Research on Transmission Line Small Target Detection and Defect Recognition Based on Machine Vision

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Abstract: At present, the unmanned aerial vehicle (UAV) is faced with two difficulties in the course of inspection of power transmission line: (1) it is difficult to find small targets. The existing machine vision methods have poor performance in the detection of small targets, and there are still deficiencies in multi-scale feature extraction and fusion. (2) because of the uneven distribution of defect sets and normal sets, the differences based on the classification of semantic information, and the fusion of shallow location features and deep semantic features, it is difficult to identify and classify defects effectively.

1 INTRODUCTION

In this project, based on the background of unmanned inspection of transmission line, taking transmission line as an example, and on the basis of deep-level machine vision, the method of small target data expansion and expansion of transmission line is studied, and on this basis, the general object detection framework YOLOV5 is improved to improve the efficiency of small target detection, and the method of fault identification and classification is explored.

With the modern society becoming more and more dependent on electricity, the overhaul of electric lines has become an important task under uninterruptible power supply conditions. A power line is made up of several components, which have different functions, such as insulators, wires, metal fittings, etc. The field work environment is complex, the climate is changeable, and has the foreign material invasion danger, causes the electric element in the electric network to be easy to have the damage. A failure of one component, such as an insulator failure, or a failure of multiple components, such as a failure of a metal joint, may result in a power outage. According to the annual development report of China's power industry 2021, by the end of 2020, the number of transmission lines of 220 kV and above had reached 794,000 km, and it is still increasing at an annual rate of about 4.6%. Under the goal of"Improving quality and efficiency", the traditional manual inspection mode will be gradually replaced by new technologies such as UAV inspection and robot inspection. In the electric power industry, it is important to speed up the establishment of information inspection platform, and to make use of digital technology to assist transmission line maintenance personnel in line maintenance.

YOLOv5-based improved model for small target detection on transmission lines YOLOV5 has a similar structure to Yolov4, but it is a new Focus (Backbone) structure, which uses hierarchical image processing, the feature map with low dimension and multi-scale is obtained. There are some differences in the selection of Backbone activation function. Yolov5 uses Leaky Re Lu as the activation function of the hidden layer, and finally the detection layer uses Sigmoid activation function, yolov4 uses Mish as the activation function of its Backbone. Leaky's formula for activating the three functions from Lu, Sigmoid, and Mish is:

$$\text{Leaky ReLU: } \mathrm{f(x)} = \begin{cases} x\ ifx \geq 0 \\ \dfrac{x}{a}\ ifx < 0 \end{cases} \tag{1}$$

$$\text{Sigmoid: } \mathrm{f(x)} = \frac{1}{1+e^{-x}} \tag{2}$$

$$\text{Mish: } \mathrm{f}(x)x \cdot \tanh(\ln(1+e^{x})) \tag{3}$$

The overall network structure of YOLOV5 is similar to that of Yolov4: the network structure diagram for Yolov5 is shown in Figure 1. Compared to Yolov4, Yolov5 has lower network complexity and is more suitable for deployment on edge computing

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devices. The Yolov5 network is then analyzed from the input side and the Backbone.

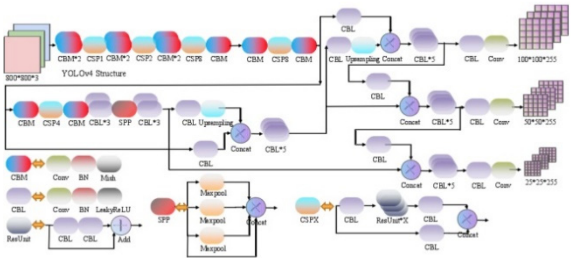

Figure 1. Yolov5 network structure diagram.

(1) YOLOv5-based digital image enhancement algorithm at the input, which randomly scales, cuts, arranges and synthesizes 4 images into a new input image. The Mosaic algorithm is used to divide the large-scale objects into smaller objects randomly, which balances the data distribution of small objects, improves the robustness of the network and the detection ability of small objects. The Mosaic-processed input image is shown in figure 3.2:

Figure 2: input data processed by the Mosaic method.

