Research on Transmission Lines Early Warning Technology Based on Deep Learning

KeLin Yang¹, YongSheng Xu¹, Peng Li¹ and Ning Shao¹

¹ State Grid Shandong Heze Power Supply Company, Heze, Shandong, 274000, China
shaoning8697@foxmail.com

Abstract. At the present stage, high-voltage transmission lines are distributed in long distance chains, with large space span, complicated meteorological and geographical environment. The operating environment of the transmission lines is poor. Hence, manual patrol and maintenance are difficult. Various faults are very likely to affect the safe and stable operation of the power grid system. Therefore, this paper proposes a transmission lines early warning method based on Deep Learning. Through object detection technology of Deep Learning, intrusion objects in the monitoring screen are automatically identified, at same time, their positions and types are marked. The experimental results show that this method has high accuracy and is suitable for the current power grid monitoring system.

1. Introduction

High-voltage electric transmission lines is the lifeblood of power grid, which plays an important role in the transmission of power. The normal operation of electric transmission lines is also an important basis and index of grid security. Due to the complex topography and landform in China, the operating environment of transmission lines is very poor, and various faults can easily affect the safe and stable operation of the system [1]. In order to ensure the efficiency and reliability of the inspection work under complex conditions and environment, by using monitoring equipment instead of manual field inspection, State Grid Corporation of China has reformed the intelligent monitoring system and greatly improved the efficiency of operation and maintenance work.

However, with the increasing coverage of monitoring equipment, the follow problems need to be solved. 1) Large monitoring data. With the number of monitoring equipment is increasing, the monitoring data and personnel workload of processing are augmented. Finding the way to deal with the monitoring data effectively becomes a major problem. 2) Small proportion of effective data. Due to the contingency of intrusion objects, most of the monitoring data is invalid data that cannot monitor intrusion objects, and the effective data takes up a very small proportion. How to select effective data becomes the second problem. 3) Low data validity. Because of the limited shooting of the monitoring equipment and the actual shooting environment, image sharpness would be greatly reduced in the case of insufficient light in rainy weather. It is difficult for the naked eye to identify the intrusion objects in the image.

At present, the moving target detection technology is main method to recognize objects near the transmission lines. For example, by analysing video frame, foreign matter is marked in key frames by frame difference method, and then the feature points can be used to track foreign matter so as to realize foreign matter recognition of transmission lines [2]. On the basis of the improved algorithm to segment the background and further filter the background according to the characteristics of transmission lines, the gradient method is adopted to find transmission lines. Hough transform and
detection of transmission lines are selected as the basis to identify foreign matter of transmission lines [3]. The images taken during the inspection are analysed, and the visual significance map is calculated in the area of interest region, that are detected in advance according to the human eye perception characteristics, and then the foreign body area is positioned uniformly by using the characteristics of colour, shape or spatial distribution [4].

Although the above methods have high accuracy for foreign object recognition, they mainly use video data, which has higher requirements on the hardware system. Meanwhile, the video data volume is larger than the image data, which causes considerable pressure on the data transmission channel and storage equipment. In the early stage of the development of power network monitoring system, the related hardware equipment is not perfect, and the popularization of these methods is limited. Moreover, the above methods can only identify the appearance of foreign objects, and cannot truly determine the species of foreign objects. For more accurate foreign object information, manual recognition is still necessary.

In order to solve these above problems for the power grid intelligent monitoring system, combined with the object detection technology, early warning technology based on Deep Learning is proposed. The inefficient manual monitoring is displaced by computers. The method improves the efficiency and reliability of intrusion objects detection, and provides valid data for the fault location and early warning. The basic principle of the method is to use the object detection technology based on Deep Learning to automatically identify intrusion objects under the electric transmission lines, and mark them out with the boundary box in the image.

2. Object detection based on Deep Learning

Deep Learning is the latest research field of machine learning, which plays a vital role in image recognition, speech recognition, face recognition and object detection. Deep Learning comes from artificial neural network. By simulating human brain neural structure, a multi-layer neural network is formed to extract low-level features from input data, and combine to form a more abstract high-level feature representation to discover distributed feature representation of data [5]. As soon as Deep Learning was put forward, people pay a lot of attention to it and devote themselves to its research. Nowadays, many model frameworks have emerged in Deep Learning, such as deep confidence network [6], self-encoder [7], convolutional neural network [8], recurrent neural network [9], etc. Among them, the convolutional neural network uses the convolution between the layers and the lower sampling weights between local connections, namely the thought of sharing and pooling processing. And its network structure has low complexity, low training difficulty, high calculation speed, strong fault tolerance and robustness characteristics. The convolutional neural network becomes the most widely used neural network structure.

