Image Detection Technology on Pin Defect to Overhead Power Lines

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Abstract: To improve efficiency of UAV in routing inspection of overhead power lines as well as detection rate of pin defect to overhead power lines, the thesis proposes a method for detection of pin defect for UAV routing inspection of overhead power lines based on Faster-RCNN algorithm. In view of the fact that UAV routing inspection is characterized by large image background and tiny size of pin, the deep residual network ResNet101 is selected as pre-feature extraction network on the basis of Faster-RCNN and training image scale is increased. Experiments show that the method has a good performance in pin defect detection in UAV patrol image on test set. Compared with other prevailing object detection methods, the detection effect is better and the generalization ability is stronger.

Keywords: UAV Patrol Image, Overhead Power Lines, Pin Defect Detection, Convolutional Neural Network

I. INTRODUCTION

In recent years, researchers have carried out numerous researches on UAV routing inspection image based defect detection[1-5]. Reference[1] aims to divide the image to identify transmission wire through hough conversion by means of edge detection and mathematical morphology following such pre-treatment measures as gray processing, optical rectification and noise elimination to image of overhead power lines. Reference [2] uses gradient operator to extract line object on the routing inspection image, identify obvious parallel wire group through parallel line calculation for long line segment, and finally carry out segmental analysis of wire for detection of such defects as broken wire strand and foreign matters based on variation to width of segment wire and gray scale similarity. Reference[3] uses the maximum entropy segmentation method for foreground extraction of insulator, which aims to realize detection and positioning of self-explosion defect to insulator without obvious superposition with the help of feature detection algorithm established based on the spatial sequence relationship. Reference[4] uses 3D block match filter to establish convolutional neural network based on Tensorflow following noise elimination of image so as to identify foreign matters on overhead power lines. Reference[5] aims to adjust the size of convolution kernel so as to identify bird nest on overhead power lines and defects to grading ring and vibration damper.

The pin aims to prevent dislocation of soft connection part in overhead power lines. Harsh environment (such as hail, acid rain, bird pest, etc.) and mechanical vibration may result in disengagement or falling of pins, which may seriously affect normal operation of other parts in overhead power lines. In view of large quantity and small size of pins, routing inspection personnel are requested to check pins as shown in UAV routing inspection image one by one by means of amplification and pulling. This may result extremely high work load as well as high missing report rate and false report rate.

There are few studies on identification of pin defect as shown by UAV routing inspection image in existing references. Reference[6] extracts features of histogram of oriented gradient in image to establish supporting vector machine for positioning of bolts. Nevertheless, it fails to judge defects to pins in bolts. Reference[7] firstly uses Adaboost classifier for positioning of bolts containing pins, and then uses simple convolutional neural network to identify disengagement of pins in bolts. However, this method has poor generalization capacity and relatively low detection rate as it uses traditional manual features for positioning.

In view of the fact that pin image presented by UAV routing inspection of overhead power lines is characterized by large background and small target, the thesis proposes an improved Faster-RCNN algorithm, which aims to enlarge training image scale, and use deep residual network as pre-feature extraction network based on Faster-RCNN network. It has satisfactory effect in detecting pin defects during UAV's routing inspection of overhead power lines.

II. PRINCIPLE AND IMPROVEMENT OF ALGORITHM

A. Faster-RCNN

In recent years, object detection algorithm based on deep learning has achieved good results in various fields. Compared with traditional methods, with the support of large data, deep learning no longer relies on traditional manual features, but automatically learns and extracts features, which has strong robustness and higher recognition accuracy. Compared with other deep learning object detection algorithms, Faster-RCNN[8] has higher accuracy and better recognition effect for small objects.

Faster-RCNN consists of three parts: Pre-feature extraction network CNN, object detection network RCNN and regional proposal network RPN. The overall network structure is shown in Figure 1. Pre-network CNN extracts features from input

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images and outputs feature maps. RPN network is a full convolution network, which acts as a "attention mechanism". It is composed of feature graphs into regional suggestion boxes. Finally, RCNN network combines feature maps with regional suggestion boxes to generate positioning rectangular boxes and their classification confidence.

