Detection Technology of Intrusion Objects in Power Transmission Corridors Based on Convolutional Neural Networks

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Abstract. Intrusion objects for power transmission corridors always present a big threat to the successful operation of the power grid. Due to the complexity and total length of the transmission corridors, the conventional field inspection methods for detecting these objects is a significant workload with low efficiency. This paper proposes the method for detecting transmission line intrusion objects, including engineering vehicles such as exactors and cranes. Object detection technology is used to locate and identify the engineering vehicles near power transmission lines. Experimental results show that, compared with traditional identification methods, the proposed method can provide improved accuracy with respect to the specific classification information of engineering vehicles and serve as an information basis for transmission line fault warning.

1. Introduction
High voltage transmission line is the core component of power transmission system. The transmission line operation is one of the most important basic indexes to evaluate the power system. However, due to the complex topography and rapid construction of cities in China, it is complicated and bad operating environment of transmission lines, and foreign body invasion is likely to occur and to affect the stable operation of transmission lines [1].

In order to solve the problem of foreign body invasion in transmission lines, State Grid Corporation of China has set up the monitoring system, on the towers along the transmission lines, to monitor transmission corridors in real time. The difficulty of inspection has been greatly reduced, due to real-time monitoring replaces manual on-site inspection. Although the operation of monitoring systems has reduced labor and time costs, new problems appear.

On the one hand, the mode of manual supervision is inefficient, and personnel are prone to fatigue. It is likely to generate false alarm of monitoring many scenes. On the other hand, with the expansion of video monitoring scale of the power grid, the video monitoring centre often needs to monitor hundreds of monitoring points at the same time, which is difficult to deal with by manual monitoring.

The traditional foreign body invasion detections use the image segmentation to segment the object in the image from the background. The improved Otsu self-adaptation threshold segmentation algorithm is used to segment the aerial images based on the mathematical morphology algorithm, and the local maxima in Hough transfer accumulator and the final line number were chosen as feature vectors to recognize extra matters [2]. Horizontal and vertical gradient operators are used to detect linear objects, which improves the problem that traditional segmentation algorithms cannot effectively
detect transmission line foreign bodies under complex background [3]. Machine learning algorithm was adopted to take the image segmentation as the image classification problem, and frame difference method was adopted to mark foreign bodies for video key frames. K-means algorithm was proposed for clustering analysis of ORB operators to simplify feature points and improve the matching rate, with high recognition accuracy and fast recognition speed [4].

With the rapid development of deep learning and artificial intelligence, it plays a vital role in image recognition, speech recognition, face recognition and object detection. This paper proposes the method of detecting engineering vehicles near power transmission line based on convolutional neural networks. The object detection technology based on convolutional neural networks is used to detect engineering vehicles under transmission lines, and the boundary box is used in the image to mark the position and type of engineering vehicles. This method replaces the inefficient manual monitoring, and improves the efficiency and reliability of foreign body diagnosis, at the same time provides a valid data for the fault location and early warning.

2. The algorithm theory

2.1. Convolutional neural networks
As a kind of hierarchical networks, convolutional neural networks can be roughly divided into input layer, convolutional layer, lower sampling layer (pooling layer), full connection layer and output layer according to the different functions and functions of each layer. The basic structure of the convolutional neural network is shown in figure 1.

![Convolutional neural network](image)

Figure 1. Convolutional neural network.

2.2. Object detection
The main function of object detection is to locate and classify the objects in the image. Traditional detection methods include pre-treatment, sliding window, feature extraction, feature selection, feature classification, the post-processing steps. The convolutional neural network itself has the functions of feature extraction, feature selection and feature classification. Therefore, the convolutional neural network is used to replace the corresponding steps in the traditional object detection, and the object detection method based on the convolutional neural network is developed.

Object detection algorithms based on convolutional neural network can be divided into two categories according to their working principles: (1) two-stage detection algorithm. Region proposals are generated in the unrecognized image, and then are classified. Its typical representative is R-CNN system algorithm based on region proposal, such as R-CNN [5], Fast R-CNN [6], Faster R-CNN [7]; (2) One-stage detection algorithm, which directly generates category probability and position coordinate value in unrecognized image, such as YOLO [8] and SSD [9].

