

PAPER • OPEN ACCESS

A Defect Detection Method Based on Faster RCNN for Power Equipment

To cite this article: Yang Cheng *et al* 2021 *J. Phys.: Conf. Ser.* **1754** 012025

View the [article online](#) for updates and enhancements.

You may also like

- [RS-RCNN: an indoor window detection algorithm for autonomous spraying robot](#)
Xiaofei Ji, Yazhou Li and Jiangtao Cao
- [Deep Learning for Image Sequence Classification of Astronomical Events](#)
Rodrigo Carrasco-Davis, Guillermo Cabrera-Vives, Francisco Förster et al.
- [Target Detection Framework for Lobster Eye X-Ray Telescopes with Machine-learning Algorithms](#)
Peng Jia, Wenbo Liu, Yuan Liu et al.



ECS
The
Electrochemical
Society
Advancing solid state &
electrochemical science & technology

DISCOVER
how sustainability
intersects with
electrochemistry & solid
state science research

A Defect Detection Method Based on Faster RCNN for Power Equipment

Yang Cheng¹, Lingzhi Xia¹, Bo Yan², Jiang Chen³, Dongsheng Hu³, Lvfu Zhu^{4*}

¹ Electric Power Research Institute of State Grid Anhui Electric Power Co., Ltd, Hefei, Anhui, 210601, China

² State Grid Anhui Electric Power Co., Ltd, Hefei, Anhui, 230061, China

³ Anhui NARI Jiyuan Power Grid Technology Co., Ltd, Hefei, Anhui, 230088, China

⁴ Anhui Jushi Technology Co., Ltd, Hefei, Anhui, 230000, China

*Corresponding author's e-mail: zlf715@zeusight.com.cn

Abstract. With the wide application of infrared image acquisition technology in power inspection, a large number of infrared images of power equipment have been obtained. The traditional machine learning method has low accuracy and poor generalization. Therefore, in this paper, the deep learning technology is applied to infrared image detection of power equipment, and a defect detection method based on Faster region convolution neural network (RCNN) is proposed. In this method, the deep residual network is used to extract image features, and the regional proposal network is optimized according to the shape characteristics of power equipment, and the network is trained with the help of shared convolution layer. The experimental results show that the proposed method has high detection accuracy, good robustness and generalization ability.

1. Introduction

Rapid and accurate detection of power equipment defects is of great significance to ensure the normal operation of power system [1]. Statistical data show that power equipment defects are usually accompanied by abnormal heating phenomenon [2]. Infrared image detection of abnormal heating has the advantages of all-weather, no power cut, high sensitivity, and has gradually become the main way of power equipment defect detection [3]. Aiming at the problem of infrared image detection of power equipment, the influence of environmental factors such as shooting distance, temperature and humidity on the detection performance of infrared image was studied in [4]. Reference [5] studied the relationship between infrared image detection of high voltage power components in power equipment and emissivity of infrared tester. Based on the infrared image of robot, a defect detection method of power equipment based on image segmentation and template was proposed [6]. Reference [7] proposed an infrared image diagnosis system based on scale invariant feature transform (SIFT) for power equipment.

In this paper, according to the actual characteristics of power equipment infrared image, the network structure and parameters of Faster RCNN are adjusted. Through the training of infrared image of power equipment, an infrared image detection model of power equipment defects based on Faster RCNN is proposed.



The rest of this paper is organized as follows. The defect detection model based on faster RCNN is given in Section 2. In Section 3, the experimental results are discussed. Finally, the conclusion is given in Sections 4.

2. Detection model based on Faster RCNN

In this paper, the infrared image defect detection model of power equipment based on Faster RCNN is constructed, and the specific frame structure is shown in Figure 1. Firstly, the Faster RCNN detection model is trained based on the power equipment infrared image training data set to generate the defect detection network, and then the power equipment infrared image test data set is input into the defect detection network to verify the network detection performance. As can be seen from Figure 1, the Faster RCNN detection network is composed of two parts: region proposal network (RPN) and RCNN.

