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Transmission Line Image Defect Diagnosis Preprocessed Parallel Method Based on Deep Learning

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***Abstract*—Deep learning has shown its potential and advantages in feature extraction and model fitting. It has also been promoted and applied in the field of transmission, and cooperates with drone inspection data to diagnose defects of transmission equipment. This paper aims at engineering application. The accuracy of defect diagnosis is improved, and multiple significant target detection is applied. Preprocess the image and implement parallel image prediction. The image preprocessing includes defogging processing, rotation, etc., and finally achieves target detection by combining logic judgment.**

Keywords-deep learning; object detection; logical decision; SSD

I. INTRODUCTION

As the demand for power transmission in China continues to increase and the scale of power systems continues to expand, the safety and stability of power systems is becoming more and more significant. With the gradual development of drone inspections and the rapid advancement of technology, the introduction of artificial intelligence in transmission line inspection has brought new impetus.

At present, domestic and foreign research has achieved certain results in the research of image acquisition of inspection images. Chao yang Li et al. [1] used Ratio operator, Radon transform and Kalman filter-like technique to extract power lines. Tong W G [2] used Hough transform, differential geometry method and digital graphics method to extract power lines. Sarabandi K [3] used the radar reflection wave polarization statistical method to extract and identify the transmission line. Li, Zhengrong, et al. [4] used the neural network method to filter the background noise and extracted the transmission line. Xiao ning huang [5] based on the maximum entropy threshold method for image segmentation, using the connected region method to extract the insulato. Although the above method can extract the power line equipment, it still needs further improvement. Maraaba [6] proposed a high voltage insulator contamination level assessment tool, and image processing is used to extract the desired features from the captured image.

The aerial line images studied in this paper are collected in a high-altitude environment. When performing image acquisition, the film grain noise caused by uneven exposure and the random noise introduced by electronic components during digitization will reduce the image quality. The extraction of power lines has an important impact. Therefore, preprocessing the acquired image is a very important stage. Various methods in image preprocessing have certain limitations, each of which is applicable to a specific situation or a specific type of situation, especially the noise processing of images. Although there are many methods of denoising, it usually causes some Important information is missing, so the choice of denoising method is based on actual conditions to achieve the desired best results.

II. SSD DETECTION MODEL AND FASTER-RCNN DETECTION MODEL

A. SSD Detection Model

SSD (Single Shot MultiBox Detector) [7] is an end-to-end target detection model that eliminates the traditional deep learning to resample the pixels or features of the bounding box hypothesis, and instead uses separate filtering with different aspect ratios. The prediction of the target type and offset in the bounding box does not require additional calculation of the Bounding Box and the recognition accuracy is high, so that it can be quickly identified [8]. The deep network-based object detector used by SSD is a single-shot detector. This small convolution filter is used to predict the positional offset and class response score of the bounding box in the feature map. When trained, the SSD only needs the target. The input image and the calibrated label box are used to evaluate and predict the default box at each position of all feature boxes of different scales during the convolution operation. The predicted content is the shape offset and confidence of all object categories. . Model loss is calculated as the weighted sum of position loss and confidence loss [9]:

$$L(\mathrm{x},\mathrm{c},\mathrm{l},\mathrm{g}) = \frac{1}{N}(\mathrm{L}_{conf}(\mathrm{x},\mathrm{c}) + \alpha L_{loc}(\mathrm{x},\mathrm{l},\mathrm{g})) \quad (1)$$

Where: x indicates whether the prediction box matches the real box: 0, 1 (0 is a mismatch, 1 is a match). Value c is the confidence level. l is the prediction box value; g is the real box value. N is the representation and ground truth. The number of default boxes matched by box. The value of weight is set to 1, and the localization borrows the calculation of the center position and width and height of the bordering boxes in Fast

