Neural Detection of Foreign Objects for Transmission Lines in Power Systems

Pengfei Xia¹, Jin Yin¹, Jingsong He¹*, Li Gu¹ and Kejun Yang²

¹University of Science and Technology of China, Hefei, China
²Anhui Nari Jiyuan Electric Power System Tech CO., LTD, Hefei, China

*Email: hjss@ustc.edu.cn

Abstract. Ensuring the normal operation of the transmission lines, which provides a path for directing the transmission of energy from one place to another, is a prerequisite for delivering power to cities and enterprises. A major threat comes from foreign objects, which may cause interruption of power transmission. Compared with traditional manual method, which not only consumes a lot of manpower, but more importantly, affects the safety and efficiency of power network, in this paper, we apply a neural detection of foreign objects for transmission lines. Transfer learning and data augmentation are used to mitigate data shortages. Experimental results show that even with small training data, the neural detection with transfer learning and data augmentation is an effective method for this task without loss of real-time property.

1. Introduction

Transmission lines are one of the most important part of power systems, which provides a path for directing the transmission of energy from one place to another, and is an essential guarantee for national life and enterprise production [1]. Suspended foreign objects is the main threat to the normal operation of transmission lines and is the primary task of power inspection. Nowadays, manual inspection is still the most common method in power inspection. However, except for requiring a lot of labor and is susceptible to environment and climate [2], more importantly, with high-intensity work, low detection accuracy affect the safety and efficiency of power network. Automatic detection of foreign objects for transmission lines in power systems is a vital part of the smart power line, and is significant for ensuring operational safety and efficiency.

Neural networks, which is to mimic the nerves of animals, have achieved remarkable results in traditional visual perception tasks, such as image classification [3,4], objects detection [5,6] and semantic segmentation [7,8]. Foreign object detection can be regarded as a visual perception task. For foreign objects detection in transmission lines, using the aircraft to photograph and then processing the images with neural based methods is a promising way, which saves lots of resources and is less affected by the environment.

Our investigation centers on the foreign objects detection on acquired images from reality. There are some pivotal issues worth concerning when considering the foreign objects detection in transmission lines:

Transmission lines are located in diverse environments, such as countryside, city, hill and so on. As a result, the background of the images is complicated;

- The images are taken by the aircraft, so the views are uncertain and variable;
- Less training data available than other tasks;
Real-time property needs to be considered. In this paper, we apply neural network to detect foreign objects for transmission lines in power systems and the results is good. In view of the issues listed above, YOLOv3 [9], a unified, real-time framework is adopted. Meanwhile, when considering the shortage of training data, which is a realistic difficult, transfer learning and data augmentation are employed to combat with it. The experimental results show that the neural foreign objects detection we adopted in this paper is an effective method for transmission lines in power systems.

2. Neural Foreign objects Detection

2.1. Task Description

Figure 1 shows three examples of foreign objects detection for transmission lines. Simply put, the task is to determine whether there are any foreign objects in the image and mark the location if exist.

![Figure 1. Three examples of foreign objects detection for transmission lines.](image)

2.2. Architecture

YOLOv3, which is an update of YOLO [10] and YOLO9000 [11], performs the state-of-the-art performance on objects detection, both in accuracy and inference time. Different from two-stage methods, such as R-CNN [12], Fast R-CNN [5] or Faster R-CNN [6], YOLOv3 is an one-stage method and can be trained end to end. The main idea is to regard objects detection as a single regression problem, straight from image pixels to bounding box coordinates and class probabilities [10].

The architecture can be roughly divided into two parts: the image feature extraction and the objects detection, as shown in Figure 2(a) and Figure 2(b) respectively. The image feature extraction is used to represent image into some fixed size tensors. Darknet-53 is adopted in YOLOv3 and three different size image features $F_a$, $F_b$ and $F_c$ are extracted for detecting objects. To detect objects with various sizes, multi-scale detection is used in this method, as shown in Figure 2(b), where $S_1$, $S_2$ and $S_3$ are three scales predictions.

We take $S_1$ as an example to explain the whole process detailedly. Assuming that the input image is resized to 416×416, and after inference we acquire $S_1$, which is 13×13×18. 13×13 means that the input image is divided into 13×13 grid. Each grid cell predicts six value: $x$, $y$, $w$, $h$, confidence and class probabilities. The ($x$, $y$) coordinates represent the center of the box relative to the bounds of the grid cell. The $w$ and $h$ are width and height of bounding box. Thus, the size of $S_1$ should be 13×13×6. But for more accurate, there are three anchors for each grid cell, so the size is 13×13×18.
2.3. Transfer Learning and Data Augmentation

Transfer learning and data augmentation are used for mitigating data shortage.

Transfer learning. We first train Darknet-53 in imagenet [13], which consists of more than 14 million images and is one of the biggest image dataset. Then we move the fully connected layers and keep the convolutional layers for foreign objects detection.

Data augmentation. Horizontal flip, scale and random crop are applied to data, as shown in Figure 3. It is noteworthy that the coordinate position of the box will also change after horizontal flip and random crop operation.