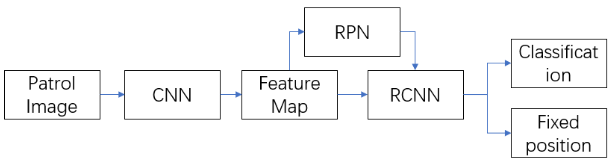


Fig 1. The overall network structure of Faster-RCNN

The joint loss function is composed of two kinds of loss weights. As shown in formula (1), L_{cls} is the classified loss function, L_{reg} is the location loss function, N_{cls} is the total anchor frame number, N_{reg} is the batch training parameter, and λ which is the loss weight is 1. p_i are the probability of predicting the target, p_i^* is the label, t_i is the location of the predicted rectangular box, and t_i* is the actual location of the rectangular box.

$$L(\{p_i\},\{t_i\}) = \frac{1}{N_{cls}} \sum_i L_{cls}(p_i, p_i^*) + \frac{\lambda}{N_{reg}} \sum_i p_i^* L_{reg}(t_i, t_i^*) \tag{1}$$

Classification loss function L_{cls} is a classical two-class cross-entropy loss function, as shown in Formula (2).

$$L_{cls}(p_i, p_i^*) = -\log[p_i p_i^* + (1-p_i^*)(1-p_i)] \tag{2}$$

The location loss function L_{reg} represents the deviation between the predicted rectangular box and the real rectangular box. As shown in equation (3), the constant σ is 3.

$$L_{reg}(t_i, t_i^*) = \begin{cases} 0.5 \cdot (t_i - t_i^*)^2 \cdot \frac{1}{\sigma^2} & |t_i - t_i^*| < \frac{1}{\sigma^2} \\ |t_i - t_i^*| - 0.5 & \text{others} \end{cases} \tag{3}$$

B. *Improvement*

The original Faster-RCNN algorithm extract image characteristic graph by the VGG16 network. The graph includes 13 convolutional layers, 13 active layers and 4 pooling layers. The convolutional layers will not change the image scale. Whereas, each pooling layer may reduce the image length and width by 50% respectively; for this reason, scale of the characteristic graph as eventually obtained is equivalent to 1/256 of original image. Small target objects on the characteristic graph only occupy several or even less than one pixel; the loss of a large quantity of details may result in lower identification rate of small target objects on the part of Faster-RCNN. Detection of pin defects in image obtained through UAV's routing inspection of overhead power lines is a typical task of large background and small target; image scale is up to 4 000×3 000 pixels; whereas average scale of pin is only up to 60×60 pixels. The thesis is expected to improve original Faster-RCNN to further improve identification rate of pin defects.

To facilitate follow-up operations, original Faster-RCNN may proceed with uniform down sampling of short side of input image to 600 pixels or down sampling of long side to 1000 pixels; meanwhile, pin scale is to be reduced accordingly. Specific distribution is as shown in Figure 2 according to statistics of average length and width of pins after sampling. Most of average length and width of pins is below 24 pixels; wherein, over half of average length and width of pins are below 16 pixels, and that mapped on the characteristic graph is less than 1 pixel. Therefore, Faster-RCNN network is difficult for effective learning.

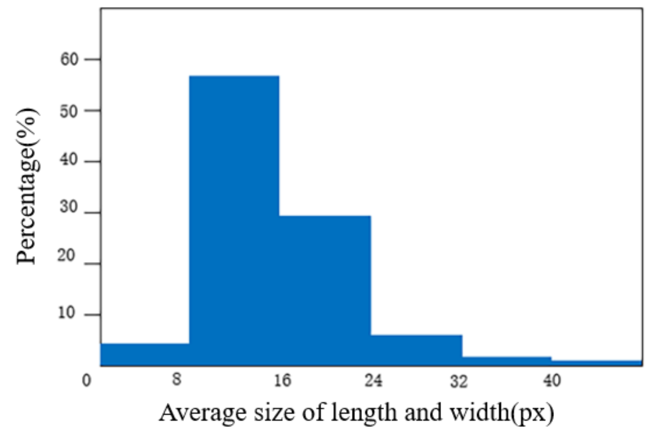


Fig 2 Average length and width of pins under the original training scale

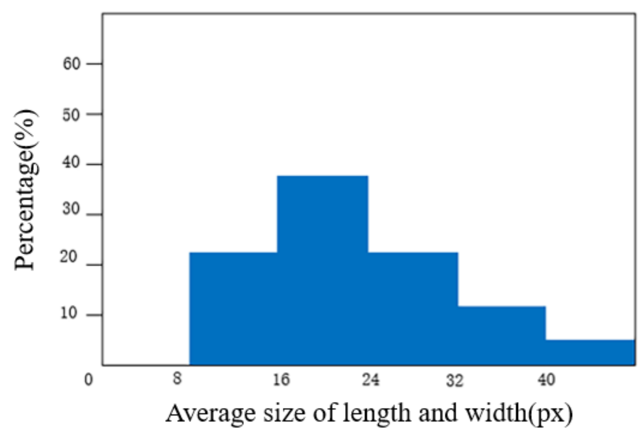


Fig 3 Average size of length and width of pins under the larger training scale

The thesis has enlarged image training scale, and balanced detection speed and precision, which is expected to proceed with uniform down sampling of short side to 900 pixels or down sampling of long side to 1500 pixels in proportion before UAV routing inspection image is input into CNN network. Distribution of average length and width of pins at large training scale is as shown in Figure 3, which is equivalent to the pin's feature map as amplified by 1.5 times. This has enlarged the characteristic graph scale, and improved identification rate of small objects.

