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Missing pin detection method for overhead transmission lines based on SPD and ASFF

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***Abstract*—In transmission lines, bolts and pins play an important role in fixing wires and connecting fittings. During the inspection of transmission lines, pins on transmission towers are important detection objects. In this paper, a missing pin identification method based on SPD and ASFF is proposed. Firstly, in order to increase the prominent defect features, the annotation information of normal category bolts is added to the database. Secondly, in order to extract richer feature information, the SPD module is used to replace the original simple convolution module. Finally, the ASFF structure is applied to reduce gradient backpropagation. According to the experimental results, the improved model's mAP of missing pin detection increased by 7 percentage points. The proposed method achieves rapid identification of missing bolts in overhead transmission lines, greatly improving the detection accuracy.**

Keywords- transmission lines; YOLO v5; SPD; ASFF; missing pin

I. INTRODUCTION

The industries and the livelihoods of people depend heavily on the safe and reliable operation of overhead transmission lines. The most common inspection techniques nowadays include manual inspection, inspection from a helicopter, inspection from a robot, inspection from a drone, etc. [1]. Compared with other inspection methods, drone inspection has the advantages of wide detection coverage, Due to the advantages of low operating requirements and high cost performance, drone inspections combined with manual inspections are currently widely used in actual power system work to improve work efficiency and safety. A large number of visible light images will be generated during the drone inspection process. By inspecting the visible light images, the bolts and pins in the transmission lines are missing. However, manual inspection has problems of low efficiency and high labor cost.

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The use of artificial intelligence to identify flaws in inspection images has become a hot topic in recent years due to the integration and development of emerging technologies like deep learning and the field of power inspection. For visually undetectable bolt flaws in transmission lines, Ke Zhang [2] et al. presented an end-to-end method based on transmission line knowledge reasoning for bolt defect detection. The accuracy of bolt defect identification is further increased by the bolt defect classifier's ability to reason about bolt faults when location and attribute knowledge are combined. Transmission line detection with deep learning was proposed by Jingguo Zhu et al. [3]. To be more precise, we create a network that use the oriented bounding box regression technique to predict the categories and spatial placement of foreign items in cluttered backdrops. Additionally, a straightforward yet efficient scale histogram matching method is put forth and applied to publicly available datasets. This method enables the detection of tiny foreign objects even with a limited number of labeled samples by allowing useful patterns to be exploited during pre-training to detect tiny foreign objects. Boost detection efficiency. A cascaded convolutional neural network-based target detection technique was presented by Yewei Xiao et al. [4]. The region of interest is first created using a small-scale shallow fully convolutional neural network, and the target is then classified and located within the obtained region of interest using a deep convolutional neural network. Subsequently, the convolution kernel is broken down and multi-scale feature maps are fused using a nonlinear multi-layer perceptron; at this point, the angle variable is included in the classification cross-entropy loss function. Multi-task learning and offline hard sample mining techniques are used in the training phase. In order to improve the representation of small targets, Hui Hea [5] developed a high-resolution feature pooling method based on bilinear interpolation; however, in order to increase the accuracy of the classification pinhole defect detection model, an attention mechanism was created to gather global features from various channels and combine their weights. Ling Xiao et al. [6] proposed a two-stage tiny defect identification methodology using the three major missing flaws of small fasteners—missing rivets, missing bolts, and missing pins—as an example. The model offers good accuracy and efficiency in detecting defects related to missing rivets, missing bolts, and missing pins, according to experimental results on a manually gathered fastener defect data set. Moreover, comparable minor fault detection can be accomplished with the model. On the basis of YOLOv5, Yiming Wei [7] added the Attention module and Transformer, modified YOLOv5's FPN, fused features of various layers using varying weights, and cropped high-resolution original images during the training phase. Its technique successfully raises the accuracy of detection. A local bolt identification module and an ultra-small object perception module (UOPM) are included in Peng Luo's proposed ultra-small bolt defect detection model (UBDDM), which is based on deep convolutional neural networks (DCNNs) (LBDM).

In the real world, detecting missing bolt defects in transmission lines must overcome the following difficulties: First, the proportion of bolt components in visible light images captured by drones is extremely small. In this instance, it is challenging to extract the distinctive details of the missing bolt pin, and the detection performance is subpar. In addition, feature information will gradually become abstract as the number of network levels increases. This research develops an enhanced target detection model based on the YOLOv5 framework to address the aforementioned issues and can automatically identify missing bolt pin faults in inspection photos. In order to make the enhanced detection model more appropriate for the identification of missing pin defects in bolts, we constructed a data set of bolts with positive defects and added the adaptive feature fusion (ASFF) module[9] and the space-to-depth (SPD) [10] deep convolution module to the backbone network.