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L1 Loss by Faster RCNN. The calculations were originally used in the predict box and ground truth box of Faster RCNN [10,11], the confidence loss (conf) is Softmax Loss, and the input is the confidence level c of each type. The basic network used by SSD is VGG-16 [12-14], and some auxiliary structures have been added. Compared with YOLO, Faster RCNN and other algorithms have great advantages in speed and accuracy. By learning the Anchor RCNN's Anchor mechanism and using multi-scale methods shown in Fig. 1. Compared with YOLO, Faster RCNN and other algorithms, SSD has a lot of advantages in speed and accuracy, by learning from Faster RCNN Anchor mechanism and using multi-scale approach. It not only guarantees the high speed that is almost the same as YOLO, but also takes into account the effect of Faster RCNN algorithm. The target detection effect and speed are better for the target. Therefore, for the defect detection of the power industry, this paper uses the SSD method to perform the first-level detection of the target existence area.

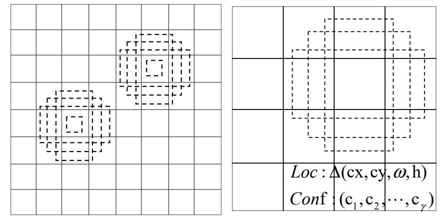

Figure 1. Multi-scale Methods

B. *Faster-rcnn Detection Model*

Design an RPN (Region Proposal Networks) network that assists in generating samples, and divides the algorithm structure into two parts. Firstly, the RPN network determines whether the candidate frame is the target, and then determines the target type by the multi-task loss of the classified positioning, and the entire network process can share the feature information extracted by the convolutional neural network. It saves computational cost and solves the problem that the Fast R-CNN algorithm generates slow positive and negative sample candidate frames. The detection speed is greatly improved, and the accuracy of the algorithm is reduced due to excessive extraction of candidate frames. Through alternating training, the RPN and Fast-RCNN networks share parameters.

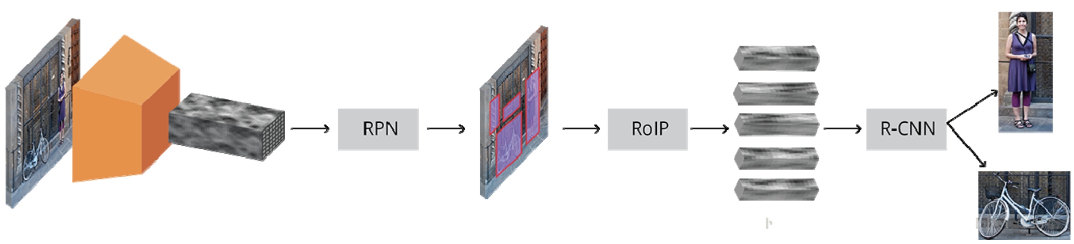

Figure 2. Complete Faster R-CNN architecture

The original Faster R-CNN used ZF and VGG pre-trained on ImageNet, but after that many different networks appeared, and the number of parameters of different networks varied greatly. For example, MobileNet, a small, efficient framework that prioritizes speed, has approximately 3.3 million parameters. The ResNet-152 (152 layers), once the winner of the ImageNet image classification competition, has about 60 million parameters. Compared to the advantages of VGG, ResNet is a deeper, larger network, so it has more capacity to learn the information it needs. These conclusions are feasible in the image classification task and should be equally effective in the problem of target detection. And ResNet is easier to train after using the residual connection and batch normalization methods, so in the second-level small target detection we use the Resnet network to implement the Faster R-CNN construction.

III. Cascading Design of Predictive Architecture and Logical Reasoning Mechanism for Parallel Target Detection Results

A. *Cascading design of predictive architecture*

This paper predicts the initial location of the target in the sample area using SSD, namely the primary target area detection. Then, the Resnet-based Faster R-CNN local area target detection is performed, that is, the secondary direct target detection.