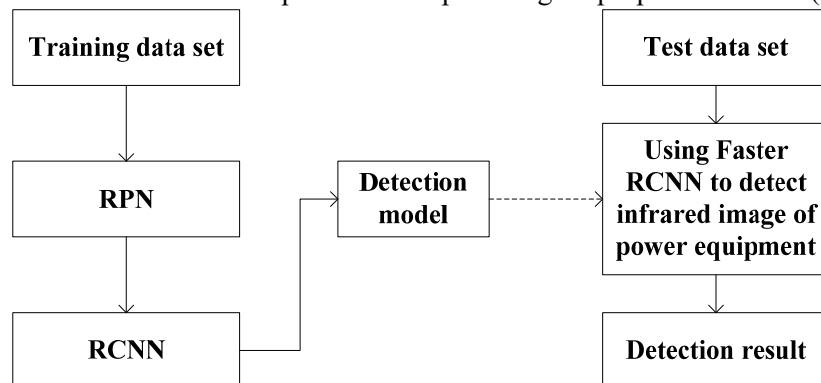


Figure 1. Power equipment defect detection framework based on Faster RCNN

2.1. Faster RCNN model

The Faster RCNN model is an integrated network which can effectively realize the detection of input image objects. It mainly completes the regional proposal and CNN detection, which are completed by RPN and RCNN respectively. RPN is a full convolution neural network, which can effectively predict the object boundary and object fraction at each position of the input image. Object boundary and object score are important indicators to evaluate whether an area is proposed. The image input proposal given by RPN will be input into RCNN to classify regional proposals and calculate the score of each proposed area. Faster RCNN model integrates RPN and RCNN into a network by sharing convolution features, and provides a joint training method. Compared with single network structure, Faster RCNN model deepens network depth and improves image detection performance. Figure 2 shows the structure of Faster RCNN model.

