Improvement of Faster-RCNN Detection Algorithms for Small Size Line Accessory Equipment

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Abstract. Aiming at the problem that the image of patrol inspection is affected by angle and distance, the target of small size accessory equipment in the image is small, and the recognition rate of current algorithm is low. An improved Faster-RCNN detection algorithm for small size accessory equipment of patrol image is proposed. By adjusting the structure of Faster-RCNN network, we can overcome the shortcomings of the current algorithm. Firstly, the deep residual network ResNet50 is used to replace VGG16 network. At the same time, the bottom and high-level features of convolution network are applied to the selection of candidate regions, so as to improve the utilization of effective information of targets, and then to improve the detection precision of small-sized targets. The results show that the detection accuracy of the improved Faster-RCNN model is 4.2% higher than that of the original algorithm.

1. Introduction
At present, there are mainly manpower unmanned aerial vehicles and helicopters in the inspection of transmission lines[1]. Acquiring the actual image and video signal of transmission line scene through the combination of various patrol modes. The defects and hidden dangers of transmission lines can be found by digital image, and then the power supply security of weft-preserving circuit can be achieved. The traditional digital image processing method extracts the target through saliency detection and image segmentation on the basis of patrol image contour map[2-4]. This method is susceptible to background environment, noise and blurred distortion. It also recognizes a class of transmission lines, which is not easy to use. Although the method of manual recognition has a high recognition rate, it can deal with all kinds of problems, such as huge workload, low efficiency, and so on. It also needs a large amount of time and energy for the training of identification personnel, which is not conducive to work on a large scale. The deep learning method is to use convolutional neural network to automatically learn and discriminate the features in the image. It has strong robustness and universality, and has become the mainstream of current target detection algorithms[5-6].

A series of methods of regional convolution neural network (RCNN) are the mainstream of current target detection algorithms. Girshick et al. proposed RCNN algorithm[7]. The deep learning classification algorithm was applied to generate candidate regions in target detection. Then the convolutional neural network (CNN) was used to extract the features of candidate regions. Finally, the classifier was used to discriminate the candidate regions. Due to repeated convolution of candidate regions, the computational time complexity of the algorithm is high. By introducing target area pooling, Girshick et al. proposed Fast-RCNN network[8], which makes the detection network scale-invariant to the input image, and extracts features from the whole image by feature mapping, avoiding repeated
convolution, improving accuracy and reducing running time. Then Ren Shaoqing et al. [9] based on Fast-RCNN, candidate region generation is also carried out by deep learning network, and target detection is unified into the framework of deep learning. The speed and accuracy of detection are further improved.

Small-size line accessory equipment is a small target in image because of its small physical size or long shooting distance[10]. However, small-size accessory equipment plays an important role in the safe operation of power grid[11]. Therefore, the research of small size target detection algorithm has important application value for intelligent circuit inspection[12].

At present, common target detection algorithms based on deep learning are proposed for conventional objects, which have good detection effect for general objects[13]. However, because of the small target of small size line accessory equipment, the detection accuracy is not high. Through the research, we can find that it is not the lack of learning and detection ability of the current network itself, but the reason that the target feature information extracted from the image is less[14]. In view of the current problems, this paper proposes a detection algorithm which modifies the structure of Faster-RCNN network. By using residual network, the detection accuracy of the detection algorithm is improved by applying high-level and low-level features to target detection at the same time.

2. Faster-RCNN Target Detection

This paper is based on Faster-RCNN algorithm to recognize small-sized accessories in patrol images. The algorithm integrates the four basic steps of target detection: candidate region generation, feature extraction, classification and location refinement into a deep network framework. There is no repetitive computation and all of them are carried out in GPU, which greatly improves the running speed[15].

The main flow of Faster-RCNN algorithm is as follows: Firstly, feature mapping maps are obtained by feature extraction of candidate regions using convolutional neural network (CNN). VGG16 network and ZF network are the main feature extraction networks. Then several candidate regions which may contain different sizes of targets are extracted from the patrol image feature map by Region recommendation strategy network (RPN). The candidate regions are mapped to feature vectors by the pooling layer of region of interest (Rol). Finally, the software Max function is used to classify the objects in the candidate region. The specific steps are shown in the flowchart.

