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Detection and recognition for fault insulator based on deep learning

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***Abstract*—Insulators are exerting an important influence in transmission lines. The timely detection of insulator explosion defects is an important guarantee for the safe operation of power systems. This paper puts forward an algorithm that detect the insulators' self-detonation defect based on deep learning. First, a Faster R-CNN target detection network is used to quickly classify and locate the insulators on the transmission lines. Then, a semantic segmentation to the located insulators is carried out by constructing a full convolutions neural network. In the end, the finished insulator image is input into the classification network to judge whether the insulator is burst. The experimental results show that the accuracy of insulator fault explosion recognition based on deep learning reaches more than 99%, and the intelligent design effectively improves the efficiency of the power transmission system.**

Keywords- deep learning; object detection; fully convolutional networks; insulator explosion; fault recognition

I. INTRODUCTION

Glass insulator is an extremely important component of the transmission line, its explosion fault is the most common fault in the power transmission system[1]. At present, manual interpretation is the most adopted way to mark the faults of the pictures of transmission line shot by drones, but this method features a long cycle and low efficiency. In reality, pictures of the poles can be collected by drones and then the explosion faults of insulators are automatically recognized by utilizing deep learning algorithm. Such method can remarkably increase the efficiency of line patrol.

Most power transmission systems are laid on mountains with complex natural conditions, which makes the background of the aerial photos of power transmission line extremely complex. In this way, it is very difficult to extract insulators from the complex background. Literature[1] put forward: local gradient-based descriptors can be used to extract individual insulator caps and then using elliptical descriptors to detect the insulator caps and utilizing local outlier factor (LOF) algorithm to determine the possible defects of insulators[2]. Traditional threshold segmentation method was adopted by the Literature[3] to extract insulators from the background. After that, faults can be recognized according to the ratio of pixels in an area. Literature[4] firstly segments the aerial photo of power transmission system with Ostu to acquire the foreground connected regions of insulators; then, it locates explosion based on the characteristics of insulators after segmentation.

The above are some traditional image processing methods using threshold segmentation of images of power transmission line and fault recognition on the segmentation based on the explosion features of insulator. Due to the difficulty of extraction the insulator from complex background through manual method, the accuracy of the recognition is critically low and the robustness is weak. The main method used by this paper were to set up the network of detection, segmentation and recognition based on deep learning, training each network through samples collected by drones and ultimately achieving the intelligent of detection and recognition. With deep learning, the subjectivity in manual extraction for features and threshold selection can be avoided. Convolutional Neural Network can automatically extract deep features of power transmission line and classification explosion of insulators. The method used in this paper can remarkably improve the inspection efficiency of power transmission system and accuracy of fault recognition.

II. OVERVIEW

A. *Convolutional Neural Network*

Convolutional neural network (CNN) is a type of neutral network constituted by multiple convolution layers developed from Artificial Neutral Network (ANN). It was put forward by Hube and Wiesel in the 1960s based on their studies about the cortex of cats[6]. In 1998, Yann Lecun[7] et al put forward the neutral network model LeNet-5 that has been successfully applied in MNIST. In 2006, Hinton and R.R. Salakhutdinov[8] put forward the method of using multiple hidden-layer neutral networks to train models and finely tuning the network through RBM (Restricted Boltzmann Machines). In 2012, Hinton research group enhanced the accuracy of picture classification by 80% through their established AlexNet[9] network.

Original CNN was put forward for MNIST figures. Until now, convolution neural network has been successfully applied to image processing, natural language processing and speech recognition and other fields.

B. *Object Detection*

Traditional object detection algorithm generally extracts the candidate region of a photo in the form of sliding window, then manually designs insulator characteristics based on the color and texture of the photo, and finally use classifiers to conduct classification recognition to the candidate region. The search method involving sliding window causes long insulator

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detection time. And manual design requires designing different characteristics for different detection items. Therefore such method is not very applicable to power transmission system photos with different forms of insulators and complicated, changeable background.