In order to overcome network degradation problem and extracte better features, deep residual network is designed. Deep residual network[9] designs a residual module and builds the network with the residual module. As shown in Figure 4, the residual module establishes a direct connection between input and output through the idea of 'short circuit connection'. Each layer of network does not need to learn the whole output, but only the residual of input and output, which reduces the complexity of network learning. If the gradient of a layer disappears, the output of the layer is equal to the input, which constitutes an identity map and does not affect the learning of the subsequent network.

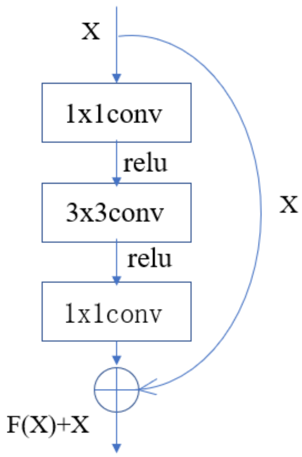


Fig 4 Residual module

The thesis use deep residual network ResNet101 to replace VGG16 network used by original Faster-RCNN. ResNet101 is formed through stacking of aforesaid residual module layers, which includes 100 convolutional layers, 100 active layers, 4 pooling layers and 1 fully connected layer. As pooling layers in the same quantity are included, variation to image scale is consistent with VGG16 network. As indicated by experiments, extraction characteristics of ResNet101 network can obtain better detection results as compared with VGG16 network.

III. EXPERIMENT

A. Establishment of dataset and evaluation index

The high-resolution image of overhead power lines as taken by routing inspection UAV of the power company is selected as training and testing samples for experiment. Wherein, 242 images are used as training samples, including 250 pin defects with image scale up to 4000×3000 pixels; 93 images (including 98 pin defects) are used as testing samples, which have the same scale as the training samples. As there is no disclosed dataset, the quantity of training samples is so limited and in consideration of variation to the angle of view and resolution during UAV shooting in case of practical application, images of training samples are increased to 968 pieces through mirror inversion and increase of Gaussian noise to improve generalization capacity of the model. All data is fabricated into PASCAL VOC format.

Precision, Recall and AP are taken as evaluation indexes for experiments. Precision refers to proportion of real defect samples as identified among all defect samples. Recall is also known as detection rate, which refers to proportion of real defect samples as identified among all defect samples. Specific computation formula is as shown in Formula (4):

$$\mathrm{Precision}=\frac{TP}{TP+FP} \qquad \mathrm{Recall}=\frac{TP}{TP+FN} \tag{4}$$

In the formula, TP refers to the quantity of identified defect samples; FP refers to the quantity of normal samples as mistakenly identified as defect samples; FN refers to the quantity of unidentified defect samples.

With regard to different confidence threshold values, certain changes may take place to the Recall and Precision. It is applicable to obtain a Precision-Recall Curve if Recall and Precision are deemed as transverse and longitudinal coordinates respectively; AP value refers to the area of zone enclosed by this curve as well as x and y axis.

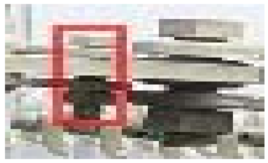
During practical application, normal setting of confidence threshold value may result in the maximum product of Recall and Precision to ensure the optimal performance of algorithm during detection. Whereas, AP value can provide an integrated and comprehensive evaluation of algorithm performance in terms of theoretical analysis.

B. Model training and testing

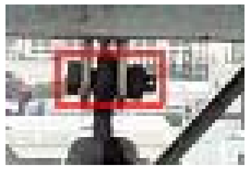
Establish improved Faster-RCNN target testing network based on Tensorflow frame; fine-tuning[10] strategy is introduced into the pre-feature network; pre-training network parameters are available for minor adjustment on ImageNet dataset, which can improve training convergence speed to some extent. Initial learning rate is set as 0.001; Stochastic Gradient Descent (SGD)[11] is selected as optimization strategy; wherein, Epsilon is 10^{-5}; Momentum is 0.9; total training steps are up to 110,000. Other conventional parameter, such as dropout, are consistent with original Faster-RCNN.

