Intrusion Object Detection on Transmission Corridors Based on Deep Learning

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Abstract. With the construction and development of Chinese power grid, the scale of the power grid continues to expand, the transmission corridors environment is becoming more and more complex, the possibility of external damage caused by intrusion objects of the transmission line is constantly increasing, which seriously threatens the normal operation of the power grid and the reliability of power supply. In order to solve the above problems, it is particularly important to study a detection method that can replace manual identification. That method helps the field personnel to timely detect the intrusion objects within the monitoring scope of the transmission line, so as to improve the efficiency and accuracy of transmission channel inspection.

1. Introduction

The function of the power system includes power generation, substation, transmission, distribution and utilization. The transmission is one of the important components part of electric power system. At present, overhead transmission line is mainly adopted for long distance power transmission, and its safe operation is closely related to the power grid stability. Therefore, operation and maintenance work should not be ignored [1].

In recent years, illegal construction of large vehicles has become the main factor of external damage of transmission lines. The following are the main reasons for the external force damage caused by the blind construction in the line protection zone. First, large excavators cut the cables above the ground during the construction; Second, the crane hang up the wire; Third, the vehicle crashed into the pole; Fourth, the excavation site is too close to the pole, but protective measures are not taken.

At present, cameras are usually installed on the high-pressure tower or by unmanned aerial vehicle (UAV) taking pictures and video, to give the back-end center to analysis, artificial screen whether there is a possible threat. The scheme needs spend many manpower, workload is big, poor real-time performance and low efficiency. Artificial intelligence is applied for abnormal transmission line monitoring to stop actions that threaten line safety achieve rapid, and realize fast and effective line safety pre-control work. It improves protection means diversification, intelligent, further improve the power grid automation degree, the realization grid layout, artificial intelligence system for power grid provides a effective and efficient route security solutions.

In practice, the depth and breadth of the convolutional neural network are usually increased, that is, the number of layers and the number of neurons in each layer are increased, so as to improve the learning ability of the neural network and facilitate the fitting of the data distribution of the training set. However, with the deepening and widening of the neural network structure, the parameters that need...
to be trained and learned in the network will also increase, and it is easy to produce the phenomenon of local optimal and even overfitting, resulting in low network generalization ability and robustness, as well as low image recognition accuracy beyond the training sample, which cannot be applied to the actual scene. At present, there is no public data set about transmission channel monitoring images. The preparation of training samples requires manual screening and labeling, which requires a large workload and cannot guarantee the efficiency.

At the same time, lighting, angle of view and some changes inside the vehicle all will affect the video and the vehicle objects in the picture, making the detection results unsatisfactory. These disadvantages limit the application of detection algorithm. With the excellent performance of deep learning in the field of image processing, deep neural network begins to subvert the traditional feature extraction method.

In order to make full use of limited samples and reduce manpower and time investment, this paper proposes a data enhancement image preprocessing method. Firstly, the original image samples were expanded with data enhancement to form new image samples. The number of neural network training samples was increased to improve the generalization ability and robustness of neural network, and the cost of acquiring new image samples was reduced.

2. The algorithm theory

2.1. YOLOv3
In terms of basic image feature extraction, YOLO3 adopts a network structure called Darknet-53 (containing 53 convolutional layers). It drew on the practice of residual network and set shortcut connections between some layers. The basic structure of Darknet-53 neural network is shown in figure 1. YOLOv3 detects the object by means of multi-scale feature maps (13*13, 26*26 and 52*52 scale feature maps are fused). In YOLOv3, logistic regression was used to predict the object scores of the bounding boxes.

![Figure 1. Darknet-53 neural network.](image)

2.2. Data Augmentation
The YOLOv3 network model requires image input resolution of 416×416. Therefore, before the image is input into the network model for training and detection, it is necessary to compress the image so as to reduce the computing burden of high-resolution image on the network model.
Image Clipping differs from scaling in that it randomly samples a portion of the original image. Then this section is resized to the original image size.