In 2006, deep learning began to attract wide attention. Since Girshick R et al put forward the deep model R-CNN used for object detection tasks, object detection algorithm based on CNN has seen surging development. The Object detection methods based on convolutional neural network are mainly divided into two categories: object detection methods based region proposal network （R-CNN[11], Faster R-CNN[12], R-FCN[13] etc.) and object detection methods based on regression approach(YOLO[14] , SSD [15]).

Compared with traditional candidate region extraction method based on sliding window, Faster R-CNN replaces inefficient select search with region proposal network, drastically improving the accuracy and efficiency of object detection and making real-time object detection possible.

C. *Semantic Segmentation*

Semantic segmentation means determining the category of an object through classifying all the pixels of a photo. Traditional image segmentation methods mainly include threshold segmentation, region segmentation and edge segmentation, most of which depend on the pixel brightness and color information of a photo. However, simple color characteristics may cause segmentation faults in parts with uneven brightness or noise impact, not clear parts and shadows.

Current end-to-end segmentation methods represented by fully convolutional networks introduce the space information of photos through establishing neutral network and then use a great number of power transmission system samples to train the neutral network. They can solve the noise and non-evenness problems in photos and have higher accuracy than traditional methods.

Fully convolutional networks (FCN) is a derivative form of CNN, put forward by Matan et al[5]. The soul of fully convolutional networks is replacing all the fully connected layers of ordinary classification network with corresponding convolution layers to achieve end-to-end pixel-level segmentation.

III. EXPLOSION RECOGNITION OF INSULATOR

A. *Overall Framework*

The general algorithm framework put forward by this paper as shown in Figure 1. First, collect the original image of power transmission system, input object detection model, and locate the insulators in the image; then, establish fully convolutional networks to separate the insulator region and the complicated background; finally, use classification models to judge whether the insulators are explosion. If so, output the corresponding photo name.

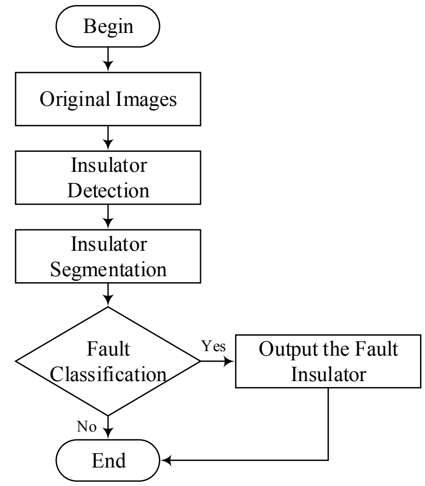

Figure 1. System structure chart

B. *Insulator Detection Based on Faster R-CNN*

From traditional sliding window to select search, edge detection and RPN, the speed and accuracy of detection have been drastically improved. This paper adopts the object detection model Faster R-CNN which has high speed and accuracy. This model mainly comprises three parts i.e. fully convolutional network, RPN and Fast R-CNN. Firstly, a photo of insulators collected by drones is input into the network. And a 13-layer fully convolutional network is used to obtain the feature map of the photo. Then, the object candidate region is selected through RPN. Finally, the objects in the candidate region are detected and recognized based on the candidate region and the feature map. The network structure of Faster R-CNN as shown in Figure 2.

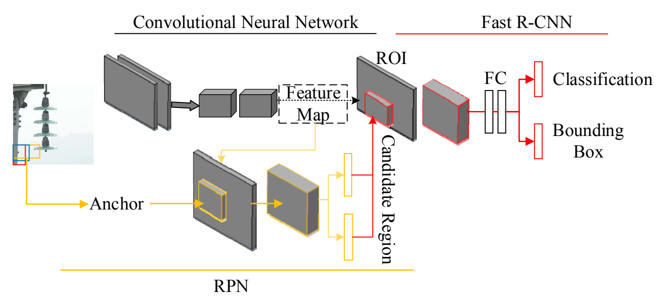

Figure 2. Network model of Faster R-CNN

RPN network and Fast R-CNN network achieve parameter sharing by means of alternate training. Network training adopts a four-step method：

Step I: Independently train RPN network. The parameters of convolutional network should be initialized through ImageNet data set pre-training model.

