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Detection Method for Bolt Missing Pins of Transmission Line Based on Improved SSD Network

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Abstract: The bolt pin structure plays a role in connecting and fixing various components in transmission lines, and the pins are prone to detachment, which may lead to the disintegration of key components and cause serious consequences. The bolt pin target size in the transmission line inspection image is small, the background is complex, and the detection effect using traditional object detection algorithms is poor. This article proposes a method for detecting missing bolts in transmission lines based on an improved SSD (Single Shot MultiBox Detector) network. Using the traditional SSD network as the foundation, a feature fusion module is first added to the network to enrich the semantic information of low-level feature maps and the detail information of high-level feature maps through the mutual fusion of high-level and low-level feature maps. Secondly, embedding a channel attention mechanism module enhances the channel features corresponding to the bolt pin structure and suppresses channel features that are irrelevant to the background; At the same time, the introduction of Focal Loss loss function reduces the unevenness of positive and negative sample classification. Finally, experiments were conducted on the collected bolt missing pin detection dataset, and the results showed that the method proposed in this paper has good performance in detecting missing pins, and the detection accuracy has been significantly improved.

Keywords: Missing pins; SSD; FPN; SE module; Focal Loss.

1. Introduction

The bolt pin structure is a widely used connecting component on transmission lines, and a large number of equipment components in transmission lines are connected and fixed through the bolt pin structure. Due to the fact that the bolt pin structure itself is made of metal material and is exposed to harsh natural environments for years[1], it is prone to pin detachment and missing faults, resulting in serious consequences. Therefore, during the inspection of transmission lines, attention should also be paid to the inspection of bolt pin components[2].

Traditional manual inspection of transmission lines is time-consuming and labor-intensive, which is not advisable in today's increasingly large and intelligent power grid[3]. Drone inspection has to some extent solved the problem of time-consuming and laborious manual inspection, but the efficiency of subsequent manual processing of the images collected by drones is still low, and it is also prone to missed and false detections . The rapid development of deep learning in the field of object detection has enabled people to apply deep learning algorithms to the processing of inspection images, achieving good results in fault detection of large target components such as insulators[4], vibration dampers[5], grading rings, and transmission lines[6]. Due to the small size of the bolt pin structure and the small difference in the shape of normal bolts and missing bolts, it is easy to miss or misidentify. At present, there is no standard dataset for bolt missing pins, and the amount of image data containing pin missing faults is relatively small. The network cannot be effectively trained, resulting in poor detection performance. These are the difficulties in detecting bolt and pin missing faults in current transmission lines.

Reference[7] proposes a bolt defect grading detection system. Firstly, the SSD algorithm was used to locate the connection parts with defective bolts and cut them out. Secondly, data augmentation was used to expand the dataset. Finally, the YOLO V3 algorithm was used to detect defective bolts, achieving real-time detection of bolt defects. Reference[8] improved the feature pyramid structure based on the Faster RCNN network, further enhancing the semantic and detail information of the underlying feature maps, and improving the ability to detect defective bolts, achieving good results.

This article uses the single-stage object detection algorithm SSD as the basic network for its detection algorithm. Firstly, a feature fusion mechanism is introduced into the network to incorporate the FPN (Feature Pyramid Networks) structure; Secondly, embed channel attention mechanism modules in the network. Finally, replace the original SSD loss function with the Focal Loss loss function ll manuscripts must be in English, also the table and figure texts, otherwise, we cannot publish your paper.

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2. A bolt missing detection model for transmission lines based on improved SSD network

The network model proposed in this article is based on the SSD network, with the addition of feature fusion module and

SE channel attention mechanism module (SE) in the backbone network, as shown in Figure 1. C1 represents the feature map of Conv4_3 layer, C2 represents the feature map of Conv7 layer, C3 represents the feature map of Conv8_2 layer, C4 represents the feature map of Conv9_2 layer, C5 represents the feature map of Conv10_2 layer, and C6 represents the feature map of Conv11_2 layer. Compared with traditional SSD networks, the improved network first inputs the inspection feature maps C1, C2, C3, C4, and C5 into the feature fusion module to obtain the fused feature maps P1, P2, P3, and P4; Then, the fused inspection feature map is input into the SE channel attention mechanism module along with feature maps C5 and C6 to obtain the channel dimension weighted inspection feature map; Finally, use channel weighted inspection feature maps of different scales to detect missing bolts and pins.

