substations, this paper applies Faster RCNN algorithm to infrared detection to realize automatic detection of electrical equipment faults. The average recognition accuracy of equipment can reach more than 85%, which has good effect.

Keywords: Electrical equipment · Infrared detection · Faster RCNN

1 Introduction

The purpose of power equipment condition monitoring is to use effective detection means and analysis and diagnosis technology to grasp the operation status of equipment timely and accurately, and to ensure the safe, reliable and economic operation of equipment. The core of condition monitoring is the determination of equipment status. The equipment status data are obtained by means of inspection, test, live detection and on-line monitoring. The location, degree of hazards and trend of equipment hidden dangers are evaluated and evaluated, so that the maintenance plan can be formulated reasonably [1]. Infrared thermal image detection technology is an effective means to monitor the thermal state of electrical equipment. It can use infrared imager to transform the infrared radiation of electrical equipment into infrared image. Through the analysis of infrared image, the possible fault of the equipment can be determined. It can inspect the electrical equipment online to ensure that the equipment can complete the diagnosis without power failure and shutdown. At the same time, it has non-contact characteristics, which can ensure the safety of operators to a large extent. These characteristics of infrared thermal image detection technology just meet the requirements of power system fault diagnosis, so it is widely used in the operation and maintenance of power system transmission and transformation equipment, and has a significant role in the early detection of electrical equipment faults [2–4].

Z. Lin et al. (Eds.): PRCV 2019, LNCS 11857, pp. 251–260, 2019.
https://doi.org/10.1007/978-3-030-31654-9_22

With the continuous development of artificial intelligence technology and the continuous improvement of intelligent substation construction, the use of intelligent inspection robots and unmanned aerial vehicles has become one of the mainstream methods of power equipment inspection. By observing the collected infrared images, the inspectors can clearly distinguish the temperature changes inside the electrical equipment, so as to know whether the electrical equipment fails or not, and find out the equipment components that fail, and repair and maintain them in time. But because there are many kinds of electrical devices when intelligent robots or UAVs take images, different devices and even different parts of the same device have their own criteria, which makes it more difficult to detect the state of the equipment. In this paper, Faster RCNN is introduced into the infrared detection of electrical equipment, and the algorithm is improved. It can realize the accurate location and recognition of multiple electrical equipment in the image, lay the foundation for subsequent fault diagnosis, and improve the operation efficiency and detection accuracy of the diagnosis system.

2 Design of Infrared State Detection Scheme

In the past, most of the thermal condition monitoring of substation equipment based on infrared thermal imaging detection technology relied on manual analysis of infrared images, so as to diagnose the thermal fault of electrical equipment. This detection method requires higher experience and professional knowledge of operators, and at the same time, manual detection method is inefficient and error-prone [5–8]. With the development of artificial intelligence, more and more substations use intelligent inspection robots and unmanned aerial vehicles for equipment inspection. The degree of intelligence is getting higher and higher, which greatly reduces human and material resources. But there are many devices in the infrared image collected by this way, which makes it more difficult to diagnose the equipment. Therefore, this paper uses Faster RCNN algorithm to analyze the infrared image, which can determine the equipment category and locate the various equipment areas in the image accurately, and lay a foundation for equipment fault diagnosis.

2.1 Infrared State Detection Method

Infrared thermal imaging detection and judgment methods mainly include surface temperature judgment method (absolute temperature judgment method), comparative judgment method of the same kind, relative temperature difference judgment method, image feature judgment method, file analysis judgment method and real-time analysis judgment method. These six infrared detection and judgment methods are not single application. In practical application, two or more methods need to be combined and analyzed. In this paper, surface temperature judgment method, relative temperature difference judgment method and image feature judgment method are selected to carry out the analysis and diagnosis of electrical equipment.

Surface Temperature Judgment Method: Mainly applicable to current-induced heating and electromagnetic heating equipment. According to the measured surface temperature of the equipment, the temperature and temperature rise limits of various components, materials and insulating media of the high-voltage switchgear and control equipment in GB/T11022 are analyzed and judged in combination with the environmental and climatic conditions and load magnitude.

Relative Temperature Difference Judgment Method: Mainly applicable to current-induced heating equipment. Especially for small load current heating equipment, the leakage rate of small load defects can be reduced by using relative temperature difference judgment method.

Image feature judgment method: It is mainly suitable for voltage heating equipment. According to the thermal image of the normal and abnormal state of the same kind of equipment, judge whether the equipment is normal or not. Attention should be paid to excluding the influence of various interference factors on the image as far as possible. When necessary, comprehensive judgment should be made based on the results of electrical test or chemical analysis.