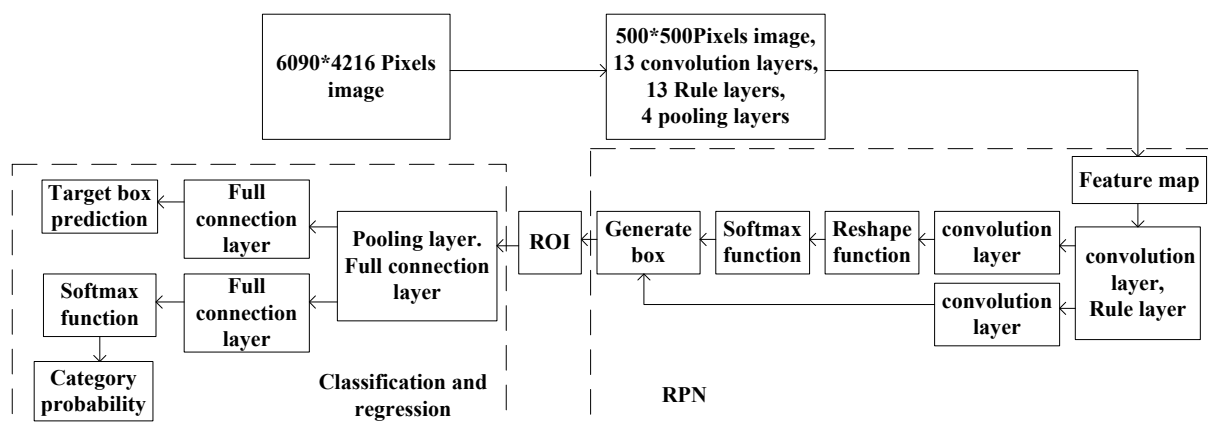


Figure 2. Faster RCNN model

2.2. Image area proposal

The input of RPN is the feature map generated by convolution neural network, and the output is a series of proposed network regions and corresponding classification probability values after the object boundary and object score evaluation. In the process of extracting image feature map by convolution neural network, window sliding method is used. Every time the window slides, anchor points with different area are set for the window center, and the local image framed by anchor points is taken as the region to be proposed. Considering that the shape of most power equipment is long strip, such as lightning rod, insulator, etc., the RPN anchor area is set as rectangle. Moreover, the infrared image of power equipment is distorted due to the influence of shooting angle and distance. Therefore, multi-size anchor area is constructed. Three anchor sizes [8,16,24] and five aspect ratios [0.25,0.5,1,2,4] are set. The purpose of adding the anchor area with aspect ratio of 0.25 is to accurately locate the distribution network equipment, which can make the network detect more slender targets and improve the detection ability of the network for the infrared image defect equipment of the distribution network. Through the above anchor region setting method, 15 proposed regions can be generated by window sliding once, which can effectively cover all targets in the infrared image.

After the infrared image of power equipment is located by sliding anchor point, the proposed area is introduced into classification layer and edge regression layer respectively. The classification layer is used to evaluate the category and calculate the probability value of the proposed area. The edge regression layer adopts convolution neural network structure to ensure that the image not belonging to the anchor area can also obtain the category suggestions close to the anchor area.

2.3. Faster RCNN detector

The input to the Faster RCNN detector is the proposed region identified in the previous section, known as the region of interest (ROI). Each ROI contains four parameters to form a one-dimensional feature vector (r, c, w, h) where (r, c) represents the upper left pixel coordinate of ROI, and (w, h) represents the width and height of ROI respectively. Faster RCNN detector is a partial convolution neural network, including pooling layer and convolution layer. The pooling layer uses the maximum pooling method to transform the ROI region image into the same size feature map (W, H) . The convolution layer proposes feature vectors with fixed length from the pooling layer, and each feature vector is imported into the full connection layer. Faster RCNN detector uses softmax layer and boundary box regression layer to determine the detection confidence of 8 types of power equipment defects corresponding to each region. The label with high confidence is taken as the detection result, and the edge information of defective equipment is further predicted based on the boundary box regression.

2.4. Joint training

When using Faster RCNN to detect power equipment defects from infrared images, RPN outputs a group of rectangular proposal areas, and each proposed area has a preset confidence value of 8 types of defects, which is used to determine the type of power equipment defects. As shown in Figure 2, 13 VGG-16 models that can be shared as convolution back ends of Faster RCNN are set up. The joint training process of RPN and RCNN is introduced as follows.

Firstly, each sliding window is convoluted with the input proposed region, so that the sliding window image is mapped to features with lower dimensions. For the VGG-16 model, the dimension value is 512. Then, the boundary box regression layer and the boundary box classification layer are convoluted with the convolution layer respectively. The boundary box regression layer outputs the central anchor value and width height value prediction results of the proposed area, and the boundary box classification layer is mainly used to determine whether the proposed area is the background of infrared image. For each region selected by sliding window, multiple proposal areas can be generated according to RPN anchor process, and the corresponding classification layer can output the object score of each proposed area, which is used to calculate the confidence degree of each proposed area corresponding to each type of power equipment defect.

According to the anchor region generation process, the proposed regions are highly overlapped. Therefore, the non-maximum consensus method is used to merge the proposals with higher overlapping regions. The non-maximum consistent method uses the intersection ratio to evaluate the degree of overlap between the two proposed regions A and B :

$$M = \frac{A \cap B}{A \cup B} \quad (1)$$

In order to train RPN effectively, Faster RCNN model provides the following multi-task loss function:

$$L(\{p_i\}, \{t_i\}) = \frac{1}{N_{els}} \sum L_{els}(p_i, p_i^*) + \lambda \frac{1}{N_{reg}} \sum p_i^* L_{reg}(t_i, t_i^*) \quad (2)$$