2.1. Convolution neural network principle

Convolution Neural Network (Convolutional Neural Network, CNN), proposed by Professor LeCun at the university of Toronto, belongs to the deep feedforward Network used as a classifier [10]. As a hierarchical structure network, convolutional neural network can be divided into input layer, convolution layer, pooling layer, full connection layer and output layer according to the functions and functions of each layer. The basic structure of convolutional neural network is shown in figure 1.
The basic principle of image recognition by convolution neural network is as follows. Firstly, the image enters the convolutional neural network from the input layer. Secondly, the multiple convolution layers and pooling layers extract the low-level features of the image and translate into a high-level feature. Finally, the connection layer and output layer categorize high-level feature and output result. The final output is a one-dimensional vector representing the category of the input image.

The following is a detailed introduction of each layer of convolutional neural network.

The Input layer is responsible for receiving and reading input signals, such as images, speech and text.

Convolution layer is composed of multiple features of surface feature (map), each feature surface is composed of many neurons, and its main function is calculating the extracted features through the convolution kernel volume. The convolution layer mathematical model is described as:

$$X_i = f(X_{i-1} \otimes W_i + b_i)$$

In this formula, $X_i$, $X_{i-1}$ is the feature map of the $i$ layer and $i-1$ layer; $W_i$ is the weight vector of the $i$ convolution layer; $b_i$ is migration vector of the $i$ convolution layer; $f(*)$ is the excitation function, and tan function or sigmoid function is usually adopted.

The convolution layer applies the concept of local connection and weight sharing. The convolution core, smaller than the image size, is used for sliding convolution calculation of the entire image to extract the prominent features, which plays a role of filtering. Multiple features can be extracted by using different convolution cores in each layer of convolution layer, and a feature map is formed to be input into the pooling layer for pooling, so as to further screen the features.

The pooling layer is set after the convolution layer. The feature map transmitted from the convolution layer is in accordance with certain rules (generally divided into average pooling and maximum pooling), so as to reduce the feature dimension under the premise that the spatial property of the feature map remains unchanged. The mathematical model of the lower sampling layer is described as:

$$X_j = p(X_{j-1})$$

In this formula, $X_j$, $X_{j-1}$ is the feature map of the $j$ layer and $j-1$ layer; $p(*)$ is pool rules.

The fully connected layer is different from the locally linked convolutional layer and the pooling layer. The neurons of the full connected layer are connected with all the neurons of the upper layer. The features, extracted by the multi-layer convolutional layers and pooling layers, are ultimately classified. The mathematical model of the full connection layer is:

$$X_i = f(W_iX_{i-1} + b_i)$$

In this formula, $X_i$, $X_{i-1}$ is the feature map of the $i$ layer and $i-1$ layer; $f(*)$ is excitation function.
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Output layer is used to classify the output features of the full connection layer by SoftMax logic regression.

3. Verification

3.1. Simple
Because the actual number of field images is small, they are not enough to be used as train samples of convolutional neural network. In addition, there is no image data set related to intrusion objects at present. Therefore, this paper chooses the method of manually photographing images and obtaining from the Internet to build the train set.

In order to improve the number of samples and reduce the workload, data augmentation is used. 1330 images of the original samples are rotated with different angle and changed contrast, to expand the training sample to 13300 pieces, improve convolution training precision of the neural network model. The data augmentation effect is shown as the figure 2.

![Data augmentation effect](image)

Figure 2. Data augmentation effect.

3.2. Image detection results and analysis
The experimental operation environment in this paper is Intel(R) Core (TM) i7-5500u CPU @2.40 GHz, 8G RAM and WINDOWS 7(64-bit) operating systems. Image detection and classification is conducted based on OpenCV and TensorFlow.

In the picture, 378 target images of non-training samples were selected, among which the intrusion objects were selected as large excavators, a total of 420 excavators, which were put into the training model for object detection.

In this paper, Faster R-CNN network model[11] and the Mobilenet_SSD network model[12] are selected as verification models.

The indicators verified by examples include: positive detection rate, false detection rate and missing detection rate, as defined below.

\[
\text{positive detection rate} = \frac{\text{the number of positive object detections}}{\text{the number of total objects}} \times 100\% \tag{4}
\]

\[
\text{false detection rate} = \frac{\text{the number of false object detections}}{\text{the number of total objects}} \times 100\% \tag{5}
\]
the number of missing object detections \( \times 100\% \) 

(6)

According to the statistics, the object detection results of the Faster R-CNN network model and the Mobilenet_SSD network model are shown in table 1.

Table 1. detection result.

|                      | Faster R-CNN | Mobilenet_SSD |
|----------------------|--------------|---------------|
| Positive detection rate (%) | 92.38        | 90.00         |
| False detection rate (%)  | 13.92        | 3.57          |
| Missing detection rate (%) | 7.62         | 10.00         |
| Running time (s)         | 33.7         | 3.62          |

It can be seen from table 1 that the detection running time of the Faster R-CNN network model is more than that of the Mobilenet_SSD network model. But its positive detection rate is higher than that of the Mobilenet_SSD network model. The main cause of this phenomenon is Faster-RCNN model network model is larger than Mobilenet_SSD network model. Faster-RCNN has more convolution layers and the lower samplings, so it needs longer operation time. At the same time, Faster R-CNN network model need generate region proposals, but the overlap between region proposals brings a lot of repetitive work. As a result, the Faster R-CNN network model is more detailed and comprehensive for the feature extraction of excavators in the image, which is more accurate in identifying multiple images of excavators, and its positive detection rate is higher than that of Mobilenet_SSD network model.