Step II: Independently train Fast-RCNN network. Use the candidate box and the feature map of the convolutional network output by RPN in Step I as the input of detection network. After passing the pooling and fully connected layer in the region of interest, use Soft function to achieve object classification and use bounding box regression to output the position coordinates of insulators.

Step III: Fix the parameters of the 13-layer fully convolutional network, re-train RPN and update the parameters of RPN only.

Step IV: Fix the parameters of the 13-layer fully convolutional network, and use the candidate box output by RPN to fine-tune Fast-RCNN network.

The method of alternately using RPN network and Fast-RCNN network to train and fix the parameters of the full convolution layers achieves parameter sharing between networks and enhances the speed of insulator detection. The iterations of Fast-RCNN network as shown in Table I.

TABLE I. TRAIN TIMES OF FASTER R-CNN

Sequence	Network	Training times
1	RPN	20000
2	Fast R-CNN	40000
3	RPN	20000
4	Fast R-CNN	40000

Anchor is the core of RPN network. Because of the differences in size and length-to-width ratio between the objects, multiple-scale windows are needed. Setting the underlying parameters, multiple and ratio of Anchor can generate Anchors of different scales. To adapt to the length-to-width ratio of the insulator objects, this paper tests two different Anchor scales as shown in Table II.

TABLE II. ANCHOR RATIOS

Number	Anchor ratios
Anchor1	0.5、1、2
Anchor2	0.2、0.5、1

Two models are respectively trained based on the scale portfolio of Anchor in Table 2, the iterations of training in Table 1 and an initial learning rate of 0.01. The test selects two insulator photos with different materials, backgrounds and slant angles. The test result as shown in Figure 3.

(a) Anchor1test results

(b) Anchor2 test results

Figure 3. Different Anchor ratios test results

Through contrast experiments, it is found that the test result of the model trained by Anchor1 has false detection, duplicated selection and missing detection. Anchor2 solves the problems mentioned above. Therefore, we adopt the training model of Anchor 2 for insulators detection.

C. *Insulator Segmentation*

When semantic segmentation algorithm is adopted to achieve insulator segmentation, this paper separates the foreground and background of the insulators by using a fully convolutional network based on VGG16. Experiments discover that if the output of the last layer of the network is directly used as the result of semantic segmentation, it will lead to incomplete retention of the marginal information of insulators, so that the accuracy of segmentation will be influenced. That is because the segmentation model based on VGG16 uses 5 subsampling layers, which makes the image resolution of the last classification layer less than that of the original image. Besides, after 32 times of up-sampling, it is hard to completely describe the marginal information of insulators. The network structure receiving 32 times of up-sampling is called FCN-32s[16, 17].

To retain the location information of low-level map and the abstract features of high-level map, we adopt multi-scale fusion method to train the fully convolutional network. The output features of well-trained FCN-32s network, after twofold up-sampling, are made to fuse with the output features of the network after 4 times of sub-sampling. Then the fused image is restored to the size of the original image after sixteen-fold up-sampling. Such network is called FCN-16s. FCN-16's accuracy is obviously higher than that of FCN-32s model. The output of FCN-16s network is made to fuse with the feature map of the third sub-sampling and receive eightfold up-sampling to get FCN-8s. The segmentation effect of FCN-8s is considerably improved than that of FCN-16s, as shown in Figure 4.

(a) FCN-16 segmentation results

(b) FCN-8s segmentation results

Figure 4. Segmentation result of FCN-16s and FCN-8s

The segmentation accuracy of FCN-8s Model is considerably higher than that FCN-16s. And the former performs better in margins and details. So, we adopt FCN-8s as the input of classification network.

D. *Explosion Classification of Insulators*

Insulators are fully separated from the background after detection and segmentation. To achieve highly accurate insulator explosion recognition, we adopt GoogLeNet[18] network with Inception structure. Inception structure is constituted by convolutions of different sizes, as shown in Figure 5.