Ckpt model document is to be generated upon completion of training. Proceed with forecast of tested images once network model parameters are introduced during testing. We use the ratio between the area of overlapped part of positioned rectangular frames and marked rectangular frames and the union part of the two frames so as to judge if the testing is successful. If the ratio is over 0.3, it will be able to locate the position of specific defective pins on the pole tower accurately, and working staffs can easily proceed with troubleshooting and maintenance. As it can basically satisfy requirements for practical application, the testing can be deemed as being successful. Partial testing results are as shown in Figure 5, in which the position of defective pin is marked with rectangular frame.

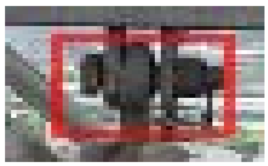
(a) Testing result 1 (b) Defect enlargement pattern 1

(c) Testing result 2 (d) Defect enlargement pattern 2

(e) Testing result 3 (f) Defect enlargement pattern 3

(g) Testing result 4 (h) Defect enlargement pattern 4

Fig. 5 Sample drawings of testing results and enlargement pattern of defective pins

C. Analysis and comparison of results

To verify validity of the improvement strategy proposed by the thesis, different improvement strategies are used for training and testing; specific testing results are as shown in Table 1. Strategy 1 refers to original Faster-RCNN network, which has higher precision in terms of testing set; however, its Recall is only 71.4%, indicating higher missing detection of pin defects. Strategy 2 has substituted pre-feature extraction network; Recall and AP have been increased by 10.2% and 3.1% respectively despite of the fact that Precision has been decreased by 6.1%. As compared with Strategy 2, Strategy 3 has increased AP by 7.5%; wherein, Precision and Recall have been increased by 3.8% and 4.1% respectively; this is due to the fact that large-scale training has enlarged the scale of characteristic graph. As indicated by experiment, various improvement strategies as proposed by the thesis can improve comprehensive testing performance of the network.

TABLE 1. TESTING EFFECT UNDER DIFFERENT IMPROVEMENT STRATEGIES

Strategies	*Front Network*	*Large Size*	*Recall(%)*	*Precision(%)*	*AP (%)*
1	VGG16	N	0.714	0.921	0.682
2	RES101	N	0.816	0.860	0.713
3	RES101	Y	0.857	0.898	0.788

D. Comparison with other prevailing detection algorithm

The algorithm proposed by the thesis has been compared with other mainstream target testing algorithms, such as SSD[12], YOLOv3[13] and original Faster-RCNN; specific testing results are as shown in Table 2. Recall and Precision of SSD algorithm are only 10.2%, which are unable to effectively identify pin defects. Recall of YOLOv3 algorithm is also extremely low, and detection effect is poor. Recall and precision of the algorithm proposed by the thesis are up to 85.7% and 89.8% respectively in terms of testing set; as compared with original Faster-RCNN algorithm, recall has been significantly improved by 14.3%; meanwhile, AP have been increased by 10.6% respectively. According to empirical comparison, algorithm proposed by the thesis has the optimal comprehensive testing effect.

TABLE 2 TESTING EFFECT OF DIFFERENT DETECTION ALGORITHMS

Algorithm	*Recall(%)*	*Precision(%)*	*AP(%)*
SSD	0.102	0.102	0.065
YOLOv3	0.347	0.944	0.401
Faster-RCNN	0.714	0.921	0.682
Ours	0.857	0.898	0.788

IV. CONCLUSION

a) The thesis has proposed a method for detection of pin defects overhead power lines during UAV routing inspection. This method is based on Faster-RCNN network, and has witnessed targeted improvements; its recall and precision are up to 85.7% and 89.8% respectively in terms of testing set; it has a relatively satisfactory effect in detection of pin defects as shown by UAV routing inspection image.

b) In view of the problem with large background and small target scale of images, the thesis uses enlarged training image scale, and takes deep residual network as pre-feature extraction network, which can improve the detection rate of small object to some extent. As compared with original Faster-RCNN algorithm, recall and AP of the method proposed by the thesis have been increased by 14.3% and 10.6% respectively.

ACKNOWLEDGMENT

We are sincerely grateful that Weihai power supply company of State Grid Shandong electric provide the valuable dataset and department of Electrical Engineering of Shanghai Jiao Tong University provide some assistances in technique for our study.

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