The false detection rate of Faster-RCNN network model is higher than that of Mobilenet_SSD network model. Thought careful analysis of image results, it shows that the Faster-RCNN only marks local area of the excavator. In addition, when multiple excavators overlap, because of their features overlap, the network model will take them as the same target, which is also an important reason for the increase of false detection rate.

Considering the actual situation of the site, the complex number of engineering vehicles such as large excavators is less. Therefore, the test images containing the complex number of large excavators are removed, and the single target image is 350, with a total of 350 excavators. The statistical test results are shown in table 2.

Table 2. detection result of single object.

|                      | Faster R-CNN | Mobilenet_SSD |
|----------------------|--------------|---------------|
| Positive detection rate (%) | 99.14%       | 98.29%        |
| False detection rate (%)  | 14.29%       | 3.71%         |

It can be seen from table 1 that when identifying a single target, the gap of positive detection rate is very small between the Faster R-CNN network model and the Mobilenet_SSD network model. However, the error detection rate of the Faster R-CNN network model almost doubles, while the error detection rate of the Mobilenet_SSD network model remains basically the same. Thus, it can be seen that the main performance difference between the Faster-RCNN network model and the Mobilenet_SSD network model is still in the running time when the number of detection targets is single and there is no overlapping cover.

The conclusion is that the Faster R-CNN network model is more suitable for the situation where the accuracy requirement of object detection is high, while the Mobilenet_SSD network model is more suitable for the situation where the efficiency requirement is high.

4. Conclusion
This paper proposes a transmission lines warning technology based on Deep Learning. Intrusion objects in the monitoring screen are automatically identified and their positions and types are marked
by target detection technology. Through the image detection experiment, it has been verified that the transmission lines early warning method based on Deep Learning has the foundation of practical application, with higher recognition efficiency and lower leakage rate and error rate. Compared to the early foreign object identification technology, the proposed method determines dangerous objects, that endanger the safe operation of the transmission channel, and provides a more detailed and accurate information for shipment inspection and maintenance for power grid. This method improves the supervision efficiency, reduces the time and human input, and reduces the fatigue may cause errors in the manual identification.

References
[1] Wang, Z. (2016) The practice of screening and controlling potential safety hazards outside transmission lines. Engineering and technology, 2016(12): 00226-00227.
[2] Jiao, S., Wang, H. (2016) Research on transmission line foreign body recognition based on ORB algorithm. Science Technology and Engineering, 44(5): 1-9.
[3] Jin, L., Yao, C., Yan, S., et al. (2013) Transmission line foreign object recognition based on aerial image. Journal of Tongji University, 41(2): 277-281.
[4] Wang, D., Zhang, J., Guo, X. (2018) A transmission line foreign body detection method based on visual significance analysis. Video Engineering, 498(01):111-115.
[5] Deng, L., Yu, D. (2014) Deep Learning: methods and applications. Foundations & Trends in Signal Processing, 7(3), 197-387.
[6] HINTON, G., OSINDERO, S., THE, Y. (2006) A fast learning algorithm for deep belief nets. Neural Computation, 18(7): 1527-1554.
[7] BENGIO, Y., LAMBLIN, P. Popovici, D., et al. (2007) Greedy layer-wise training of deep networks. Information Processing Systems, 19: 153-160.
[8] ABDEL-HAMID, O., LI, D., DONG, Y. (2013) Exploring Convolutional Neural Network Structures and Optimization Techniques for Speech Recognition. INTERSPEECH, 2013:1173-5.
[9] MARTENS, J., SUTSKEVER, I. (2011) Learning recurrent neural networks with hessian-free optimization. International Conference on International Conference on Machine Learning, 2011: 1033-1040.
[10] Lecun, Y., Bottou, L., BEGIO, Y., et al. (1998) Gradient-based learning applied to document recognition. Proceedings of the IEEE, 86(11): 2278-2324.
[11] Ren, S., He, K., Girshick, R., Sun, J. (2015) Faster R-CNN: towards real-time object detection with region proposal networks, 2015: 91-99.
[12] Liu, W., Anguelov, D., Erhan, D., Szegedy, C., Reed, S., Fu, C. Y., et al. (2015) SSD: single shot multibox detector. European Conference on Computer Vision. Springer, 2016: 21-37
[13] Howard, A. G., Zhu, M., Chen, B., Kalenicenko, D., Wang, W., Weyand, T., et al. (2017) Mobilenets: efficient convolutional neural networks for mobile vision applications. 2017.