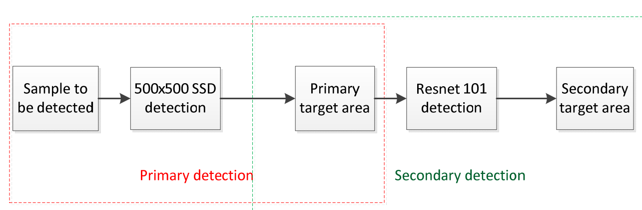

Figure 3. Cascading design block diagram of predictive architecture

B. Parallel target detection result logical reasoning mechanism

Due to weather factors such as light, sun radiation, and cloud cover, camera attitudes such as shooting attitude, shooting angle, relative motion of the camera during camera shooting, and noise are introduced during the acquisition process, so that the flying robot is inspected. The acquired image has the characteristics of distortion, distortion and blur. At the same time, the change of the environment will result in complex background image and reduced contrast. Therefore, in the image preprocessing stage, images are defogged, denoised, debounced, and enhanced and restored. Through this operation, an image to be predicted with relatively high image quality is obtained, but the acquisition of a priori noise information cannot be performed during image preprocessing, so the restoration of low quality images is generally blind restoration. Therefore, the method of image preprocessing in prediction is not well determined, so this paper designs the logical reasoning mechanism of parallel target detection results to realize the defect diagnosis of the image collected by the power line equipment UAV.

The IOU calculation formula is:

$$IOU = \frac{Detection\,\mathrm{Re}\,sult \cap GroundTruth}{Detection\,\mathrm{Re}\,sult \cup GroundTruth} \qquad (2)$$

The logical judgment s of the design of the voting decision mechanism of the IOU test result is as follows:

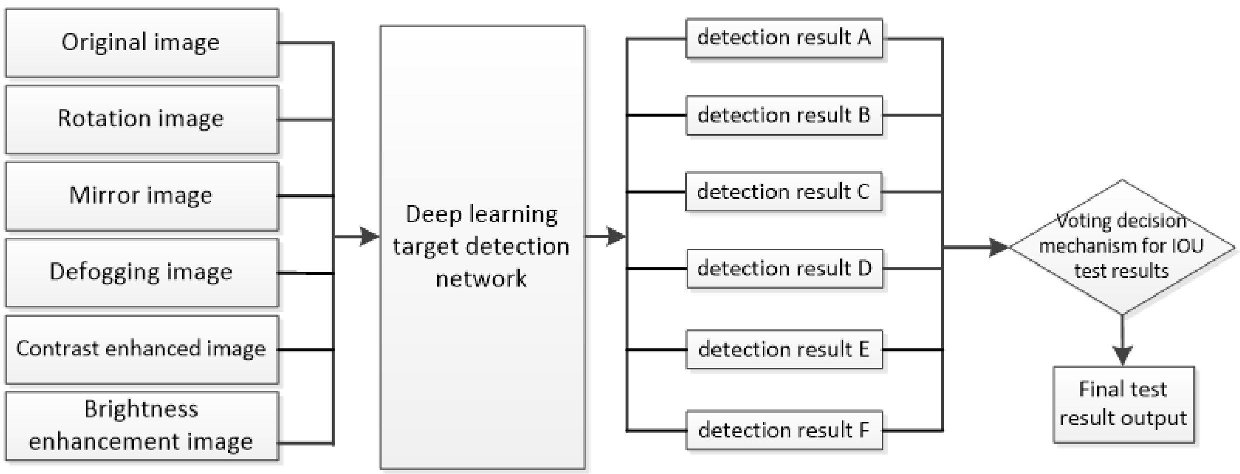

Figure 4. Parallel target detection result logical reasoning mechanism structure diagram

1) The number of targets detected by the deep learning target detection network is N. $N=\{a_1,a_2,\cdots a_i\}$, $i \in N$, and the IOU calculation is performed on the detection picture results A, B, C, and D. It is assumed that the detection picture result A prediction target is N_A, and the picture result B prediction target is N_B, The picture result C prediction target is N_C, the picture result D prediction target is N_D.

2) Combine the N_A, N_B, N_C and N_D sets into N_{all}. Soft-NMS [15] method is used to achieve the filtering of overlapping frames to achieve the output of the final target frame.

The NMS is used in the R-CNN to determine the final target frame. One of the main problems of the NMS algorithm is that when the ground overlap of the two ground truths is high, the NMS will remove the frame with lower confidence (confidence change to 0). The soft-NMS improvement method is to change the confidence level to the IoU function: it can have a lower value without being deleted from the sorted list, thereby improving the detection accuracy.

