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Cracked Insulator Detection Based on R-FCN

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Abstract. The insulator is an important component of the high voltage transmission line. Inspecting the defects of the insulator plays an important role in ensuring the normal operation of the transmission line. The cracked insulator is the most common type of insulator defects. The traditional cracked insulator detection method is to use image denoising, single insulator disk segmentation, and the adjacent European distance to locate and identify cracked insulators. Experiments show that the robustness of these methods is poor and their ability to adapt to the environment is not good. Image denoising and image segmentation with the complex environment in images are very difficult tasks. Based on the extracted insulator strings, we change the problem to cracked insulators detection under complex conditions with deep learning. Region-based Fully Convolutional Networks (R-FCN), a deep learning algorithm, is adopted. Firstly, we apply image correction and cropping to images with different sample sizes and directions. Secondly, we use image enhancement technology to expand the dataset of samples. Finally, sliding window and coordinate mapping method are used when testing samples. The experimental results after the algorithm being applied to UVA dataset show an average accuracy rate of 90.5%. The inspection time of a single image is less than 1 second, and the model proposed in this paper has strong robustness and environmental adaptability.

1. Introduction

In recent years, "smart grid" has aroused people's attention, which mainly aims to utilize the advanced technology and equipment to detect and maintain the transmission line efficiently, safely and automatically. Insulators, which are used to guarantee the normal operation of transmission lines, play an important part of transmission lines. Because of long-term exposure to the natural environment, insulator strings will be broken, rust, and cracked. Once the insulators are destroyed, it will cause equipment damage, power outage and even disasters. The cracked defect is the most common and urgent defect of insulators among the insulator defects.

At present, the solutions to detecting cracked defects mainly require manual work, take high financial expenses and reach lower efficiency than expected. In addition, the electric field detection, electromagnetic pulse detection, ultrasonic detection, UV corona imaging and infrared detection are also used. These methods are costly to complicated operation. With the development of UAV, we can analyze and locate insulator defects by UVA images.

There are many achievements in the detection of insulator defects through the image. Lin and Han [1], propose histogram statistics and matching method for explosion insulator detection, which gets

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low missing rate but the defect is not located. Wang [2] puts forward to analyze the connected field

and shape of insulator strings to detect, which is not applicable because of various insulator strings. Yang Wu [3], Angelika [4], propose to use template matching with a single created insulator plate. However, the template cannot cover all insulator string patterns. Another kind of methods [5] has three steps. Firstly, extract insulators from the complex background, and obtain pure insulator string through image denoising technology. Secondly, build the characteristics of the insulator such as HOG or SIFT, and separate insulators one by one. Finally, locate the position of the cracked insulator from the normal insulator by the distance judgment between adjacent insulators. The experiment showed that this kind of method is not easy at all. On the one hand, it is difficult to obtain pure insulator in the complex background. On the other hand, it relies on the accurate segmentation of all the insulator disks. However, image segmentation, is another hard problem.

Deep learning, however, is an effective method for image classification, image detection as well as image segmentation. To solve problems mentioned above, we detect the cracked insulator directly with deep learning. Specifically, this paper regards cracked insulators as targets, and normal insulators act as the background. Deep learning [6] can extract both the bottom features of the image and the high-level semantic features, which is very suitable for the object detection in the complex background. There are many methods of object detection. Object detection in deep learning can be divided into two branches, one is a two-stage detection method based on Faster RCNN [7], and composed of RPN and Fast RCNN, the other is the SSD [8] that makes use of regression to achieve the detection directly. In general, Faster RCNN is slightly higher than SSD in precision and slightly lower than SSD in speed. R-FCN [9], a fully convolutional network, which is a deformation network of Faster RCNN. R-FCN introduces the concept of position sensitive feature maps, and achieves detection sensitivity about the position. Besides, the voting mechanism replaces the full connection layer in R-FCN, which improves the detection speed. Cracked insulators will be considered as a position sensitive target. Under the consideration of accuracy and speed, we choose to use R-FCN network as the detection network of insulator's defect.

In this paper, the sample of the cracked insulators taken by UAV has a difference in angle of view, length, and size, and sample quantity may not be enough. Image correction, image enhancement, and image cropping technologies are taken to solve these problems. We can obtain a robust model via training R-FCN with preprocessed samples. At the time of testing, we take advantage of image correction and the sliding window to test any size images. Details of preprocessed R-FCN can be found in section 2. Experiments and experimental results are in section 3. The experimental results show that our preprocessed R-FCN model has high detection precision, fast detection speed and good adaptability.