Figure 2. Two part of YOLOv3. (a) is the image feature extraction and (b) is the objects detection.

Figure 3. An example of data augmentation.
3. Experiments

3.1. Training Details
We implement all code of our model based on PyTorch [14], which is one of widely adopted deep learning frameworks. 387 images are divided randomly into two parts: 300 for training and 87 for testing. Adam optimizer [15] is used to optimize the parameters of the neural network. The initial learning rate is 0.0001 and the batch size is set to 24. Weight decay [16] with 0.00005 is used to prevent overfitting. The max epoch is set to 300. All training is finished with a NVIDIA GTX 1080Ti GPU.

3.2. Results
YOLOv3 (Yv3), YOLOv3 with transfer learning (Yv3+TL), Yv3 with data augmentation (Yv3+DA), YOLOv3 with transfer learning and data augmentation (Yv3+TL+DA) are included in experiments. The results of precision and recall-precision curves are shown in Table 1 and Figure 4. The results show effective performance of detection in the test data, and transfer learning and data augmentation improve the generalize of the model in small training data. The average inference time is 46 ms at 416×416 resolution.

|                     | Yv3  | Yv3+TL | Yv3+DA | Yv3+TL+DA |
|---------------------|------|--------|--------|-----------|
| Precision           | 0.558| 0.638  | 0.674  | 0.724     |

Table 1. Test precision of Yv3, Yv3+TL, Yv3+DA and Yv3+TL+DA.

In order to better show the performance of detection, three types of results, i.e., correct detection, excessive detection and false detection are shown in Figure 5(a), Figure 5(b) and Figure 5(c) respectively. The results indicate generalization, such as the objects in row 1 and column 4, row 3 and column 3 are not present in the training set. However, there are some mistakes, which mainly reflect in the case of metal brackets and background interference. This situation can be alleviated with more training data.
Figure 5. Qualitative results from test data. (a) shows some results with correct detection, (b) shows some results with excessive detection, and (c) shows some results with false detection.

4. Conclusion
Foreign objects detection is an important protection measure to ensure that the normal work of the transmission lines in power systems. Compared with conventional methods, neural detection, which is a data-driven approach, can be able to deal with complex environments and save a lot of labor resources. In this paper, we apply a neural detection of foreign objects for transmission lines in power systems. Transfer learning and data augmentation are used to mitigate data shortages. Experimental results indicate that the neural detection is effective in detecting foreign objects with keeping the real-time property.

Acknowledgments
This study was funded and supported by the National Natural Science Foundation of China through Grant No.61273315.
References

[1] Wadell B C 1991 *Transmission line design handbook* (Artech House)
[2] Koshelev V and Kozlov D 2015 Wire recognition in image within aerial inspection application *Embedded Computing (MECO), 2015 4th Mediterranean Conference on* (IEEE) pp 159–162
[3] Krizhevsky A, Sutskever I and Hinton G E 2012 Imagenet classification with deep convolutional neural networks *Advances in neural information processing systems* pp 1097–1105
[4] He K, Zhang X, Ren S and Sun J 2016 Deep residual learning for image recognition *Proceedings of the IEEE conference on computer vision and pattern recognition* pp 770–778
[5] Girshick R 2015 Fast r-cnn *Proceedings of the IEEE international conference on computer vision* pp 1440–1448
[6] Ren S, He K, Girshick R and Sun J 2015 Faster r-cnn: Towards real-time object detection with region proposal networks *Advances in neural information processing systems* pp 91–99
[7] Ronneberger O, Fischer P and Brox T 2015 U-net: Convolutional networks for biomedical image segmentation *International Conference on Medical image computing and computer-assisted intervention* (Springer) pp234–241
[8] Badrinarayanan V, Kendall A and Cipolla R 2015 arXiv preprint arXiv:1511.00561
[9] Redmon J and Farhadi A 2018 arXiv preprint arXiv:1804.02767
[10] Redmon J, Divvala S, Girshick R and Farhadi A 2016 You only look once: Unified, real-time object detection *Proceedings of the IEEE conference on computer vision and pattern recognition* pp 779–788
[11] Redmon J and Farhadi A 2017 arXiv preprint
[12] Girshick R, Donahue J, Darrell T and Malik J 2014 Rich feature hierarchies for accurate object detection and semantic segmentation *Proceedings of the IEEE conference on computer vision and pattern recognition* pp 580–587
[13] Deng J, Dong W, Socher R, Li L J, Li K and Fei-Fei L 2009 Imagenet: A large-scale hierarchical image database *Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on* (Ieee) pp 248–255
[14] Paszke A, Gross S, Chintala S, Chanan G, Yang E, DeVito Z, Lin Z, Desmaison A, Antiga L and Lerer A 2017 Automatic differentiation in pytorch NIPS-W
[15] Kingma D P and Ba J 2014 arXiv preprint arXiv:1412.6980
[16] Krogh A and Hertz J A 1992 A simple weight decay can improve generalization *Advances in neural information processing systems* pp 950–957