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A Detection Network Combining UAV with Deep Learning Technology for Wind Turbine Blades in Electric Power Industry

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Abstract: Electricity is an important energy source, and it is particularly important for the normal development of industry. Among them, wind turbine is an important source of power resources, the integrity of wind turbine blades directly affects the electricity generation. However, the detection of wind turbine blades is a very difficult task. To solve the problem, the study proposes a method that uses the combination of UAV and deep learning to carry out the detection work. The prime minister utilizes the UAV equipped with data acquisition equipment to obtain the status image of blades, and then the blade status is recognized by the trained detection network deployed on the drone. At the same time, in order to improve the performance of the detection network, on the one hand, the detection accuracy is improved by improving the network ability to express features. On the other hand, the data used for network training is augmented so that sufficient data can be used for network training. In addition, it improves the robustness of the network. The experimental results show that the detection network in the study can accurately detect the faults of various characteristics of wind turbine blades. This lays a solid foundation for the research on the automation detection of wind turbine blades.

Keywords: wind blade detection; UAV; deep learning; data augmentation; robustness.

1. Introduction

As an extremely important energy source, electric power is the power source of modern industrial development. In order to reduce the environmental damage caused by dynamic power generation, wind power generation has been more and more widely used. Wind power generation mainly uses the wind to push the blades. Therefore, the daily inspection of the wind turbine blade is a very important task. However, due to the environment in which the wind turbine is located is specific, it brings great challenges to the inspection work. Fortunately, the development of modern technology can solve the problem. In particular, the combination of UAV and deep learning brings great convenience to detection work.

For the detection of wind turbine blades, many excellent detection methods have been proposed. Xu et al. Xu et al. [1] considered the problem of wind turbine blade detection as an image recognition problem. Therefore, three convolutional neural networks were constructed. And the best performing VGG-16 model was used as the final detection model. Then the alternating direction method of multipliers algorithm was employed to reduce the high equipment requirements for network training. In order to reduce the large economic loss caused by wind turbine blade fault, Shihavuddin et al. [2] proposed a detection system based on deep learning, which can locate and analyze blade damage. In addition, in order to increase the generalization capacity of the proposed network, data augmentation technology was introduced to augment the data. Finally, the detection results of the algorithm were basically consistent with those of manual detection. Abouhnik et al. [3] detected the blades based on theprinciple of vibration. The normal and cracked blades were analyzed by ANSYS, and then the basic vibration characteristics of the blades were extracted. Therefore, the state of the blade can be detected more accurately. In terms of wind turbine (WT) blade surface crack detection, Wang et al. [4] used Haar-like features that were applied to depict crack regions and a trained cascading classifier for crack detection. The UAV obtained the WT blade image, and the image was sent to the cascading classifier. The classifier showed its advantages in the image-based crack detection. In order to detect wind turbine blade damage, the machine learning algorithm was adopted by Regan et al. [5]. Logistic regression (LR) and support vector machine (SVM) methods and binary classification algorithms were combined for decision making. Yang et al. [6] proposed a detection method based on vibration measurement using a image-based system, which can measured various vibration frequencies and displacement amplitudes. Then the results were compared and analyzed. There are all kinds of defects using traditional methods to detect wind turbine blades. So the detection method based on the image processing technology was proposed by Chen et al. [7]. During image processing, the calibration, image splicing, pretreatment and threshold segmentation algorithm were used. The proposed method has highly accurate and good detection effect. Ice accretion on wind turbine blades can cause significant damage to equipment. In order to solve the problem, Liu et al. [8] proposed a detection technology based on the wind turbine SCADA data. The detection technology was realized by data preprocessing, automatous feature extraction and detection model. The method showed good performance in actual wind farms fault detection.