Compared with Faster R-CNN with high accuracy but complicated model, YOLOv3 runs faster and is suitable for computers with lower hardware conditions while ensuring relatively high accuracy. Therefore, YOLOv3 network model is selected for the test model.
2.3. Data
There is not yet special detection database for engineering vehicles that invade into the monitoring area of overhead transmission lines. In this select appropriate pictures from the captured scene images are produced training set and testing set. Excavators and cranes are the most common objects that appear at the construction site and are easy to cause short circuit interference to the power lines. Of course, there also includes other large engineering vehicles, such as heavy trucks and mixing trucks. Because the types of other large engineering vehicles are relatively complex, they are uniformly classified as vehicles. Therefore, our purpose is to detect excavators, cranes and vehicles in the monitoring area of overhead transmission lines. The data is collected by cameras installed at multiple monitoring points of power line corridors.

3. Results
By modifying the network structure of the feature extraction and classification, we performed experiments based on TensorFlow to test the robustness of the detection model. We used a graphics workstation to run our experiments with an Intel Xeon E5-2620 v4 with 2.1 GHz, 32GB RAM, GTX1080Ti and a Windows 7 (64 bits) operating system.

3.1. Experiment evaluation criteria
There are many evaluation criteria in the field of object detection but the meanings of different evaluation criteria are often confused. The brief introduction of several commonly used evaluation criteria are as follows.

Firstly, there are 3 basic definitions:

True Positive (TP): which means an instance belongs to positive class and is also determined to be a positive one.
False Negative (FN): which means an instance belongs to positive class but is determined to be a negative one. This indicates that the detection model fails to detect the instance.
False Positive (FP): which means an instance belongs to negative class but is determined to be a positive one. This indicates that the detection model has misjudged the instance.

According to the definition above, the calculation formulas of the common evaluation criteria are given below:

The precision rate (P) reflects the proportion of true positive examples in the positive case determined by the detector.

\[
P = \frac{TP}{TP + FP}
\]  

The recall rate (R) reflects the proportion of positive cases which are judged correctly. RR is also called True Positive Rate.

\[
R = \frac{TP}{TP + FN}
\]

3.2. Experimental results and analysis
The number of the images in the training set is 3477 and the number of test images is 386. The number of the objects included in the training set and the testing set for each experiment is shown in the Table 1.

|                       | excavator | crane | vehicle |
|-----------------------|-----------|-------|---------|
| training set          | 1669      | 5315  | 5953    |
| testing set           | 100       | 618   | 685     |
| total                 | 1769      | 5933  | 6638    |

Table 2 shows precision rate (P) values of excavators, crane and vehicle. The last row in the table shows the recall rate (R) value on the testing set of each experiment. From Table 2, we can see that the detection accuracy of targets is high, the accuracy of the three types of targets is over 90%. The
excavator detection has the highest accuracy of 94.12%, and the lowest accuracy of engineering vehicles detection reached 90.57%.

Table 2. Test result of image detection.

|          | TP  | FP  | FN  | P (%) | R (%) |
|----------|-----|-----|-----|-------|-------|
| excavator| 80  | 5   | 20  | 94.12 | 80.00 |
| crane    | 522 | 39  | 96  | 93.05 | 84.47 |
| vehicle  | 423 | 44  | 262 | 90.57 | 60.75 |

Some detection results are shown as Figure 2. As can be seen from Figure 2, the detection model can accurately locate and identify excavators, crane and vehicle in the background of complex and diverse circumstances, which shows that the detection model can effectively extract the feature information of objects and can distinguish it from the feature information of the complex background.

![Figure 2. The detection results of varied scenes.](image)

4. Conclusions

This paper presents a method for detecting engineering vehicles that invade the monitoring areas of transmission lines. The proposed method is based on object detection technology of convolutional neural networks. Through image detection experiments, the detection model has higher recognition accuracy. Compared with the early intrusion objects identification technology, the proposed method can provide improved accuracy with respect to the specific classification information of engineering
vehicles and serve as an information basis for transmission line fault warning. In future work, we will focus on the more appropriate network architecture designed for engineering vehicles detection, so that we can handle more complex application scenes.

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