2.2 Overview of Faster RCNN

Faster RCNN is another work of Ross Girshick team, the leader in target detection field, after RCNN [9], fast RCNN [10]. It is the first real end-to-end deep learning detection algorithm. The detection speed of simple network is 17 fps, and the accuracy of PASCAL VOC is 59.9%, while that of complex network is 5 fps, the accuracy is 78.8%.

The idea of Faster RCNN is to integrate the four basic steps of target detection (region proposal, feature extraction, classification and regression) into a deep network framework. All calculations are completed in GPU without repetition, which greatly improves the speed of operation. A comparison of algorithm evolution is shown in Fig. 1.

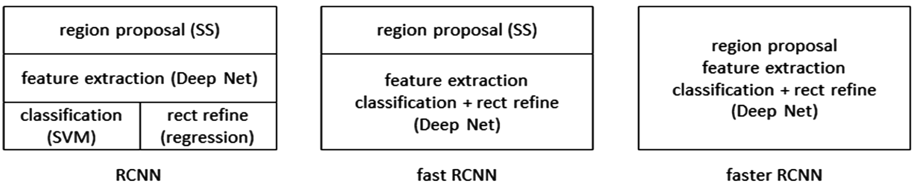


Fig. 1. Evolution of target detection algorithms.

The overall framework of Faster RCNN is divided into the following four parts. The network structure is shown in Fig. 2.

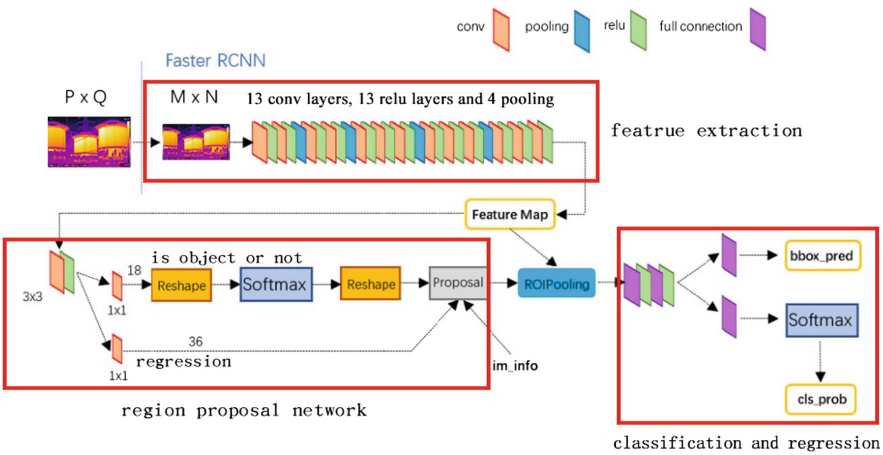


Fig. 2. Faster RCNN overall structure.

(1) CONV layers. The main function of this part is to extract the feature map of the input image. The input image is the whole picture, and the output image is the extracted feature map. In this paper, VGG16 network structure is used to extract image feature map, which is shared for subsequent RPN layer and full connection layer.
(2) Regional Proposal Networks. RPN network is mainly used to generate region suggestions. Firstly, a group of candidate regions (anchors) are generated, then they are cut and filtered, and then the candidate regions are judged to be foreground or background by Softmax classifier. At the same time, another branch makes border regression to modify the candidate regions to form more accurate proposals [11–17].
(3) ROI Pooling. The main function of this layer is to convert input of different sizes into output of fixed length. Fixed-size feature maps are obtained from the last layer of proposals and VGG16 generated by RPN. After entering, target recognition and location can be achieved by full-connection operation.
(4) Classification and Regression. The output of this layer is the ultimate goal. It outputs the classes of candidate regions and the exact positions of candidate regions in the image.

2.3 Improvement of Faster RCNN

In practical application, the whole equipment is easy to distinguish because of its appearance. However, some specific parts of different equipment (such as porcelain bottles, sleeves, wiring heads, etc.) are similar in shape, and it is difficult to distinguish them in infrared images. Therefore, recognition errors will inevitably occur, and the error rate is relatively high. Because the candidate boxes obtained by Faster RCNN are independent of each other, they can't modify the equipment category, which will lead to the subsequent diagnosis will be analyzed and diagnosed according to the type of model identification errors, thus making the diagnosis results wrong and increasing the workload of the relevant personnel.