2. **R-FCN Detection Method**

R-FCN is a two-stage object detection method based on RPN and FCN [10]. We choose RPN to generate the region proposals, and FCN to obtain feature maps. Resnet101, a somewhat fully convolutional neural network, is adopted. The connection between RPN and Resnet101 is the position sensitive ROI Pooling layer. The voting mechanism replaces the full connection layers to obtain the result. Figure 1 shows R-FCN network structure.



Figure 1. R-FCN network structure

2.1. Resnet101[11]

ResNet introduces the residual network structure, through which, we can enhance the network layer. In order to solve the vanishing gradient problem caused by deeper network, ResNet adds a shortcut connection between input and output in residual network. Experiments show that ResNet performs better than VGG16 and GoogleNet. Figure 2 shows the unit of ResNet. Each block of the Resnet101 is composed of three layers of coiling layers, as shown in Figure 3.



Figure 2. A building block of ResNet



Figure 3. A block of Resnet101

During the experiment, we make Resnet101 as the feature extraction network and remove the final average pooling layer and full connection layer. So ResNet-101 outputs W * H * 2048 feature maps. Then, a full convolution 1 * 1 * 1024 with a randomly initialized weight is used on that W * H * 2048 feature maps. Ultimately, we got W * H * 1024 feature maps.

2.2. RPN

The RPN is used to generate region proposals. RPN uses softmax classifier to determine whether anchors belong to the foreground or background and bounding box regression to correct anchors to get precise proposals.

2.3. Position Sensitive Score Maps and PS RoI Pooling

The cracked insulators are very similar to the normal insulator. We regard cracked insulators as a type of position-sensitive object. R-FCN introduces position-sensitive feature maps to achieve the object detection that can response to translation of detecting windows. In the experiment, we adopt $k^2(C + 1) * 1024 * 1 * 1$ convolution kernels to convolve the W * H * 1024 feature maps and obtain $k^2(C + 1) * W * H$ position sensitive features. For each ROI, each cell corresponds to a different position of the ROI. As shown in Figure 1, the upper left corner corresponds to the yellow color feature map while the lower right corner corresponds to the light blue. Therefore, each ROI will form a feature map of $k^2(C + 1)$ size. Finally, we vote on this feature map and then make softmax classification and bounding box regression to get the final detection results.

2.4 Loss Function [12]

The loss function of R-FCN is similar to Fast RCNN, called cross entropy loss, which includes classification loss and regression loss. Eqn.(1) shows the cross-entropy loss function.

$$L(s, t_{x,y,w,h}) = L_{cls}(S_{C^*}) + \lambda[c^* > 0]L_{reg}(t, t^*)$$
(1)

in which L_{cls} demonstrates the classification loss, while L_{reg} demonstrates the regression loss. Eqn. (2) and Eqn.(3) show them respectively.

$$L_{cls}(S_{C^*}) = -\log(S_{C^*})$$
⁽²⁾

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$$L_{\text{reg}}(t, t^*) = \sum_{i \in \{x, y, w, h\}} \text{smooth}_{L1}(t_i - t^*)$$
(3)

Here c^* indicates the labels of RoI (Region of Interest), and $c^* > 0$ shows that the RoI is a target. S_{C^*} represent the scores of each RoI. Symbol t are the coordinates of samples detection targets, t^* are our network outputs, representing the coordinates of detect targets after bounding box regression.

Besides, x, y represent the (x, y) coordinates of detected boxes, and w is the width of detected boxes, and h stands for height.

3. Experiment

3.1. Data Preprocessing

Firstly, we cleaned the data, including removing duplicate samples, deleting damaged images and extremely blurred images. Secondly, we defined two forms of targets based on the characteristics of cracked insulators, as shown in Figure 4. The left one represents the defect at the boundary of the insulator string while the right one represents the defect in the middle, and marks these effective samples. Thirdly, insulators have a variety of forms, including the different shapes, the inconsistent arrangement, the different lengths, the large differences in aspect ratio, and the complex background. These problems cause the different scales in samples. To solve these problems, we adopted image correction and image cropping techniques.

Specific steps are as follows:

- Get width and height of the sample;
- If height>width, rotate the images counter clockwise by 90 degrees so that the insulator string is horizontal. Update its corresponding coordinate values at the same time;
- Get the coordinate values of the sample and expand it, keeping the original image high and cropping the sample with 1: 2 aspect ratio of the image. Update its corresponding coordinate values at the same time too, see Figure 5 and Figure 6;



Figure 4. Two kinds of defect patterns



Figure 6. Data preprocessing flow chart

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After these processes, training samples are roughly the same scales. Unfortunately, the number of samples is insufficient, only 687 samples. So we need to enhance the samples by image enhancement. Image enhancement methods include flip, color change, affine transform, rotation, random crop, etc.