II. METHOD

It is challenging to directly detect small items like bolts and obtain the desired results because of the huge viewing angle of the transmission line image captured by the drone and the small size of the bolt. Therefore, this study designs a bolt missing pin detection based on SPD and ASFF in order to increase detection accuracy. Figure 1 shows the general layout of the enhanced YOLOv5-ASFF-SPD network that is suggested in this research.

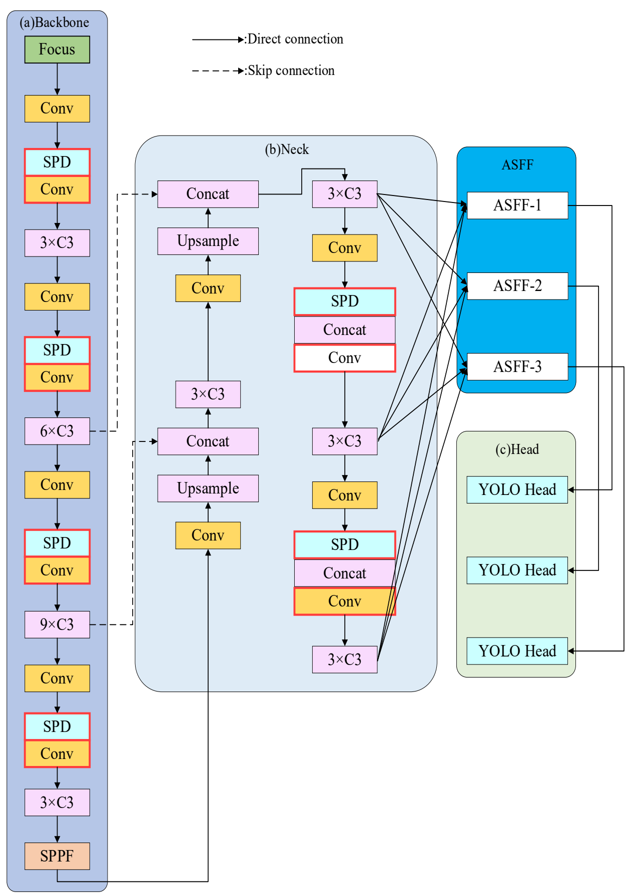

Figure 1 YOLOv5-ASFF-SPD network

A. Adaptively spatial feature fusion

By allowing the network to adaptively learn the weight of each position on each feature layer, adaptive spatial feature fusion (ASFF), a new and powerful feature fusion algorithm, enables the merging of critical information features. Other feature layers are first transformed to the same resolution before being trained to determine the optimal weight for fusion for each feature layer that will be combined. In Figure 2, the structure diagram is displayed.

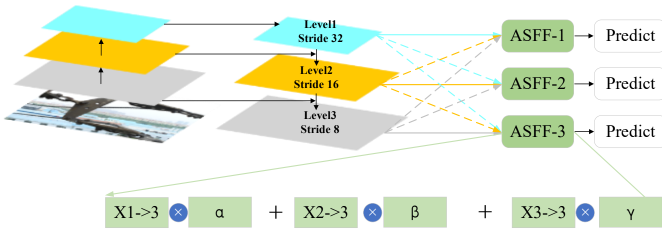

Figure 2 Structure diagram of ASFF

The purpose of feature scaling is to address the issue of size irregularity during feature fusion. In the figure, the up sampling and down sampling procedures of feature layers with various scales must be changed in order to obtain consistent size. Apply 1*1 convolution to reduce the number of channels in the feature layer to the same level as the preceding level before up sampling the interpolation to boost the resolution. A 3*3 convolution with a stride of 2 is used to simultaneously increase the number of channels and decrease the resolution for one down sampling of the feature layer. Perform a 2-stride pooling operation on the feature layer before the secondary down sampling to halve the resolution of the feature layer. Then, perform a 3*3 convolution with a 2-stride stride to simultaneously change the number of channels and resolution.

The output of the Neck component of the YOLOv5s network is the feature map of Levels 1, 2, and 3. In the case of ASFF-1, the characteristics from Levels 1, 2, and 3 are multiplied by the learnable weight, weight, to create the fused ASFF-1 input. As shown in formula 1.

$$y_{ij}^{l} = \alpha_{ij}^{l} \bullet x_{ij}^{1\to l} + \beta_{ij}^{l} \bullet x_{ij}^{2\to l} + r_{ij}^{l} \bullet x_{ij}^{3\to l} \tag{1}$$

Because the feature layers have varying sizes, up-sampling or down-sampling operations on the feature maps of separate layers are required when changing the feature map's size. The feature maps are compressed to one dimension by 1*1 convolution after separate closest neighbor interpolation and pooling are applied to the feature maps of three different sizes to provide global spatial information. The three compressed single-channel spatial information are merged to generate channel correlation. Next, the channel correlation attention weight between the three sizes and the spatial attention weight for each size are ascertained using the softmax activation function..