$$L_{els}(p_i, p_i^*) = -\log[p_i p_i^* + (1 - p_i)(1 - p_i^*)] \quad (3)$$

$$L_{reg}(t_i, t_i^*) = \sum_{i=\{x,y,w\}} smooth_{L_i}(t_i, t_i^*) \quad (4)$$

Where i is the index of the anchor area in the training sample (test sample), p_i and p_i^* denote the probability that the i -th anchor area is the target and the corresponding sample classification, respectively. When the target set by the anchor area is a positive sample, the value of p_i^* is 1, otherwise p_i^* is 0. t_i is the parameterized eigenvector of the i -th anchor region, and t_i^* is the parametric eigenvector of the real target region. λ is the weight parameter, N_{els} and N_{reg} are the normalization parameters of the loss function, respectively. $L_{els}(p_i, p_i^*)$ and $L_{reg}(t_i, t_i^*)$ denote the loss function of binary classifier and the loss function of regression process, respectively. $smooth_{L_i}$ denotes the robustness loss function of regression process.

$$smooth_{L_i}(x) = \begin{cases} 0.5x^2 & , \|x\| < 1 \\ \left| \|x\| - 0.5 \right| & , \|x\| \geq 1 \end{cases} \quad (5)$$

Where $x = t_i - t_i^*$.

The boundary regression process of the proposed region is to find the anchor area closest to the target area. The coordinates of the regression process are defined as follows:

$$\begin{aligned} t_x &= (r - r_a) / w_a, t_c = (c - c_a) / h_a \\ t_w &= \log(w / w_a), t_h = \log(h / h_a) \\ t_x^* &= (r^* - r_a) / w_a, t_y^* = (c^* - c_a) / h_a \\ t_w^* &= \log(w^* / w_a), t_h^* = \log(h^* / h_a) \end{aligned} \quad (6)$$

Where, (r, c, w, h) denotes the predicted coordinate of the target area; (r_a, c_a, w_a, h_a) denotes the bounding coordinate of the anchor area; (r^*, c^*, w^*, h^*) denotes the coordinate of the real target area.

In order to improve the adaptability of the model, the feature map with the same spatial size is used to realize the boundary regression in the anchor area, and the boundary box regression is trained under different image sizes. In order to improve the training efficiency of Faster RCNN, the Faster RCNN model can be trained jointly based on the RCNN and RPN. The steps are as follows: 1) training RPN model; 2) training RCNN with trained RPN convolution layer; 3) regression training of RPN specific layer by RCNN; 4) regression training of RCNN with newly trained RPN.

3. Performance evaluation

The infrared defect recognition model of Faster RCNN distribution network equipment is realized based on Caffe architecture. The CPU of the experimental computer is Intel Core i5-4590, the memory is 8G. The experimental data set includes 2856 infrared images of normal equipment and 1204 infrared images of defective equipment. In order to avoid the subjective influence of artificial selection of training set and test set on the experimental results, a total of 3000 infrared images were selected as the training set, and the remaining 1060 infrared images were used as the test set.

In order to effectively train Faster RCNN model, RPN number is set to 40, L2 regularization weight is set to 0.0005, each mini-batch adopts momentum acceleration technology in gradient descent algorithm, and momentum value is set to 0.95. During the training process, the threshold value of boundary box for de overlapping anchor area is set to 0.85. The convergence of multi-task loss function in the training process is shown in Figure 3.

