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Transmission Line Image Object Detection Method Considering Fine-Grained Contexts

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***Abstract*—It takes a huge amount of works to take pictures of transmission line towers and check electrical fittings manually. In spite of the introduction of deep learning technology to transmission line inspection, it is not well utilized that fine-grained contexts on components in state-of-the-art research. On the basis of region-based fully convolutional network (R-FCN), a novel object detection method is proposed considering fine-grained contexts among electrical fittings. Deformable convolution layers and squeeze-and-excitation (SE) blocks are adopted in the detection method. A comparison experiment is conducted on a transmission line aerial inspection dataset. The proposed method shows better accuracy than R-FCN.**

***Index Terms*—deep learning, object detection, aerial inspection, SE block, deformable convolution, R-FCN**

I. Introduction

With the development of ultra-high voltage and ultra-high-voltage power transmission technology, the scale of power grid is increasingly bigger [1]. A considerable number of over head transmission lines are located on rugged terrain. It takes a lot of time and effort to inspection manually.

Unmanned aerial vehicle (UAV) provides to a new tool for transmission line inspection. UAVs are equipped with high-resolution camera to take photos of electrical fittings, such as insulators, grading rings, and screw bolts on towers of over head transmission lines. UAV improves inspection efficiency due to the maeuverability. However, UAV pilots have to take pictures of every electrical fittings in several perspective, because it is difficult to see defects clearly on electrical fittings through a UAV controller. A work mode that viewing photos afterwards is established. The brand new ”photographing and viewing” workflow brings a huge amount of work [2]. It is vital to develop an intelligent defect detection method to check transmission line photos automatically [3].

Deep learning methods are adopted in several researches [2], [3]. Early research attempts to verify the effectiveness of deep learning in transmission line inspection [4], [5]. Zhao *et al.* in [4] propose a method combining convolution neural network (CNN) and support vector machine (SVM) to classify insulator status. Gao *et al.* present the effectiveness of deep blief networks in the insulator classification task in [5]. Both papers shows the potential of deep learning methods in the field of transmission line inspection. The algorithms are not suitable for application because these classification methods could not cover the entire fault detection process [4], [5].

Some researchers try to use object detection methods based on deep learning to localize components on transmission line tower [6]–[10]. Liu *et al.* in [6] construct a dataset with two foreground classes of objects, and train a six-layer neural network. Faster region-based convolution neural network (Faster R-CNN) algorithm is employed in [7]–[9]. Zhou *et al.* propose a insulator and vibration damper detection model based on ”you look only once” (YOLO) algorithm in [10]. These studies only apply deep-learning-based object detection methods to localize components on towerm, but fail to detect defects in transmission line photos.

Increasingly, research is focusing on the defect detection [11]–[20]. Some studies utilize two-stage methods, for example, Faster R-CNN [11]–[15], and the other studies utilize one-stage methods, for example, YOLO or SSD [16]–[19]. The majority of the research focuses on the insulator failure detection while Wang *et al.* study detection of foreign bodies in [16]. Gao *et al.*, Ling *et al.*, and Tian *et al.* present cascading models which conbine U-net in [15], fully convolutional network in [11], and ResNet in [17]. Chen *et al.* introduce super-resolution convolution neural network to augment training data of insulator or damper failures in [19]. Liu *et al.* take advantages of online hard example mining, soft nonmaximum suppression and sample balance in [20]. These studies provide preliminary solutions of defects detection in transmission line aerial photos.

However, these CNNs only utilize fine-grained features rather than context information due to their relatively small receptive fields. Considering the composition and combination of the transmission line fitting, transmission line aerial photos are supposed to be rich in context information. For example, grading rings should be installed at the top of the insulator strings.

In this paper, a transmission line defect detection algorithm based on region-based fully convolutional network (R-FCN) is proposed [21]. Deformable convolution layers, position sensitive regional pooling layers, and squeeze-and-excitation (SE) blocks are used to enhance fine-grain context features of the images and to enlarge receptive field of the neural network [22], [23]. In addition, a fourteen-class transmission line aerial inspection image dataset is established. Results of the comparison experiment conducted show that the proposed method can realize detection of transmission line defects