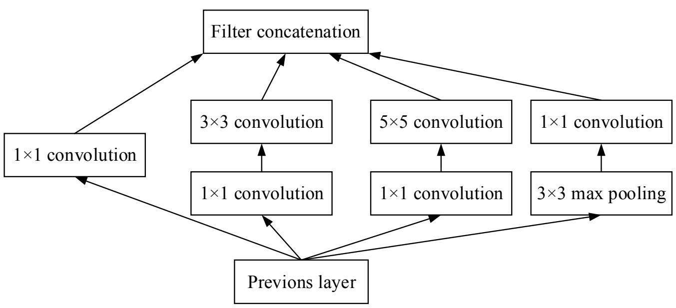

Figure 5. Inception network

Model GoogLeNet comprises 2 convolution layers, 9 Inception modules, 4 pooling layers, 1 average pooling layer and 1 fully connected layer. The sizes of the output images are standardized as 224×224×3, and then zero mean value is used for preprocessing. The pooling layers conduct twofold sub-sampling to the feature map output by the convolution layers to reduce the space size and overfitting. ReLU is added after each convolution layer as activation function and nonlinear factors are introduced. Average pooling layer is used to replace the fully connected layer to map the output feature map of the convolution layers into a 1024D feature vector. The last fully connected layer uses Soft as activation function, and feature vector as input to judge whether the insulators are explosion and output the image names of explosion insulators.

IV. EXPERIMENTAL RESULT AND ANALYSIS

The specifications of the test bench are as follows: Ubuntu 16.04 64-bit OS and Nvidia GTX 1060ti GPU. This paper adopts the deep learning framework Caffe, the compiling interface Python, and enables GPU acceleration. Drones are used to collect images of power transmission system of different road sections and with different backgrounds. Altogether 19,000 pieces of images in 3936×2624 pixel are collected.

A. *Detection Test*

The insulator detection samples are made in the form of marker box. First, the images are normalized to 1,500×1,000. Then, making software is used to mark the images. Altogether 3,900 images containing insulators are marked.

As shown in Figure 6, this paper selects 400 insulator images of different types and different angles, and with different backgrounds to test the insulator detection model. The test results suggest that the detection model used by this paper demonstrates excellent universality to insulators of different types.

Figure 6. Detection results of insulators

Accurate and efficient insulator detection from complex background lays good foundation for follow-up insulator segmentation and explosion recognition.

B. *Segmentation Test*

Semantic segmentation samples are made with PS. In total, 500 insulator samples with different backgrounds, lights and shooting angles are chosen from the collected original power transmission system images. Then, the images are cut into 500×500. The foreground and background of insulators are separated by means of sectional drawing. The produced data set is used to successively train FCN-32s network, FCN-16s network and FCN-8s network.

Based on the positions of the target boxes output by insulator object detection, cut the corresponding insulator regions on the original images as test samples for insulator segmentation as shown in Figure 7, including 4 images of non-explosion insulators and 2 images of explosion insulators.

Figure 7. Cutting results of insulators

Input the cut images of insulators into the trained FCN-8s model and obtain the result of insulator segmentation as shown in Figure 8. The test result suggests: insulator segmentation achieved by established fully convolutional network avoids manually designing features and threshold selection; the segmentation results almost remove the disturbance of complex background. That fully demonstrates the advantages of fully convolutional network.

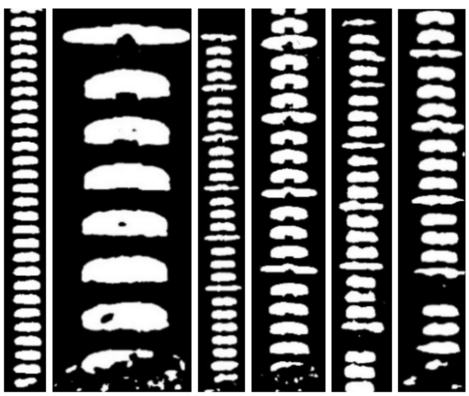

Figure 8. Segmentation results of insulators

C. *Explosion Recognition Test*

1) *Treatment of Samples for Training*

Semantic segmentation samples are made with PS. In total, 500 insulator samples with different backgrounds, lights and shooting angles are chosen from the collected original power transmission system images. Then, the images are cut into 500×500. The foreground and background of insulators are separated by means of sectional drawing. The produced data set is used to successively train FCN-32s network, FCN-16s network and FCN-8s network.