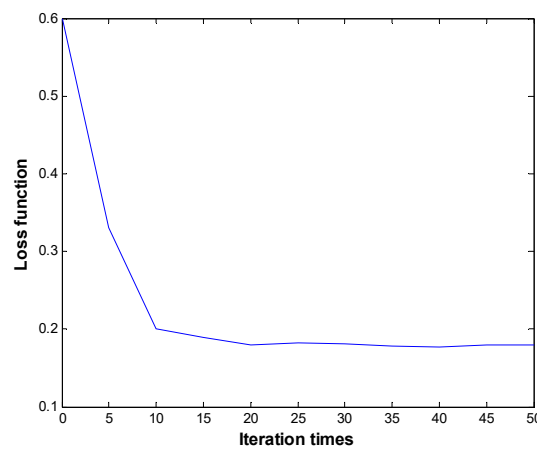


Figure 3. Convergence curve of Faster RCNN model

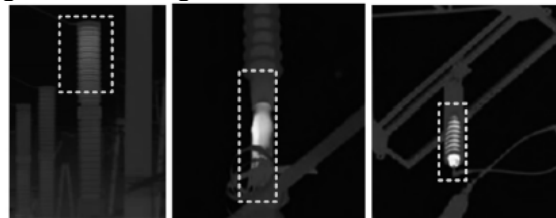


Figure 4. Detection results of infrared image of defective equipment

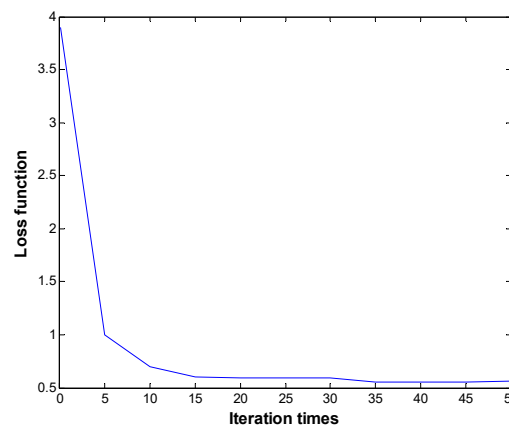


Figure 5. Convergence curve of traditional Faster RCNN model

It can be seen from Figure 3 that with the increase of iteration times, the value of multitask loss function of Faster RCNN model decreases. The value of multi-task loss function fluctuates slightly around 0.12 to achieve convergence. After the model training is completed, the power equipment defect detection test is carried out using the test set data. The part of the test results are shown in Figure 4, and the dotted line box in the figure shows the detected defective equipment.

It can be seen from Figure 4 that when using Faster RCNN model to detect different power equipment defects, the detection accuracy is very high, and multiple types of target detection can be realized. The detection accuracy rate of power equipment defects is shown in Table 1, and the average detection accuracy rate reaches 91.28%.

In order to further test the detection performance of the Faster RCNN model on the infrared image of power equipment defects, a comparative experiment was carried out between the model and the infrared image detection method based on SIFT. SIFT algorithm is based on computer vision to detect the local features of infrared images. It searches image extremum points through spatial scale transformation, estimates the location, scale and rotation invariants of image extremum points, so as to detect image types. It has a very wide application in image stitching and gesture recognition. The experimental results show that the detection result of SIFT algorithm is not good for the infrared image of power equipment defects, and the error detection occurs for the image with complex background. In order to effectively evaluate the detection performance of the two detection methods, the accuracy, recall rate and F1 value are selected for performance evaluation.

$$P = \frac{S_r}{S_a} \times 100\% \quad (7)$$

$$R = \frac{S_r}{S_o} \times 100\% \quad (8)$$

$$F1 = \frac{2PR}{P+R} \quad (9)$$

Where S_r is the number of correctly detected images in the infrared image detection results of power equipment defects; S_a is the actual number of detected images of power equipment defects; and S_o is the number of images that should be detected in the power equipment defect data set. 50 Monte Carlo experiments are carried out for the two detection methods, and the detection accuracy, recall rate and F1 value of each method are counted. The results are shown in Table 2.

Table 1. Detection accuracy of Faster RCNN model.

Equipment type	Detection accuracy rate (%)	Equipment type	Detection accuracy rate (%)
Bushing	94.72	Lightning rod	89.05
Insulator	87.85	Circuit breaker	88.94
Wire	93.96	Isolating switch	93.24
Voltage transformer	90.04	Transformer	90.50

Table 2. Comparison results of different methods.