Image rotation a common data enhancement method. The key problem with rotation enhancement is that the dimensions of the image may not remain the same after rotation. If the image is square, rotating it at right angles will keep the image size. If the image is a rectangle, then the rotation of 180 degrees will remain the same size.

Image translation only involves moving the image in the X or Y direction (or both). In the following example, the image has a black background beyond its boundaries and is appropriately shifted.

The adjustment of image brightness, saturation, contrast and hue will not affect the recognition effect in many image recognition applications. Therefore, when training the neural network model, the image color properties will be adjusted randomly, and the trained network model will be affected by image color factors as little as possible.

3. Results

By modifying the network structure of the feature extraction and classification. The operating environment of the experiment was CPU Intel(R) Core(TM) I7-8750h CPU @2.21GHz, memory (RAM) 16.0GB, graphics card NVIDIA GeForce GTX 1060, and image detection and classification were based on OpenCV and TensorFlow.

3.1. Experiment evaluation criteria

Experimental indexes of target detection include Precision and Recall. The precision rate represents the proportion of the correct detection target in the model detection target. The recall rate represents the proportion of the test samples that should detect the correct target.

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\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \tag{1}
\]

\[
\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \tag{2}
\]

True Positive: which means an instance belongs to positive class and is also determined to be a positive one.

False Positive: 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.

False Negative: 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.

3.2. Experimental results and analysis

According to the results of the monitoring images and the investigation of the external damage incident, it is found that the blind construction of the construction team is the main reason for the external damage.

After manual screening, 3860 images containing the designated target were selected for annotation. According to the ratio of 9:1, the annotation images were divided into 3474 image training samples and 386 image test samples. 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 | engineering vehicle |
|----------------|-----------|-------|---------------------|
| training sample| 1671      | 5320  | 5942                |
| testing sample | 106       | 620   | 690                 |

Table 2 and Table 3 show the precision rate (P) and recall rate of excavators, crane and vehicle. The number of targets correctly detected by the network model trained by the data enhancement
sample set increased, and the number of mischeck and missed check decreased. The precision rate of all kinds of targets was improved by about 1%~3%, and the recall rate was increased by about 5%~8%. From Table 2, the precision of the three types of targets is over 90%. The excavator has the highest precision of 92.47%, and the lowest number of engineering vehicles also reached 88.36%.

| True Positive | False Positive | False Negative | Precision (%) | Recall (%) |
|---------------|----------------|----------------|---------------|------------|
| excavator     | 81             | 7              | 19            | 92.04      | 81.00      |
| crane         | 487            | 83             | 131           | 85.44      | 78.80      |
| vehicle       | 459            | 75             | 226           | 85.96      | 67.01      |

Table 3. Test result of image detection.

| True Positive | False Positive | False Negative | Precision (%) | Recall (%) |
|---------------|----------------|----------------|---------------|------------|
| excavator     | 86             | 7              | 14            | 92.47      | 86.00      |
| crane         | 524            | 67             | 85            | 88.66      | 86.04      |
| vehicle       | 509            | 67             | 177           | 88.36      | 74.19      |

As can be seen from Figure 2, the detection model can accurately locate and identify three types of targets (excavators, crane and vehicle) on transmission corridors, which shows the overfitting phenomenon of the detection model training samples is avoided, and the generalization ability and robustness of the neural network are improved by enhancing the data of the original image.

4. Conclusions
In this paper, data enhancement is proposed to pre-process monitoring images to reduce the impact of insufficient samples and environmental changes on the training and recognition of detection models. Excavators, cranes and large engineering vehicles in the image are marked as the targets for identification of dangerous objects, and the enhanced sample set training and detection model is formed by data enhancement, so as to improve the robustness and generalization ability of the model. Through comparative experiments, it is verified that the enhanced training samples with enhanced data can improve the detection performance of the detection model.
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