2. Blade detection framework design

The inspection of wind turbine blades is an important work. However, due to the remote location and high elevation of the wind turbine, the maintenance work has great challenges. At the same time, the manual inspection of wind turbine blades need to stop the wind turbine, which will cause some economic losses. In addition, the repair work is very dangerous. However, the wide application of UAV brings convenience to maintenance work. UAV is flexible, convenient and easy to be controlled. More importantly, it can be equipped with a camera and other detection equipment to detect the working state of wind turbine blades. That can avoid the economic loss caused by downtime detection, and the safety of the staff is fully guaranteed. UAV equipped with detection equipment provides hardware support for the acquisition of wind turbine state information, but the real-time status of the wind turbine need to be automatically detected. The convolutional neural network based on deep learning can realize the real-time detection task. Many excellent object detection networks have been proposed, such as Faster RCNN [9], PVANet [10], SSD [11], YOLO [12], etc. In the study, optimized PVANet has been used to realize the detection of wind turbine blades. The overall framework for wind turbine blade detection is shown in Figure 1.

3. Wind turbine blades detection algorithm

UAV is widely used in many fields. In the study, the combination of UAV and convolutional neural network is utilized to detect the wind turbine blade. The convolutional neural network in the study is classical PVANet, which is more lightweight than Faster RCNN. The network improves the detection speed on the basis of ensuring the accuracy, and it has shown good performance in many detection projects. However, there are many challenges in the wind turbine blade fault detection in the study. Therefore, in order to realize the accurate and rapid detection of wind turbine blade fault, some effective measures are taken in the study. On the one hand, the structure of feature extraction network of PVANet is modified to enlarge the final feature map size, and the expression ability of small objects is enhanced. On the other hand, the image of wind turbine blade collected by UAV is enhanced to improve the accuracy and robustness of network detection.

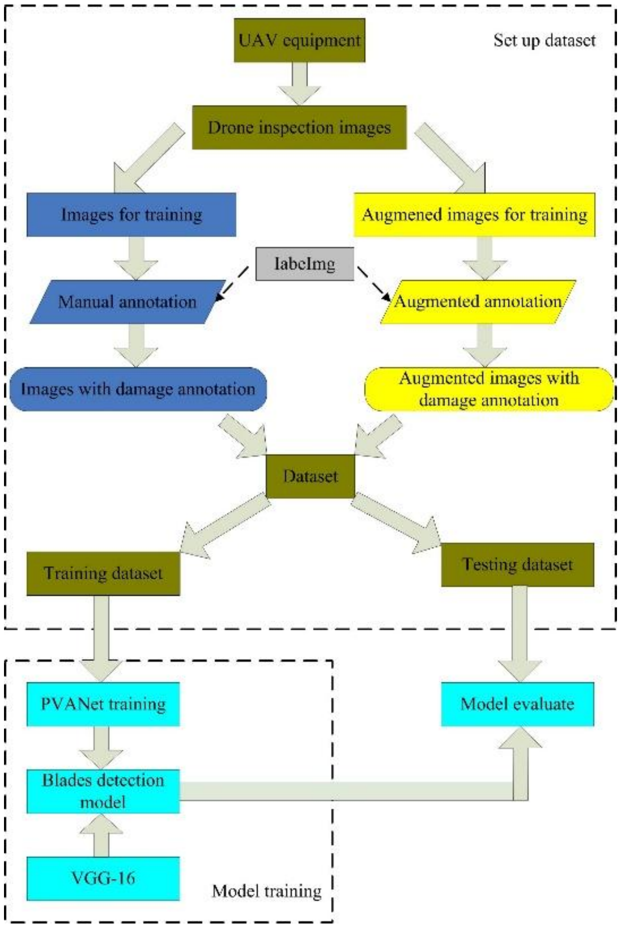

Figure 1: Framework for wind turbine blade detection

3.1 PVANet detection algorithm

The classical PVANet algorithm is a lightweight algorithm, which has a good performance in real-time detection. Because many redundant parameters will be generated in the network training process, the C.ReLU activation function is applied to reduce the computation. There are multi-scale objects in complex scenes, and different scale objects have different requirements on receptive field. Inception structure enables the integration of feature maps at different scales, the network ability of detecting objects at multiple scales is enhanced.