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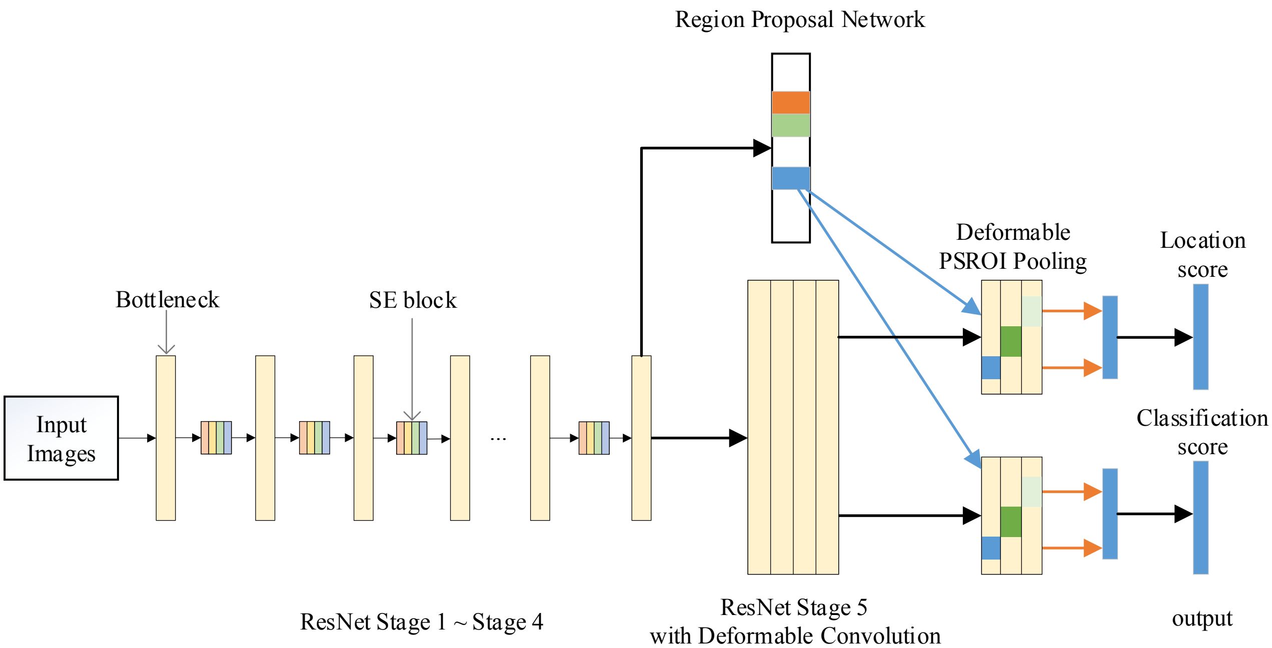

Fig. 1. The Framework of R-FCN with Deformable Convolution Layers and Squeeze-and-Excitation Blocks

effectively.

The other parts of the paper are organized as follows: Section II describes the proposed mehod and the training procedures in details. Section III shows the dataset established and the experiment. Experimental results and evaluation of the proposed method and comparison with other methods are discussed in Section IV. Finally, Section V concludes this paper.

II. Methodology

In this section, the framework of the neural network is presented. Firstly, residual network (ResNet) backbone and R-FCN detector is introduced briefly. Secondly, the modifications using deformable convolution layers and SE blocks are discussed. Thirdly, training procedure is given.

The framework of the proposed neural network is shown in Figure I. In the architecture, ResNet is applied as backbone network and R-FCN is applied as the head of detector. The algorithm follows the classical two-stage object detection CNN paradigm. A feature map is extracted from input images via the backbone network, and a bunch of regions of interest (ROI) are suggested by region proposal network (RPN). Feature maps in a small scale are generated by region of interest pooling (ROI Pooling) layer. Finally, the head of detector predicts the class and location of these region proposals.

In the paper, the proposed algorithm has two modifications. The first modification is to use SE blocks after all residual bottleneck blocks in the ResNet to enhance key features. The second modification is to use deformable convolution and deformable position sensitive region of interest pooling (PSROI Pooling) layers in the fifth stage of ResNet to improve the robustness of fine-grained feature extraction.

Deformable convolution was proposed by Dai *et al.* in [22]. Figure II shows the differences between a convolution operation and a deformable convolution operation. Deformable convolution shown in 2(b) carried a set of offsets which are learned from the feature map through additional convolution layer. Therefore, deformable convolution makes the sampling grid deform freely in a small range.

Accompany with deformable convolution, deformable PSROI Pooling layer is used in the proposed neural network. Similarly, it adds an offset to regular PSROIPooling.