B. Space-to-depth

A real-world inspection image is the data set used in this study. Very few missing bolt pins are visible in the image, and the bolt has poor quality. Because of this, the fine-grained information in the pooled data is smaller and easier to lose. When training low-resolution images, inefficient feature representation learning causes the training effect to be significantly poorer than anticipated. Due to strided convolution and pooling layers, fine-grained information will be lost, and feature representation will have a low learning efficiency. Remove all pooling and strided convolution layers from the YOLOv5 network structure and replace them with the SPD Conv. The input feature map will initially be downscaled by the SPD layer while keeping all of the data in the information dimension. Therefore, there won't be any information loss as a result of this structure replacement approach. Figure 3 displays the flow chart.

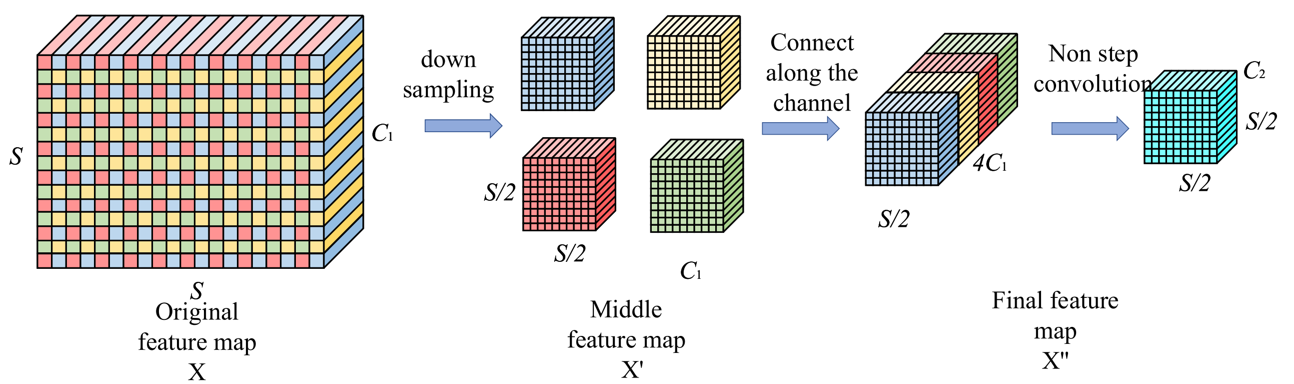

Figure 3 Process diagram of space to depth

III. EXPERIMENTAL RESULTS AND ANALYSIS

A. Data set

The data set for this article was compiled using aerial photographs taken by drones while the State Grid Electric Power Company was conducting daily inspections. First, 992 images with holes for bolts and pins were filtered out. A ratio of 8:2 was used to divide the training and test sets, with the training sets incorporating application data improvement techniques. Some datasets are shown in the Figure 4.

Figure 4 Partial dataset display rendering

B. Evaluation index

To conduct a thorough assessment of the enhanced YOLOv5 model's performance, precision (P), recall (Recall, R), mean average precision (mAP) indicator measurement, and model size (MB) are used as the evaluation indicators of the model. Specific calculations the announcement is as follows.

$$P = \frac{TP}{TP + FP} \tag{2}$$

$$R = \frac{TP}{TP + FN} \tag{3}$$

$$AP = \int_0^1 P(R)dR \tag{4}$$

$$mAP = \frac{\sum_{i=0}^{N-1} AP_i}{N} \tag{5}$$

AP is the accuracy of a single detection category, mAP is the average AP of each detected target category, and N is the total number of categories of detected targets. The larger the mAP, the better the performance of the network and the better the detection accuracy.

C. Results

The detection accuracy of bolt missing pins is shown in Table 1.