Method	Detection accuracy(%)	Recall rate(%)	F1 value(%)
SIFT algorithm	83.37	86.91	85.10
Faster RCNN model	92.54	95.64	94.06

The experimental results show that for the same infrared image data set of power equipment defects, the detection accuracy, recall rate and F1 value of the Faster RCNN model proposed in this paper are 9.17%, 8.73% and 8.96% higher than SIFT algorithm respectively. This is because SIFT algorithm relies on manual determination of image local features, and has strong subjectivity. In this paper, the proposed region of power equipment infrared image is determined adaptively by using RPN, which avoids the subjectivity of feature selection and conforms to the image characteristics of power equipment. Therefore, it has a high detection accuracy.

In order to verify the training efficiency of the Faster RCNN infrared image detection model for power equipment defects in this paper, the training efficiency is tested with the traditional Faster RCNN detection model in the same training parameters and training data set. The variation relationship of the multi-objective loss function of the traditional Faster RCNN detection model with the number of iterations is shown in Figure 5. After about 20 rounds of training, the multi-objective loss function of the model converges. Compared with the traditional Faster RCNN, the Faster RCNN detection proposed in this paper has faster convergence speed than the traditional Faster RCNN. According to the statistics of the detection accuracy of traditional Faster RCNN model, the average detection accuracy of power equipment defects is only 86.82%.

Comprehensive experimental results show that, compared with SIFT algorithm, the proposed Faster RCNN model has higher detection accuracy for power equipment defects; compared with the traditional Faster RCNN detection model, the proposed Faster RCNN model is more efficient in terms of convergence speed and detection accuracy.

4. Conclusion

In this paper, a defect recognition method of power equipment infrared image based on Faster RCNN is proposed. The image features are extracted by using the deep residual network, and the regional proposal network is optimized. With the help of shared convolution layer training, the loss calculated by the quantization network only needs to be transferred to the floating-point number of the corresponding position according to the gradient back-propagation rule. Experimental results show that the proposed Faster RCNN model has higher detection accuracy for power equipment defects compared to SIFT algorithm. The proposed Faster RCNN model is more efficient in terms of convergence speed and detection accuracy compared to the traditional Faster RCNN model.

References

- [1] Gao, B., et al. (2017) A temperature gradient-based potential defects identification method for IGBT module. *IEEE Transactions on Power Electronics*, 32: 2227-2242.
- [2] Zhang, X., Shi, M., He, C., et al. (2020) On site oscillating lightning impulse test and insulation diagnose for power transformers. *IEEE Transactions on Power Delivery*, 35: 2548-2550.
- [3] Wang, J., Ding, W., Liu, Y., et al. (2010) Application of x-ray inspection for ultra high voltage gas-insulated switchgear. *IEEE Transactions on Power Delivery*, 34: 1412-1422.
- [4] Wang, B. et al. (2020) Automatic fault diagnosis of infrared insulator images based on image instance segmentation and temperature analysis. *IEEE Transactions on Instrumentation and Measurement*, 69: 5345-5355.
- [5] Bastan, M., Yap, K.H., Chau, L.P. (2019) Remote detection of idling cars using infrared imaging and deep networks. *Neural Computing & Applications*, 5: 1-11.
- [6] Li, C., Wang, J., Li, Y., et al. (2019) Infrared image defect diagnosis through LAB space transformation. In: 2019 2nd International Conference on Information Systems and Computer Aided Education (ICISCAE), Dalian, pp. 126-130.
- [7] Guo, C., Ren, M., Xia, C., et al. (2020) Fault diagnosis of power equipment based on infrared image analysis. In: 2020 IEEE International Conference on Advances in Electrical Engineering and Computer Applications (AEECA), Dalian, pp. 659-663.