IV. EXPERIMENTS

In this paper, the data collected by the drone inspection is used for experimental work. Transmission line detection targets are insulator damage, including glass insulators and composite insulators. The damage is divided into the case where the insulator piece is dropped or cracked.

Hardware lab environment: Intel(R) Xeon(R) CPU E5-2683 v3 @ 2.00GHz CPU, NVIDIA GTX 1080TI.

Software experiment environment: Linux Ubuntu 16.04, python 2.7, cuda8.0, gcc 5.4.0.

Fig.5 shows the image to be detected. Fig. 6 shows the effect of a test using SSD.

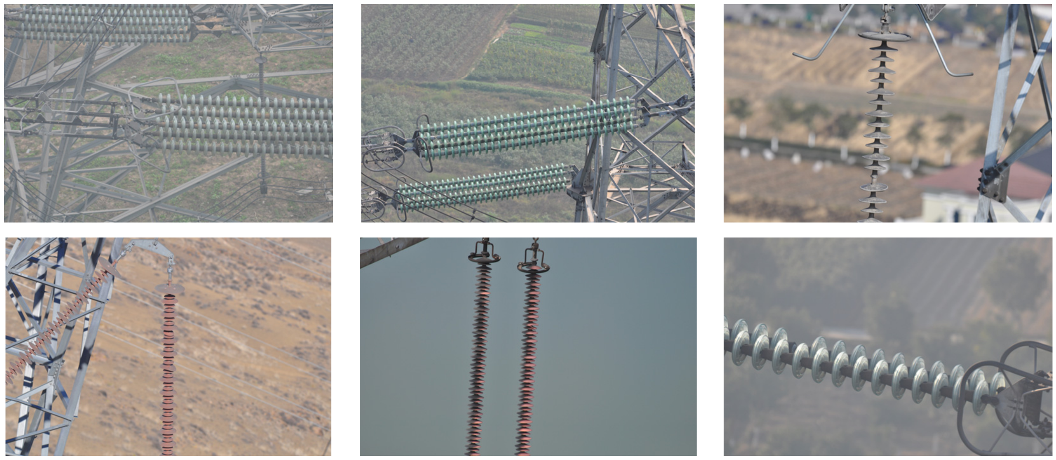

Figure 5. Test picture original

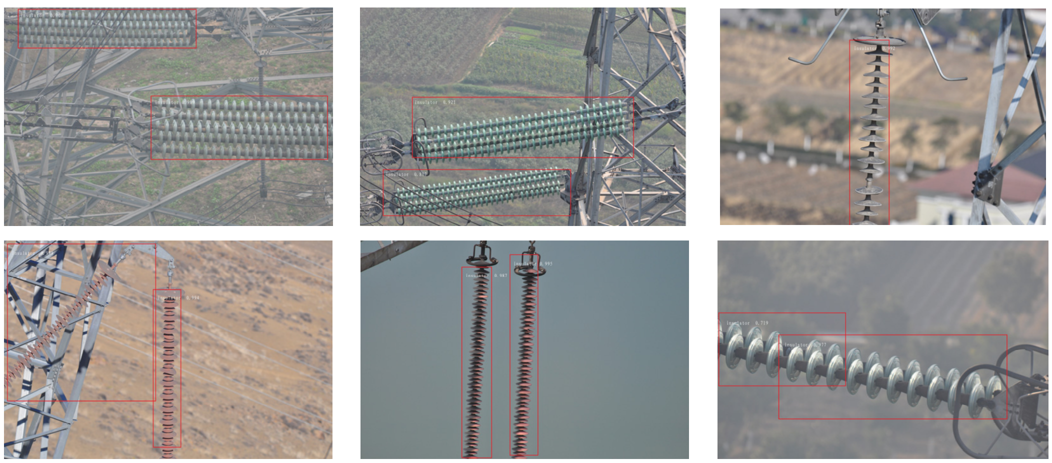

Figure 6. SSD algorithm first-level detection effect chart

The target area obtained after the first-level detection has a large aspect ratio. Therefore, in order to cooperate with the subsequent fixed-size detection, the target area is filled, and the original target detection size is 2300*856, and the image expansion is performed according to the aspect ratio 1.5. The expanded image size is 2300*1532, and the expansion processing effect comparison chart is as follows:

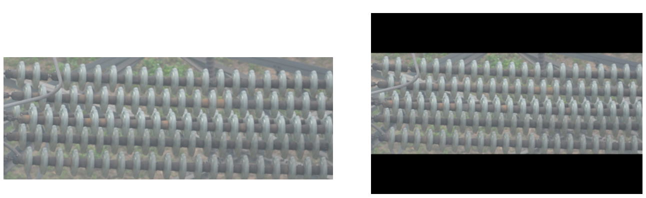

Figure 7. Level 1 target area expansion

Secondary detection preprocessing method, including image rotation, mirroring, defogging, contrast enhancement, and brightness enhancement. The image rotation method is rotated 5 degrees counterclockwise. Image dehazing uses the dark channel prior defogging algorithm [16], the filter radius is set to 11, and the window size is 25. The pretreatment effect diagram is as follows:

The cascading design of the predictive architecture and the logical reasoning mechanism of the parallel target detection result are used to diagnose the damage of the insulator damage. The same data set is used for model training, and the three prediction modes A, B and C are compared for the control experiment. The A mode is the end-to-end single model prediction, which refers to the use of the ResNet-101 model for defect detection; the B mode is the cascade design of the prediction architecture using SSD and ResNet-101; the C mode is a test using SSD, and the logical reasoning of parallel target detection results is used. The mechanism cooperates with ResNet-101 for secondary testing.

The end-to-end single model prediction and the AP value, the false negative rate, and the false positive rate predicted by the logical reasoning mechanism of the parallel target detection result are shown in Table 1. It can be seen that the B mode is higher than the A mode AP value. The rate of report and false positive rate is lower, but the speed is slightly slower: C mode has improved the accuracy of A and B mode detection, but the use speed is longer, so the B mode and C mode used in this paper are used for defect diagnosis. It is effective.

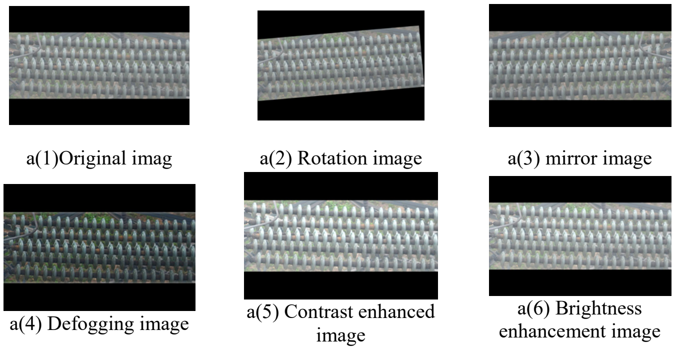
a(1)Original imag a(2) Rotation image a(3) mirror image
a(4) Defogging image a(5) Contrast enhanced image a(6) Brightness enhancement image

Figure 8. Preprocessed image

TABLE I. COMPARISON OF PREDICTIVE INDICATORS OF THREE PREDICTION METHODS A, B AND C

Method	AP	Missing rate	False alarm rate	speed
Method A	65.34%	32.42%	24.65%	425ms/ frame
Method B	72.78%	18.61%	20.64%	786ms/ frame
Method C	85.56%	11.43%	19.43%	1203ms/ frame

V. CONCLUSION

In this paper, we use the cascade design of predictive architecture and the logical reasoning mechanism of parallel target detection results. It can be seen from the experimental results that the B mode and C mode designed in this paper have obvious improvement effect. Considering the defect diagnosis mode of the current transmission line, the inspection images are mostly offline data, and the daily data increase is not large. Therefore, the cascade design of the prediction architecture and the logical reasoning of the parallel target detection result are used without considering the time cost. The mechanism can improve the application effect of the algorithm under the project faster. Although the method is effective, the speed increase will be the focus of the next step.

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