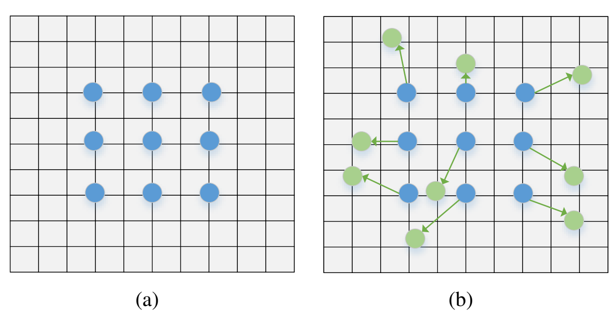

Fig. 2. Comparison between Convolution and Deformable Convolution

SE block is first mentioned by Hu *et al.* in [23]. The basic idea of SE blocks is squeezing the most significant features in the features map by global pooling, and enhancing or suppressing these key features on original feature maps. The structure of a residual bottleneck block with an SE block is shown in Figure II.

A conventional residual bottleneck block consists of a 1×1 convolution layer, a 3×3 convolution layer, and a 1×1 convolution layer. The dimension of the output feature map is

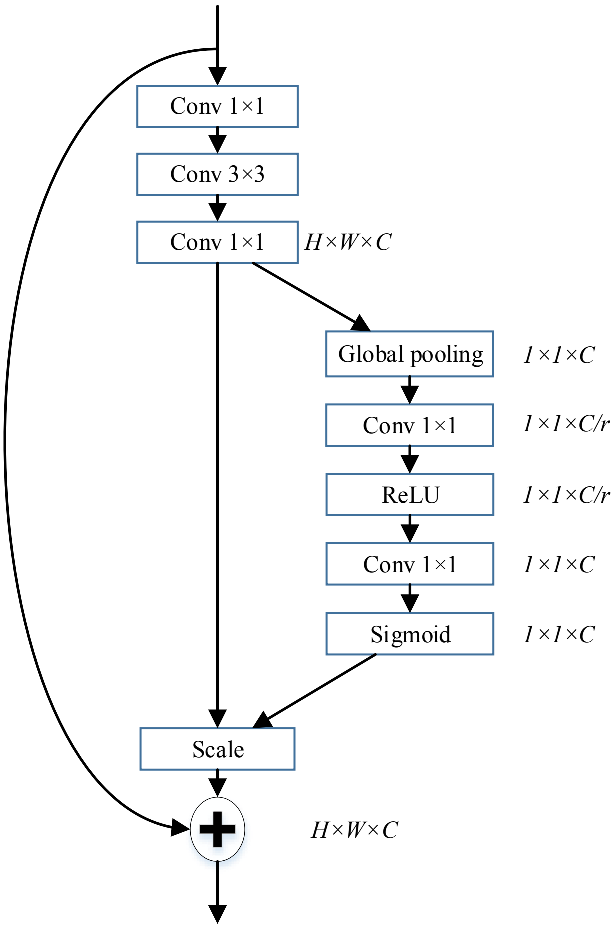

Fig. 3. The Structure of Residual Bottleneck with a Squeeze-and-Excitation Block

$H \times W \times C$, where H and W are the height and width of the featrue map, and C is the number of convolution kernels in the layer before.

Squeeze operation is to take a global pooling operation on the feature map as key features. By convolution operations and activation operations, excitation operation encodes the extracts to a set of coefficient, representing the correlation correlation among feature channels in a wide spatial range. In the reweight operation, the origin feature map is scaled by the coefficient to express the relationships.

III. Experiments

In this section, compositions of dataset, experimental environment, experiment design, and evaluation method are introduced.

A. dataset

In order to verify the effectiveness of the method we proposed, a image dataset consisting inspection photos taken by helicopters and UAVs is constructed. It is involved in the dataset that fourteen classes, including insulator strings, spontaneous explosion of insulators, ground-wire insulators, faults on discharge gaps, dampers, damaged dampers, slipped dampers, grading rings, bird nests, tilt ground-wire clamps, fittings of suspension conductor, fittings of tension conductor, fittings of suspension ground wire, fittings of tension ground wire. The dataset contains over 5,000 photos totally, dividing into a training dataset with 3,300 photos and a test dataset with 1,700 photos.

B. experimental environment

The basic configuration of workstation used in the model training is as follows: AMD Ryzen 1800X, dual NVIDIA GeForce RTX2080Ti griphics cards, 32GB memory. The software environments are as follows: Ubuntu 16.04 operating system, NVIDIA graphic card driver version 410.78, cuda library 10.1, MXNet deep learning framework 1.3.1.

C. experiment design

An experiment was set up to evaluate the improvement of the modifications. R-FCN, R-FCN with deformable convolution, and R-FCN with both deformable convolution and SE blocks are compared on the dataset. The same hyperparameters are used in the three algorithms. The training process lasts 9 epoches. The initial learning rate is 0.015. The learning rate decay strategy is stepped at 5.1th, 6.3th, and 7.5th epoch, and the coefficient is 0.1.