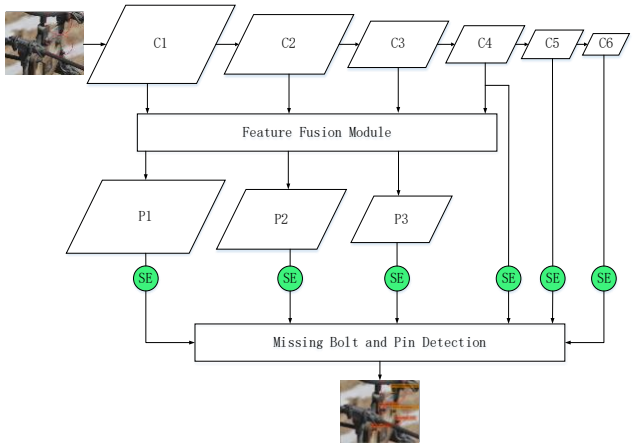


Figure. 1 Detection Model of The Improved SSD Network

2.1. Feature Fusion Module

The size of the bolt pin structure that needs to be tested in this article is relatively small, and the low-level output feature map in the SSD network is mainly used for detection. The FPN structure conveys semantic information through top-down branching, and then fuses feature information through horizontal connections.

The structure of the feature fusion module is shown in Figure 2. The detailed information of feature maps C1, C2, and C3 is supplemented upwards, and the rich semantic information of feature maps C5, C4, C3, and C2 is supplemented downwards. This effectively supplements the feature information of the output feature map used for prediction, resulting in feature enhanced feature maps P1, P2, P3, and P4.

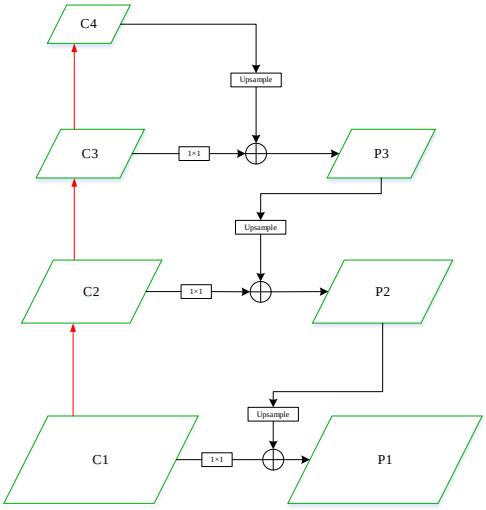


Figure. 2 Feature Fusion Module Structure

The specific process of feature fusion is:

(1) Upsample feature map C4 to 10×10; After passing through a 1×1 convolution kernel, C3 transforms the number of channels from 512 to 256; Then, it is added and fused with the upsampled C4, and finally, a convolution operation with a kernel size of 3×3 is performed to eliminate the aliasing effect caused by the addition of feature maps, resulting in the output feature map P3.

(2) Feature map P3 is upsampled to 19×19; C2 transforms the number of channels from 1024 to 512 through a convolution operation with a kernel size of 1×1; After adding and fusing with the upsampled P3, a convolution operation with a kernel size of 3×3 is performed to eliminate the aliasing effect caused by the addition of feature maps, resulting in the output feature map P2.

Similarly, the output feature map P1 can be obtained, which will not be repeated here.

At this point, the output feature maps P1, P2, and P3 are fused, effectively supplementing the semantic information of low-level feature maps and the detailed information of high-level feature maps that facilitate pin missing detection, thereby improving detection accuracy.

2.2. SE module

This article embeds the SE channel attention mechanism module in the SSD network, as shown in Figure 1. After feature fusion, the fused inspection feature map is input into the SE module. The SE module takes into account the different importance levels of each channel in the inspection feature map. Through squeezing and excitation operations, the importance weights corresponding to each channel are obtained. Then, based on these weights, the feature channels corresponding to the bolt pin structure are improved while suppressing feature channels with useless backgrounds. Finally, the obtained weights are multiplied by the values of each channel on the feature map to obtain a channel weighted feature map. The structure is shown in Figure 3. Meanwhile, the SE module utilizes fewer additional parameters to achieve higher detection accuracy.