Based on this, this paper proposes to improve the Faster RCNN. In the original algorithm classification step, it adds the equipment location category correction function, which can correct the wrong equipment location and improve the recognition accuracy of the equipment location. At the same time, the CNN for fault diagnosis based on image features is integrated into Faster RCNN, which can give the preliminary diagnosis results of the equipment, and then combined with the surface temperature judgment method and the relative temperature difference judgment method to realize the detailed diagnosis of electrical equipment. The network structure of the improved algorithm is shown in Fig. 3.

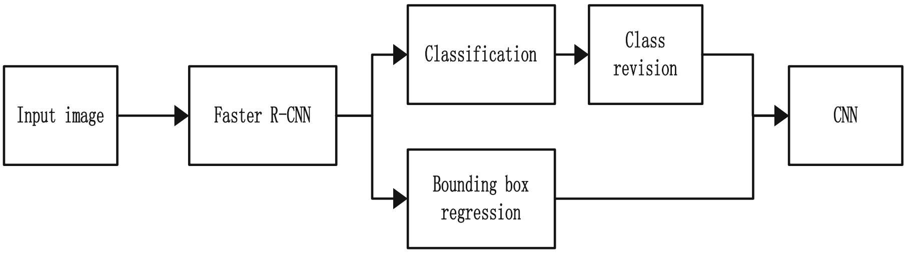


Fig. 3. Improves the structure of Faster RCNN.

The main idea of category revision is to mark the equipment in the way of "equipment + equipment parts". It not only marks the whole equipment, but also marks the specific parts of the equipment. In the test step, all the candidate boxes identified in the infrared image are divided into two categories: equipment and location. Then, the equipment category is corrected by using the idea of NMS (Non-Maximum Suppression). The specific steps are as follows:

(1) A and B represent the collection of equipment and equipment parts respectively. Sort all candidate boxes in A and B by size.
(2) The Overlapping area ratio (OAR) is calculated by traversing the candidate box (B_i) in B and comparing it with the candidate box in A: OAR = area of overlap area/area of B_i, and then comparing it with the set threshold of 0.8. If the OAR is greater than 0.8, the B_i candidate box is considered to belong to the whole device, and the B_i candidate box is classified. Adding an array index ensures that subsequent traversals are no longer accessed, reducing computation and processing time.
    If the OAR is less than 0.8, the B_i candidate box is not considered to belong to the overall device, and the next candidate box is not processed.
(3) Repeat operations (1) and (2) until all candidate boxes are modified.

2.4 CNN

Convolutional neural network (CNN) is an efficient recognition algorithm widely used in pattern recognition, image processing and other fields in recent years. Unlike traditional neural networks, the neurons in each layer of the network are not fully connected, but partially connected. Its weight sharing network structure reduces the complexity of network model and the number of weights. The network avoids the complex pre-processing of the image, can input the original image directly, avoids the complex feature extraction and data reconstruction process in traditional recognition algorithm, and has good abstraction ability.

Temperature is the most important diagnostic basis in condition detection and fault diagnosis of electrical equipment, and the direct expression of temperature in infrared image is the gray value of the image. CNN can extract and analyze the gray image of infrared image very well. It plays a very important role in condition detection and fault diagnosis of electrical equipment. By comparing the maximum gray value with the average gray value of the equipment area identified by Faster RCNN, the operation state of the electrical equipment can be preliminarily determined. If the difference between the maximum gray value and the average gray value exceeds a certain proportion, the abnormal condition of the equipment in this area can be determined, and the more accurate quasi-segment results can be obtained by combining the surface temperature judgment method and the relative temperature difference judgment method.

The complete flow of electrical equipment condition detection and fault diagnosis is shown in Fig. 4.