It is utilized in the experiment that multi-scale training strategy with four sets of image resolutions, 800×1200, 600×900, 876×1314 and 400×600.

D. evaluation indices

Accuracy and recall rate are the basic indices to measure the performance of the algorithm under specific intersection over union (IoU) thresholds. However, both accuracy and recall rate are affected by the threshold of probablity. Considering either of the indices, it is hardly to evaluate the algorithm comprehensively. Therefore, the average precision (AP), average precision under different recalls, is used as the evaluation index of each class in the paper. Mean AP between different classes (mAP) is used as the comprehensive evaluation index of the algorithm.

IV. Results

The results of the experiment are displayed in Table I. According to the results, deformable convolution layers increase mAP by 2.59%. SE blocks provide an extra promotion of mAP by 1.39%. It is worth noting that there is a significant improvement on categories of transmission line defects. For example, AP of damages dampers increased by 13.42% totally, and AP of bird nests increases by 6.69% totally. The dramatic increase may be due to the classes with less samples could make more effective use of fine-grained context features than other classes.

TABLE I
EXPERIMENT RESULTS AMONG R-FCN, DEFORMABLE R-FCN, AND THE PROPOSED METHOD

Algorithms			
R-FCN	✓	✓	✓
Deformable Convolution		✓	✓
SE blocks			✓
AP@0.5 of Electrical Fittings			
Insulator Strings	89.26%	**90.13%**	89.83%
Fittings of Suspension Conductor	85.73%	**87.29%**	87.18%
Fittings of Tension Conductor	84.52%	84.45%	**86.78%**
Fittings of Suspension Ground Wire	88.25%	86.03%	**88.57%**
Fittings of Tension Ground Wire	79.89%	**83.63%**	82.30%
Ground-wire Insulators	72.12%	74.37%	**74.99%**
Dampers	84.85%	87.25%	**87.69%**
Grading Rings	66.87%	**69.83%**	69.58%
AP@0.5 of Transmission Line Defects			
Spontaneous Explosion of Insulators	95.19%	97.25%	**97.39%**
Faults on Discharge Gaps	72.06%	75.31%	**77.98%**
Damaged Dampers	51.98%	59.49%	**65.40%**
Slipped Dampers	81.30%	86.25%	**86.94%**
Bird Nests	65.65%	68.10%	**72.34%**
Tilt Ground-wire Clamps	72.24%	76.83%	**78.38%**
mAP	77.85%	80.44%	**81.81%**

V. CONCLUSION

In this paper, an object detection method for transmission line inspection based on R-FCN with deformable convolution and SE blocks is proposed. An object detection dataset for transmission line aerial images covering fourteen kinds of object is constructed. On this basis, the proposed method is compared with R-FCN algorithm.

The proposed method takes advantages of deformable convolutional layers and SE blocks to improve 3.96% AP by making better use of context information than similar research.

In the future work, more ways to use multi-scale context information in the image will be studied. Furthermore, a larger dataset with more classes will be constructed than the one in the paper.

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REFERENCES

[1] Y. Shu and W. Chen, "Research and application of uhv power transmission in china," *High voltage*, vol. 3, no. 1, pp. 1–13, 2018.

[2] Z. ZHAO and Y. CUI, "Research progress of visual detection methods for transmission line key components based on deep learning," *Electric Power Science and Engineering*, no. 3, p. 1, 2018.

[3] V. N. Nguyen, R. Jenssen, and D. Roverso, "Automatic autonomous vision-based power line inspection: A review of current status and the potential role of deep learning," *International Journal of Electrical Power & Energy Systems*, vol. 99, pp. 107–120, 2018.

[4] Z. Zhao, G. Xu, Y. Qi, N. Liu, and T. Zhang, "Multi-patch deep features for power line insulator status classification from aerial images," in *2016 International Joint Conference on Neural Networks (IJCNN)*. IEEE, 2016, pp. 3187–3194.

[5] Q. Gao, W. Yang, and Q. Li, "A faulted insulator identification algorithm of sparse difference-based deep belief network," *Electrical Measurement & Instrumentation*, no. 1, p. 4, 2016.

[6] Y. Liu, J. Yong, L. Liu, J. Zhao, and Z. Li, "The method of insulator recognition based on deep learning," in *2016 4th International Conference on Applied Robotics for the Power Industry (CARPI)*. IEEE, 2016, pp. 1–5.