3.2. Experimental Parameters Setting

In this paper, 4104 effective samples have been obtained after data preprocessing. In the experiment, the training set is 64%, the validation set is 16% and the test set is 20%, corresponding to 2626, 656 and 822 images respectively.R-FCN detection model was trained under the framework of mxnet. In the training process, initialize weights by ResNet-101 model trained on ImageNet. Next, set the shortest edge of the sample size to 600 pixels with the aspect ratio unchanged. Then, train the R-FCN network. Meanwhile, OHEM is added to balance positive and negative samples of cracked insulators.

3.3. Cracked Insulators Detection

In the test, the images may be any size, so we use a sliding window to achieve the detection. The final test result is obtained through a combination of the sliding window testing and coordinate mapping. The test process is as follows, as shown in Figure 7.

- Get the width and height of the image, if the height is larger than the width, the insulator string in the image is likely to be in a vertical suspension state, so rotate it counterclockwise by 90 degrees;
- Take the height of the image as the reference, and make the sliding window's width twice as long as its height. The step size is set to be height. Test the obtained multiple sub-samples through the trained model;
- Add all test results of step 2, and map the coordinates back to the original image. Delete duplicate targets with IOU> 0.7 of two or more detection results.



Figure 7. The test example

Method	Convergence	mAP value
R-FCN	No	Nan
R-FCN + A	Yes	40.8%
R-FCN + B	No	Nan
R-FCN + C	No	Nan
R-FCN + A+B	Yes	85.6%
R- FCN + A + C	Yes	74.2%
R-FCN + B+C	No	Nan
R-FCN + A+B+C	Yes	90.5%

Table	1.	Effect	of	image	correction	cropping	and	enhancement
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Table 2. Compa	rison between	different methods
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Method	Missing rate	False rate	mAP value
Traditional	15.2%	18.8%	76.9%
Faster RCNN+A +B+C	4.6%	5.7%	87.1%
R-FCN+A+B+C	2.8%	3.5%	90.5%

3.4. Experimental Comparison

We choose 500 images randomly for tests. In this paper, we compare the R-FCN detection with the traditional method and Faster RCNN. We use A to stand for image correction, B for image cropping, and C for image enhancement. Table 1 emphasizes the role of image correction, image cropping, and image enhancement. Figure .7 shows the final detect results of our algorithm and Table 2 shows the results of these methods. Traditional method in Table 2 represents that detect cracked method through image segmentation and distance judge.



Figure. 8 Correct tested examples with our method



Figure. 9 Wrong tested examples with our method

Table 1 shows the effect of image correction and image cropping as well as image enhancement. Obviously, image correction doesn't affect the model convergence directly. Image enhancement increases the number of samples to improve the detection accuracy. It is worth mentioning that image cropping significantly improves the detection accuracy. Because cracked insulators are targets in this paper, normal insulators act as the background, the shape and size of the normal insulator are the same. Therefore, image cropping will not lose the information around the target but make the relative scale of the target larger and easier to detect.

From the Table 2, we can find that the proposed method reaches lowest false detection rate and missed detection rate but the highest mAP. By contrasting Faster RCNN and R-FCN, we can see that it is reliable to make the cracked insulators as a type of position-sensitive target. Besides that, single image detection only costs 0.0013ms with R-FCN. Figure.8 shows that the detection results of the proposed method for different target numbers, various defect forms, and various insulator arrangements.

Figure. 9(a), however, missing detection occurred, because the original test picture has a very serious occlusion phenomenon, which is hard to find. Figure. 9(b) caught the wrong detection, which was caused by the high similarity between normal insulators and that form of cracked insulators.

4. Conclusion

In this paper, we solve the insulator defect problems not by image segmentation but by object detection. The object detection method, R-FCN is used as the basic detection network, and the states of the two kinds of the defect are defined as targets to detect. As for the training samples, the image correction and cropping techniques are adopted in this paper to adjust the input image to roughly same size and the insulator string to roughly same pose, and the dataset of samples is expanded by using image enhancement technology. During network's training, we use techniques such as sample warming up and OHEM to enhance the robustness of the model, and parallel GPU computation trick to accelerate training. As for the test images, sliding window and coordinate mapping method are adopted so that the network can be used to detect objects in images of any size.

Finally, this paper verifies the superiority of the proposed method by comparing it to the traditional method and the Faster RCNN method by different standards, which are false detection rate, missed detection rate and mAP value. Considering the missed detection rate caused by the serious occlusion in the insulator strings, the detection accuracy of the cracked insulator can be further improved by controlling the flight path of the UAV or enhancing the networks' learning of samples with occlusion.

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