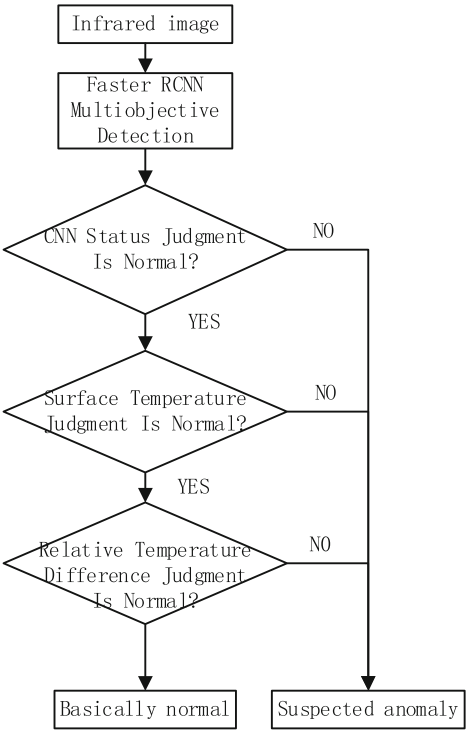
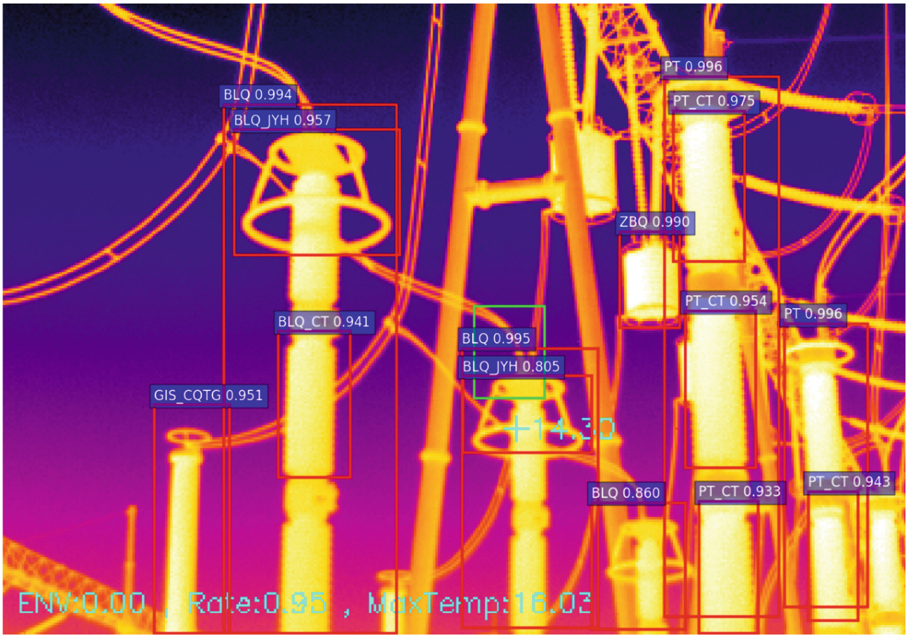


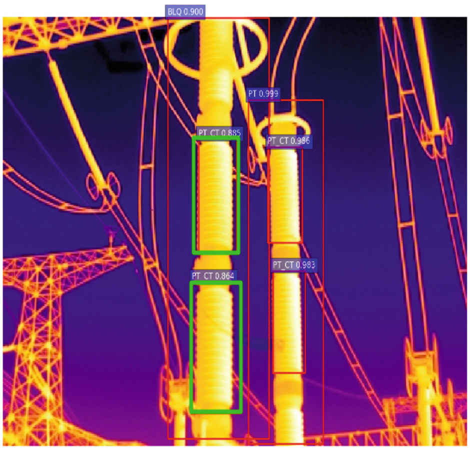
Fig. 4. Complete process of condition detection and fault diagnosis for electrical equipment.

3 Experiments

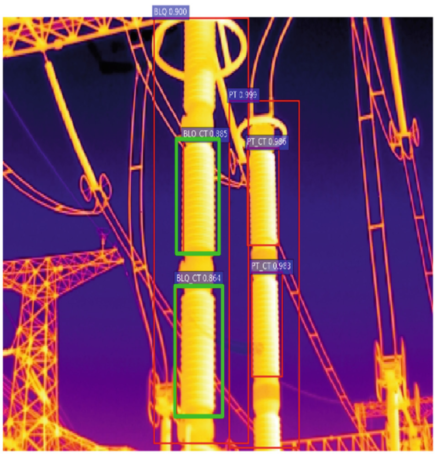
The experiment selected 16581 infrared images with good quality as training samples, and used PASCAL VOC2007 format data set to iterate the algorithm 70,000 iterations, with a learning rate of 0.001. In the training process of the algorithm, the first 100 score



(a)



(b)



(c)

Fig. 5. (a) is the result of Faster RCNN algorithm recognizing correctly, (b) is the result of Faster RCNN algorithm recognizing errors, (c) is the result of improved Faster RCNN algorithm.

predictions are selected for each infrared image by non-maximum suppression (NMS) operation with a threshold of 0.5. At this time, all predictions are independent and unrelated. In the process of algorithm testing, a kind of inclusion relationship between equipment and equipment parts is established by category correction function, which improves the accuracy of equipment parts classification.