According to the fact that the small size equipment of small patrol image has smaller target and smaller proportion of pixels, the improved algorithm proposed in this paper mainly includes two aspects:

(1) The deep residual network is used to replace VGG16 in the original algorithm, and the deeper network is used to extract more abundant features. The short-connection feedback of residual learning module reduces the connection layer by jumping, reduces the difficulty of learning objectives, and reduces the computation of the whole network while increasing the number of network layers.

(2) High-level and low-level feature maps are used for subsequent candidate region selection. After obtaining candidate regions with different features, feature vectors of uniform length are generated by pooling operation. Finally, feature classification is carried out to realize target detection. By making full use of image details, current depth learning detection algorithms are solved. The defect of low recognition rate of small size targets can improve the detection quality.
The flow chart of the improved algorithm is as follows:

![Flow Chart](image)

**Figure 2. Improved Faster-RCNN**

### 2.1. Residual Neural Network

Generally speaking, the depth of the deep learning network is proportional to the accuracy, but with the stacking of the network depth, the gradient dispersion phenomenon will become more prominent, making the accuracy of the model decrease with the increase of the depth. Therefore, a residual neural network is proposed to reduce the computational complexity of the network while increasing the number of layers of the network by using residual learning. The core of this method is that in the standard neural network aggregation, some layers are bypassed by adding jump connections, and the layer bypassed is residual. The definition of residual module is as follows:

\[ y = F(x, \{W_i\}) + x \]

Among them, \( W \) is the weight of the \( n \)th layer. \( F() \) is the residual mapping, the original mapping is \( y \). The research proves that it will be much easier to optimize the residual mapping than the original mapping.

![Residual Network Learning Module](image)

**Figure 3. Residual Network Learning Module**

### 2.2. Feature Map Extraction

The specific flow chart shows that the input patrol image is fed into the neural network, and the selected feature maps at the top and bottom are fed into the subsequent region generation network. After obtaining candidate regions of different layer feature maps, the feature vectors of uniform length are generated through the pooling layer for classification, so as to realize the detection of small target objects.
3. Experimental Verification

The experimental data used in this paper are collected by the UAV of Shandong Luneng Intelligent Technology Co., Ltd. A total of 10361 images of pins and bird protection facilities on the patrol line are obtained. Among them, 8000 images are selected as training set and 2361 images are selected as test set. The identification types include normal pins, pin out, nut removal, normal bird protection facilities.

3.1. Experimental environment

In this experiment, using Tensorflow deep learning framework, the selected hardware is configured to strong processor, 32G memory, NVIDIA GTX1080 graphics card, and software is configured to Ubuntu 16.04 system, Python 3.6, GPU acceleration library is CUDA8.0, CUDNN9.0.

3.2. Experimental Result

This experiment improves the Faster-RCNN model in two aspects:

1) using residual neural network ResNet50 instead of VGG16 model;
2) feeding high and low level feature maps into feature recognition. The original Faster-RCNN algorithm is compared with the improved algorithm in this paper. The test results are shown in the following table:

| Model       | ls  | lstx | lslm | fnss |
|-------------|-----|------|------|------|
| Original    | 0.53| 0.48 | 0.59 | 0.68 |
| Improve     | 0.58| 0.50 | 0.62 | 0.75 |

The expression of average recognition rate:

\[ AP = \int_0^1 P(R)dR \]

\( P \) is the accuracy rate, \( R \) is the recall rate.

The results show that the overall recognition rate of the algorithm is improved by 4.2% by using ResNet network instead of VGG16 network and feeding high-level and low-level feature maps into target detection. The test results of some test sets are shown in the figure.
4. Conclusion and Discussion
The research direction of this paper is to use the method of deep learning to recognize the accessory equipment of patrol image. Aiming at the low recognition rate of Faster-RCNN algorithm for small size equipment, the original algorithm is improved. In feature extraction model, the deep residual network ResNet is used for feature extraction. In the stage of classification and recognition, the high-level and low-level feature maps are fed into the candidate area network for classification and recognition. The experimental results show that the improvement of the improved algorithm is more obvious than that of the original algorithm. The accuracy of the small size target is improved by 4.2%, and the recognition rate is also improved. The improved algorithm has good performance and provides the robustness of the deep learning model in the application of patrol image recognition. However, the model can not fully detect the small size target of patrol image. Improving the detection rate of the model will be the research direction of the follow-up work.

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