2) *Experimental results*

The insulator explosion classification model has a total training frequency of 40,000 times. The initial learning rate is set at 0.01; the learning rate reduces to 0.1 times of the previous rate for every 15,000 iterations of the model. The training model is preserved once every 10,000 trainings.

The test samples contain 350 explosion insulator samples and 350 non-explosion insulator samples. Respectively test 700 samples according to the preserved models, and compare the influence of different training times on accuracy. The test result as shown in Table III.

TABLE III. ACCURACY COMPARISON OF SELF-EXPLOSION

Training times	**Accuracy for exploded**	**Accuracy for not exploded**	**Average accuracy**
10000	99.14%	96%	97.57%
20000	100%	92.29%	96.14%
30000	99.71%	96.29%	98%
40000	99.71%	98.86%	99.29%

It can be seen from Table III that when the training times reach 40,000, the average accuracy of achieving insulator explosion reaches 99.29%, effectively achieving insulator explosion recognition.

Conduct insulator explosion recognition based on convolutional network algorithm and traditional algorithm to the test set according to the model output when the training times reach 40,000. Traditional insulator explosion recognition method: count the number of white pixel points in the insulator region first. Then, the number is compared with the preset threshold value to judge whether insulator explosion exists[2]. The corresponding recognition accuracies as shown in Table IV. It can be proven from Table IV that the convolutional network method is obviously more useful than traditional ones, improving the insulator explosion recognition accuracy by over 10%.

TABLE IV. EXPERIMENTAL RESULT OF FAULT INSULATOR

Method	**Accuracy for exploded**	**Accuracy for not exploded**	**Average accuracy**
Traditional method	86%	91.5%	88.75%
This paper method	99.71%	98.86%	99.29%

Insulator explosion detection and recognition method based on deep learning can avoid the subjectivity and uncertainty of manually designing features and threshold selection in traditional methods. Automatic extraction of image features through convolutional network can achieve end-to-end smart insulator explosion recognition, and enhance the efficiency of fault detection and the accuracy of fault recognition for power transmission system.

3) *Comparison with 0ther Algorithms*

To verify the practicability of the algorithm adopted by this paper in insulator explosion recognition, experiments are done to compare this paper's algorithm with the Local Outlier Factor algorithm put forward by literature[1], the insulator pixel number threshold method put forward by literature[2], the distance between the central points of insulators put forward by literature[4], and the algorithm of Euclidean distance between two neighboring insulators put forward by literature. The recognition effects of different algorithms as shown in Table V.

TABLE V. RECOGNITION EFFECTS OF DIFFERENT ALGORITHMS

Algorithm	Accuracy for exploded	Noise factor	Average accuracy
Literature[1]	95%	12%	91.5%
Literature[2]	86%	8.5%	88.75%
Literature[4]	76.9%	23.1%	76.9%
Literature[19]	87%	13%	87%
This paper	99.71%	1.14%	99.29%

It can be learned from Table 5 that this paper's algorithm is obviously superior to other algorithms in the accuracy of insulator explosion recognition. The algorithm adopted by this paper shows the lowest false detection rate and an average accuracy of 99.29%, drastically improving the accuracy of insulator explosion recognition. To sum up, the algorithm adopted by this paper makes excellent effects in insulator explosion recognition and it has certain application values.

V. CONCLUSION

Insulators are indispensable components of power transmission system. Currently prevailing fault detection methods are mostly achieved by men. Manual fault detection, with long cycles and low efficiency, usually cause delayed fault discovery, thus impacting the safe operation of power transmission system. This paper, based on deep learning, puts forward an efficient algorithm for insulator fault recognition. Test results have suggested that insulator extracting and segmentation by means of deep learning can enhance the robustness of algorithm and improve the accuracy of insulator explosion recognition against complex background to certain degree. In future work, we will use bigger sample database and multi-layer convolutional network models to enhance the accuracy of explosion detection. Besides, we will study more algorithms for typical faults recognition of power transmission system.

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