The experiment selected 761 infrared images from the same station and 846 infrared images from other stations as test samples to test the application effect of the algorithm, and counted the recognition rate and accuracy of the equipment. The author chooses arresters, voltage transformers, current transformers and circuit breakers with a large number of samples to illustrate the application effect of the algorithm (Fig. 5).

The experimental results show that Faster RCNN algorithm has good application effect in infrared detection of electrical equipment and high recognition accuracy of equipment. As can be seen from (a), Faster RCNN can accurately identify most of the

Table 1. Accuracy of algorithm recognition.

Electrical equipment	Faster RCNN		Improved Faster RCNN	
	Same station	Different station	Same station	Different station
Lightning arrester	84.7%	77.9%	95.4%	85.9%
Voltage transformer	74.5%	68.4%	93.2%	87.6%
Current transformer	79.3%	70.8%	90.1%	86.3%
Circuit breaker	81.3%	73.4%	91.2%	85.7%

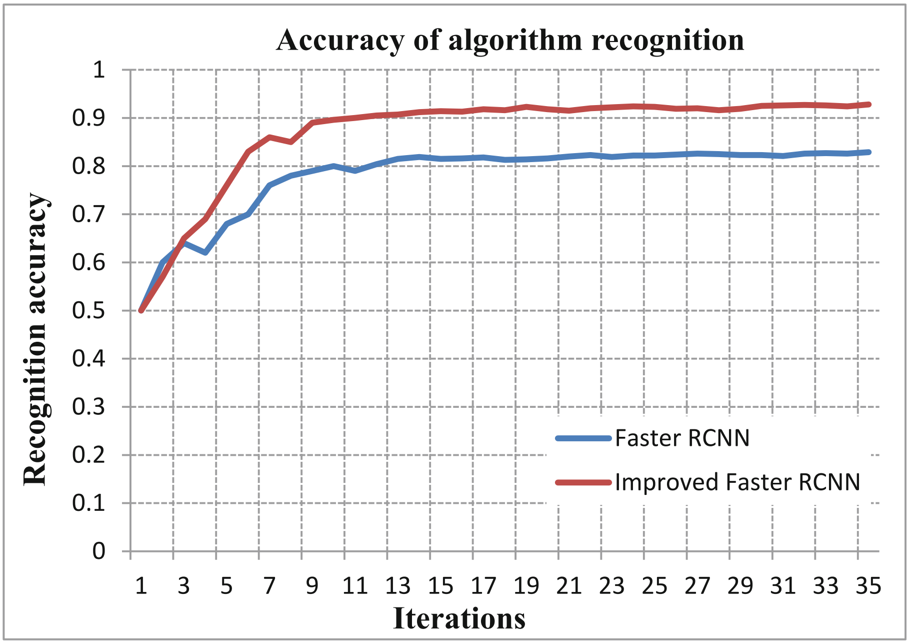


Fig. 6. Comparisons of recognition accuracy of algorithms.

devices and their parts in infrared images. By comparing (b) (c) two graphs, it can be seen that the improved Faster RCNN algorithm can modify the type of equipment and further improve the accuracy of electrical equipment identification.

Aiming at the situation of equipment location recognition error, this paper improves the algorithm, and counts the recognition effect of more than 1000 pictures from the same station and different stations. The result of equipment identification is shown in Table 1.

From the data in Table 1 and the curve in Fig. 6, it can be seen that the recognition accuracy of the improved Faster RCNN algorithm is much higher than that of the original Faster RCNN algorithm, about 10% higher than that of the original Faster RCNN algorithm. In addition, because the voltage level of different stations is different, the appearance of the equipment is also different, resulting in the same station identification accuracy will be a little higher than different stations.

4 Conclusion

The normal operation of high-voltage electrical equipment is related to the normal development of the national economy. Ensuring its efficient and sustainable operation is an effective means to promote rapid economic development. Infrared detection technology has been widely recognized and applied in the diagnosis of high-voltage electrical equipment. The application of infrared detection technology has a direct impact on the fault monitoring of high-voltage electrical equipment. In this paper, Faster RCNN, a target detection algorithm, is applied to infrared detection of electrical equipment and improved. Good detection results and accuracy are obtained. But there are also some problems. The improved algorithm modifies the category names of the parts it contains by the whole device. Therefore, once the overall identification of the equipment is wrong, the parts of the equipment will be modified with the error, and the algorithm will continue to be studied and improved to further improve the recognition rate and accuracy of electrical equipment.

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