3.2 Optimized detection algorithm

In the study, the scale variation of wind turbine blade faults collected by UAV is relatively large, and multi-scale objects will bring great challenges to the detection network. At the same time, the fault features of the wind turbine blades are quite different, and these features have different light and dark characteristics. Based on this, the detection network with good performance is very important for the detection of wind turbine blades. In the study, the original PVANet was optimized. In the original network, the output of conv3_4 and conv5_4 at the convolutional layer be dealt with up sampling and down sampling for obtaining outputs of the same size for subsequent feature fusion. However, the output of the same size is reduced compared with the input image, which is very unfavorable for the feature expression of the wind turbine blade with small objects. Therefore, by adjusting the sampling parameters, the size of the final output feature map is doubled compared with the original map. The modified scale is 1/8. The network structure of the optimization part is shown in Figure 2.

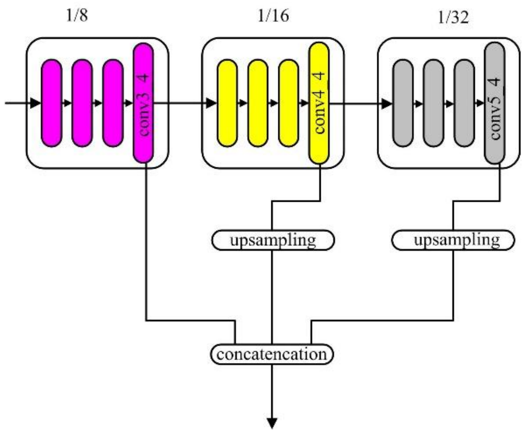

Figure 2: Network optimization part.

3.3 Data Augmentation

The high quality dataset is essential for network training. At present, there is no publicly available wind turbine blade fault dataset, and the relevant images collected in the study are few. For this reason, data enhancement technology has been introduced. The image has been reversed, rotated and so on. On the one hand, the number of images in the dataset has been fully expanded, which provides basic conditions for network training. On the other hand, data enhancement also increases the diversity of features, which can train a high-precision and robust detection network. The processed image is shown in Figure 3.