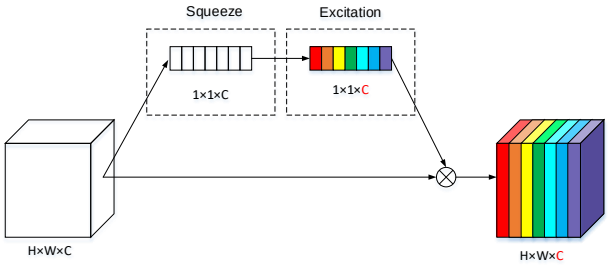


Figure. 3 SE Attention Mechanism Module Structure

2.3. Loss Function

The loss function of the network model in this article consists of two parts: classification loss function and regression loss function. The original SSD network used the cross entropy loss function as the classification loss function. In this study, it was found that the distribution of positive and negative samples in the bolt and pin missing detection dataset was extremely uneven. The number of negative sample backgrounds far exceeded the number of positive sample bolt and pin structures, which affected the detection effect of bolt and pin missing. Therefore, this article uses the Focal Loss loss function when calculating the classification loss, as shown in equation (1), which reduces the proportion of simple negative sample background in calculating the classification loss, thereby increasing the proportion of positive sample bolt pin structure, which is beneficial for detecting bolt pin missing.

$$L_{fl} = \begin{cases} -\alpha\left(1-y'\right)^{\gamma}\log y', & y=1 \\ -(1-\alpha)y'^{\gamma}\log\left(1-y'\right), & y=0 \end{cases} \quad (1)$$

Among them, γ is the adjustment factor, γ =2; For the balance factor α , α =0.25.

3. Experimental results and analysis

The operating system used in this experiment is Windows 10, the GPU is NVIDIA GeForce GTX 1080Ti, and the deep learning framework is Pytorch 1.3.1.

3.1. Dataset and Experimental Parameters

A total of 479 inspection images containing missing bolt and pin faults were collected. This article first cropped these original inspection images to ensure that at least one bolt pin structure was included in the cropped images, resulting in a total of 968 images; This not only filters out most irrelevant backgrounds as much as possible, increases the proportion of bolt pin structures in the image, but also increases the number of images. Next, 6776 images were amplified by rotating, flipping, and adjusting different brightness levels on the cropped images. They were annotated according to the format of the PASCAL VOC dataset to establish a dataset for detecting missing bolts and pins in transmission lines. The training and testing sets were randomly divided in an 8:2 ratio, with 5420 and 1356 images in each set, respectively.

During the training process of the model in this article, the threshold for the intersection to union ratio was set to 0.5; The momentum parameter and weight decay are set to 0.9 and 0.0005, respectively; Set batch size to 32; The initial learning rate is set to 0.001, with 80000 iterations and 100000 iterations being the places where the learning rate decreases by 10 times. The total number of iterations is 120000.

3.2. Experimental Results

The experiment in this article uses Average Precision (AP) as the evaluation metric. The comparison and analysis of experimental results are mainly divided into three parts: (1) comparing and analyzing the impact of prior box optimization on model detection accuracy before and after; (2) Experimental results of improved SSD network; (3) Compare with Faster RCNN network and other methods.

3.2.1. Identification results of missing bolts in transmission lines based on improved SSD network.

In order to verify the effectiveness of the model proposed in this paper, comparative experiments were conducted. The experimental results are shown in the table below, where AP1 represents the recognition results of missing pin categories in the dataset, and AP2 represents the recognition results of normal bolt categories.

Table 1. Detection and Recognition Results

Methods	AP1/%	AP2/%
Original SSD	82.92	81.67
Improved SSD	84.78	83.44
Faster RCNN	82.21	82.85

According to the experimental results, the improved SSD network showed a 1.86% increase in AP values for the missing pin category and a 1.77% increase in AP values for the normal category compared to the original SSD network; Compared with the Faster RCNN network, the improved SSD network also has significant accuracy advantages, which fully demonstrates that the improved SSD network has better performance in detecting missing pin categories and normal bolt categories, and the detection accuracy has been improved.

3.2.2. Comparison with other models.

This article also compared the methods for detecting missing pins proposed in other literature, and the experimental results are shown in the table below. Among them, the model in this article refers to the improved SSD network model after prior box optimization.

Table 2. Comparison with Other Methods

Methods	AP1/%	AP2/%
Original SSD	82.92	81.67
Reference [9]	74.26	78.20
Ours	87.16	85.39

From the experimental results in the table above, it can be seen that the model proposed in this paper has increased the value of AP1 by 4.24% and AP2 by 3.72% compared to the original SSD network; Compared with the methods proposed in references [9], the AP values for missing pins was 12.9% higher.

4. Conclusion

In order to improve the detection effect of bolt and pin missing faults in transmission lines, this paper proposes a bolt and pin missing detection model based on an improved SSD network. Multiple experiments were conducted on the bolt and pin missing dataset, and the experimental results proved the effectiveness of the proposed method for bolt and pin

missing fault detection. Compared with the original SSD network, it can effectively improve the detection accuracy.

CONFLICTS OF INTEREST

The authors declare that they have no conflict of interest.

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