Table 1 Comparison of detection accuracy before and after improvement

Name	P/%	R/%	mAP/%
Singe	73.6	61.8	66.4
double	65.7	77.2	72.3
ASFF	75.6	64.5	72.4
SPD+ASFF	70.6	68.9	73.4

Normal class objects are usually not added because in typical defective object detection, the identified objects are defective objects. However, this work found that single-category missing pin detection is less effective. This method can greatly improve the detection accuracy of damaged bolts after adding normal category bolt annotations. Here's an explanation for this:

First and foremost, the fault of bolts with missing pins is the major inspection focus when it comes to transmission lines. Bolts with missing pins are not much different from regular bolts without pins. The majority of faulty bolts are pin missing. The hole in the damaged bolt typically only makes up a very small percentage of the hole shown in the image. As seen in Figure 5, standard bolts typically have a larger and more noticeable pin than the actual bolt hole. Therefore, the features of holes are partially lost in the deep feature layer after numerous convolution operations and pooling operations. As a result, the missed detection rate and accuracy are both poor, and the network's detection effect for single-category missing pin sub-targets is not optimal. The network can successfully learn the differences between regular bolts and missing bolt pins after adding the annotation of normal bolts during the training process. The accuracy of bolt missing pin identification is indirectly increased by the efficient detection of normal bolts. The number of bolts with missing pins rose by 5.9 percentage points when compared to single-category detection.

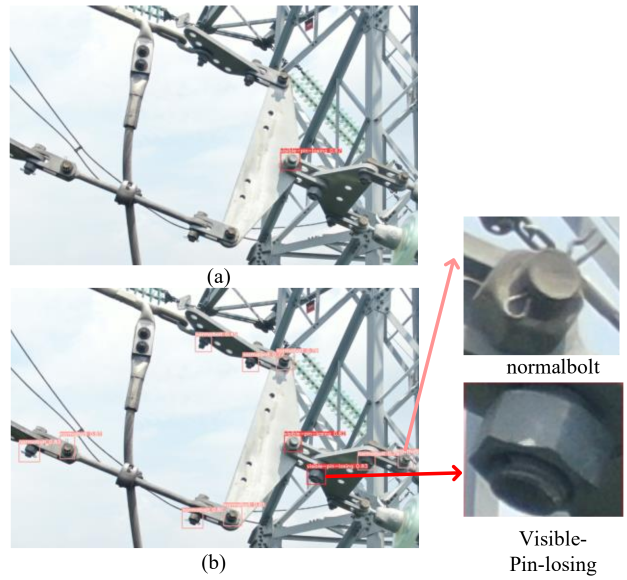

Figure 5 Single category and dual category comparison chart

New models of ASFF and SPD network structures are introduced on the basis of this. While SPD substitutes the strided convolution and pooling layers to improve the accuracy of small-scale features, ASFF fully utilizes features of various scales through the re-fusion of high-level features and low-level features. The target object's feature extraction ability has an overall mAP improvement of 1.1% over the original model.

Table 2 Comparison of classical model detection accuracy

Method	mAP/%	model size /MB	inference time/s
Faster RCNN	62	108	0.31
SSD	66	91.1	0.31
YOLOv5	66.4	14.4	0.20
Ours	73.4	34	0.22

The following visual detection effect diagram of the model before and after the improvement is supplied, as indicated in the figure, in order to more clearly illustrate the improvement effect of this article. Table 2 compares this article's improved effect with other conventional target identification techniques in order to more clearly illustrate how effective it is. Comparing the improved approach suggested in this study against many popular target recognition models, the detection accuracy is as high as 73.4%. Though not the lowest, the model volume has not increased considerably. Compared to YOLOv5, the model with the smallest volume, the volume has increased by 20MB, and the accuracy has improved by 7 percentage points. In exchange for some volume loss, we think the accuracy enhancement is worthwhile. The accuracy of this article has enhanced when compared to Faster RCNN and SSD by 11.41 and 7.4 percentage points, respectively, while the volume is 31.4% and 37.32

percent of theirs, respectively. In conclusion, this paper has the highest detection accuracy and is relatively small compared to other models. It works well for transmission line inspection practice because it can more accurately identify the target of missing bolt pins.

IV. CONCLUSIONS

Drone aerial pictures pose challenges in locating lost nuts and pins due to their unstable environment, complex background, various interference effects, and small objects. For overhead transmission lines, a leaky pin approach based on SPD and ASFF is described to achieve better image resolution. Drone aerial pictures pose challenges in locating lost nuts and pins due to their unstable environment, complex background, various interference effects, and small objects. For overhead transmission lines, a leaky pin approach based on SPD and ASFF is described to achieve better image resolution .Experiments show that the method described in this article can greatly improve detection skills, as seen by a 7 percentage point improvement in mAP to 73.4 percent. This can help inspectors complete daily transmission line inspections more swiftly and effectively while also improving the accuracy of target recognition during bolt inspection procedures. It is required for transmission lines to operate safely and dependably as well as for their autonomous inspection.

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