[7] W. Wang, B. Tian, Y. Liu, L. Liu, and J. Li, "Study on the electrical devices detection in uav images based on region based convolutional neural networks," *Journal of Geo-information Science*, vol. 19, no. 2, pp. 256–263, 2017.

[8] L. Ma, C. Xu, G. Zuo, B. Bo, and F. Tao, "Detection method of insulator based on faster r-cnn," in *2017 IEEE 7th Annual International Conference on CYBER Technology in Automation, Control, and Intelligent Systems (CYBER)*. IEEE, 2017, pp. 1410–1414.

[9] Q. Chen, B. Yan, R. Ye, and Z. Xiaojia, "Insulator detection and recognition of explosion fault based on convolutional neural networks," *Journal of Electronic Measurement and Instrument*, vol. 31, no. 6, pp. 942–953, 2017.

[10] Z. Zhou, G. Yuan, W. Feng, S. Gu, and P. Fan, "Target recognition and evaluation of typical transmission line equipment based on deep learning," in *Proceedings of PURPLE MOUNTAIN FORUM 2019-International Forum on Smart Grid Protection and Control*. Springer, 2020, pp. 701–709.

[11] F. Gao, J. Wang, Z. Kong, J. Wu, N. Feng, S. Wang, P. Hu, Z. Li, H. Huang, and J. Li, "Recognition of insulator explosion based on deep learning," in *2017 14th International Computer Conference on Wavelet Active Media Technology and Information Processing (ICCWAMTIP)*. IEEE, 2017, pp. 79–82.

[12] R. Bai, H. Cao, Y. Yu, F. Wang, W. Dang, and Z. Chu, "Insulator fault recognition based on spatial pyramid pooling networks with transfer learning," in *2018 3rd International Conference on Advanced Robotics and Mechatronics (ICARM)*. IEEE, 2018, pp. 824–828.

[13] X. Liu, H. Jiang, J. Chen, J. Chen, S. Zhuang, and X. Miao, "Insulator detection in aerial images based on faster regions with convolutional neural network," in *2018 IEEE 14th International Conference on Control and Automation (ICCA)*. IEEE, 2018, pp. 1082–1086.

[14] Y. Wang, J. Wang, F. Gao, P. Hu, L. Xu, J. Zhang, Y. Yu, J. Xue, and J. Li, "Detection and recognition for fault insulator based on deep learning," in *2018 11th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI)*. IEEE, 2018, pp. 1–6.

[15] Z. Ling, D. Zhang, R. C. Qiu, Z. Jin, Y. Zhang, X. He, and H. Liu, "An accurate and real-time self-blast glass insulator location method based on faster r-cnn and u-net with aerial images," *CSEE Journal of Power and Energy Systems*, 2019.

[16] B. Wang, R. Wu, Z. Zheng, W. Zhang, and J. Guo, "Study on the method of transmission line foreign body detection based on deep learning," in *2017 IEEE Conference on Energy Internet and Energy System Integration (EI2)*. IEEE, 2017, pp. 1–5.

[17] B. Tian, D. Li, W. Wang, Y. Liu, Q. Yin, G. Liu, and W. Wang, "Transmission line image defect diagnosis preprocessed parallel method based on deep learning," in *2018 3rd International Conference on Mechanical, Control and Computer Engineering (ICMCCE)*. IEEE, 2018, pp. 299–303.

[18] H. Ohta, Y. Sato, T. Mori, K. Takaya, and V. Kroumov, "Image acquisition of power line transmission towers using uav and deep learning technique for insulators localization and recognition," in *2019 23rd International Conference on System Theory, Control and Computing (ICSTCC)*. IEEE, 2019, pp. 125–130.

[19] H. Chen, Z. He, B. Shi, and T. Zhong, "Research on recognition method of electrical components based on yolo v3," *IEEE Access*, vol. 7, pp. 157 818–157 829, 2019.

[20] S. Liu, B. Wang, K. Gao, Y. Wang, C. Gao, and j. Chen, "Object detection method for aerial inspection image based on region-based fully convolutional network," *Automation of Electric Power Systems*, vol. 43, pp. 162–172, 2019.

[21] J. Dai, Y. Li, K. He, and J. Sun, "R-fcn: Object detection via region-based fully convolutional networks," in *Advances in neural information processing systems*, 2016, pp. 379–387.

[22] J. Dai, H. Qi, Y. Xiong, Y. Li, G. Zhang, H. Hu, and Y. Wei, "Deformable convolutional networks," in *Proceedings of the IEEE international conference on computer vision*, 2017, pp. 764–773.

[23] J. Hu, L. Shen, and G. Sun, "Squeeze-and-excitation networks," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2018, pp. 7132–7141.