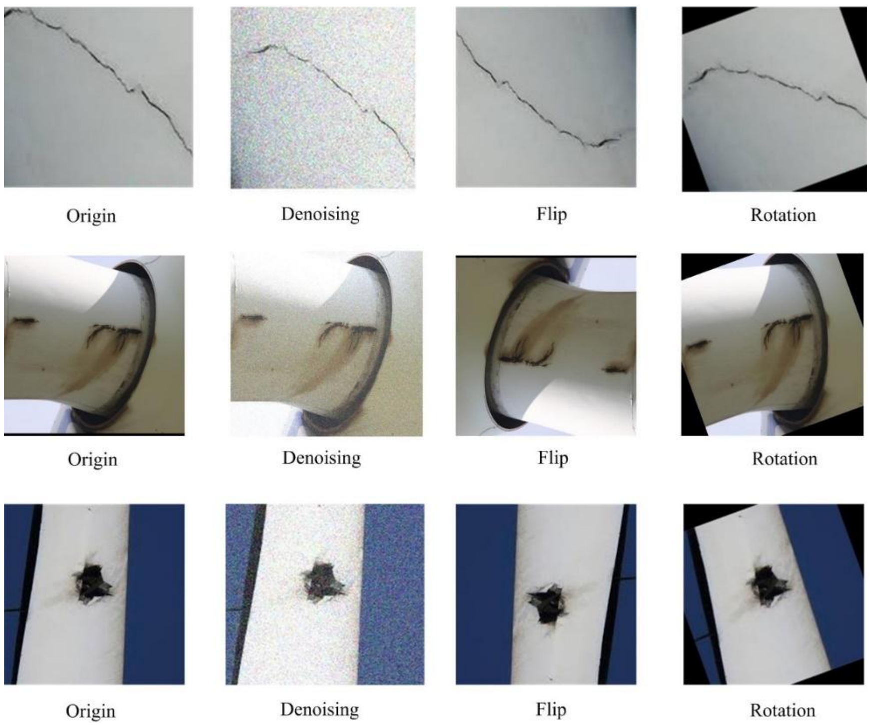

Figure 3. Data Augmentation

4. Experimental verification and analysis

4.1 Experimental conditions

In order to train the optimized network effectively, an experimental platform is built. The platform uses Ubuntu18.04 system. Caffe is used as the deep learning framework. The hardware device includes a Core i5 8400 CPU, 16GB RAM and the GPU that is GeForce RTX 2080 Ti with the memory size of 11GB.

Since there is no published wind turbine blade fault dataset that can be used for network training, the study made a dataset containing 5240 pictures. The dataset is then divided into 3930 train set and 1310 test set according to 3:1 scale. The dataset contains common failure types of wind turbine blades. Because some fault types are difficult to distinguish, the study divides all the fault types into two categories, namely crack and breakage.

4.2 Evaluation Indicators

In the process of blades detection, testing the performance of the proposed network usually requires evaluation of classification and positioning. The detection task mainly involves the recognition of multiclass faults. In the actual verification, the model performance is quantitatively evaluated. Among them, the mean average precision (mAP) represents the detection model accuracy.The precision (P) and recall(R) can be defined as:

$$P = \frac{TP}{TP + FP}$$
$$R = \frac{TP}{TP + FN} \quad (1)$$

where TP is the positive samples number predicted as positive samples, FP is the negative samples number predicted as positive samples, and FN is the positive samples number predicted as negative samples.

The average precision (AP) value can be calculated from the area between the P-R curve and the coordinate axis. The mAPis the average AP value for all classes. The parameter is defined as:

$$AP = \int_0^1 P(R)\mathrm{d}R$$
$$mAP = \sum_{i=1}^{N} \frac{AP(i)}{N} \quad (2)$$

Where N is thenumber of object classification.

4.3 Results analysis

In order to verify the performance of the proposed blade fault detection network, quantitative and qualitative verification are performed. From a quantitative point of view, the detection model is utilized to detect multiple kinds of blade faults.The detection accuracy of the model is shown in Table 1. The qualitative validation results are shown in the Figure 4.

Table 1: Detection accuracy of the model.

Blade Fault	Crack (%)	Breakage (%)	mAP (%)
Value	76.82%	63.15%	69.99%

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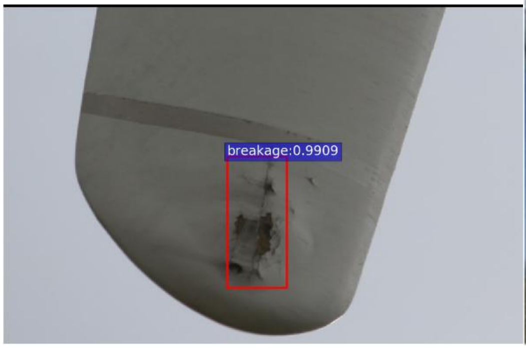
(a)

(b)

(c)

(d)



(e)

(f)

Figure 4: Detection effect.

5. Conclusion

Aiming at the difficult problem of wind turbine blade detection, the study proposes a detection method combining UAV and PVANet to perform the detection work. The fault on the blade can be detected. Due to the feature diversity of blade faults, the feature extraction network of detection network is optimized. The optimized network structure improves the feature expression of small objects to a certain extent. At the same time, the robustness of the network is improved by enhancing the dataset. Therefore, detection network can adapt to detection tasks in most environments. In conclusion, the blade fault detection method proposed in the study shows good performance in the detection process of wind turbine blades.

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