Backbone part of Yolov5 Backbone part of Yolov5 is shown in Figure 3. It is based on the Yolov3 Backbone network Darknet53. It is a reference to the design ideas of CSPNet, thus the backbone structure of CSP Dark Net53 is formed. CSPDARKNET53 uses the idea of cross-phase local area network (CSP) to extract multi-level features from the input image to reduce the number of parameters and the scale of the model.

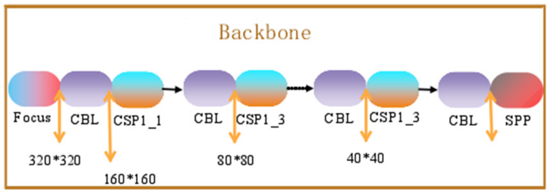

Figure 3. Yolov5 Backbone network structure.

2 IMPROVED SMALL TARGET DETECTION MODEL OF TRANSMISSION LINE BASED ON YOLOV5S NETWORK

2.1 Improved Backbone Network Based on Weighted Bidirectional Characteristic Pyramid Network

At present, an important problem in small target detection is the efficient expression and processing of multi-scale features, the traditional top-down method based on backbone network organically combines the multi-scale features, and thus realizes the top-down organic combination of multi-scale features, when multi-scale features are fused with each other, only the weight of the shallow features is considered, while the rich location information contained in the shallow features is ignored. In this project, a new multi-scale feature fusion network (Panet) is proposed by introducing the“Bottom-up” feature aggregation network (Panet) on the basis of the existing FPN, and make it the Backbone of the Yolov5s open source Backbone. In view of the shortcomings of the existing Yolov5s network model, this project intends to use the weighted binary feature cone network to distinguish the weights of different features by introducing learnable weights, in order to enhance the existing small target features in the role of feature fusion network. Weighted bidirectional feature cone network (BI-FPN) is a kind of backbone network which can replace the traditional FPN for small target detection in transmission lines. In figure 4, you can see the difference between the weighted bidirectional feature pyramid (Bi FPN) and the feature pyramid (FPN) and the path aggregation network (Panet).

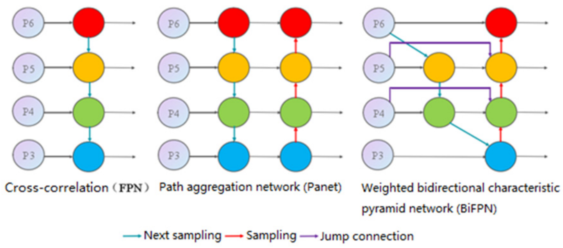

Figure 4. structure comparison of FPN, Panet, Bi FPN.

Compared with Panet (Polar-Agency Network), BiFPN (BiFPN) with weighted bidirectional features has a different node join pattern from Panet (Panel Agency Network), the optimization methods of the cross-scale join include:

(1) deleting the unique input nodes in the PANET -LRB-Path Agency Network). Because there is no node with fusion characteristic, the nodes of p 3 and P 6 are eliminated, and a small simplified binary network is obtained.

(2) at the same scale, the frequency-hopping connection between the input and output nodes is increased, so that the frequency-hopping connection on the same feature layer can be fused at more levels with limited computation.

(3) unlike Panet (Patholic Agency Network) , which has only one top-down and one bottom-up feature channels, Bi-FPN (weighted bidirectional feature cone) treats each bidirectional channel as a feature Network layer, and through repeated processing of this layer features, thus achieving a higher dimension of feature fusion.

Swin-Transformer improves the prediction head based on Swin Transformer encoder. Swin-transformer replaces the moving window with the moving window, performs self-attention computation on the non-overlapping local feature layer, and completes the neighbor feature aggregation by using the method of layer connectivity.

In the field of object detection, due to Transformer's dependence on high-resolution images, its attention complexity is about the square of image size. On this basis, a sparse representation method based on multi-scale features is proposed. SWINTRANSFORMER fuses adjacent smaller image blocks to create a hierarchical feature map for deep mining. When the number of image blocks in each feature layer is constant, the computational complexity is linear with the image size.

This method makes use of the common hierarchical construction method in convolutional neural network and the concept of image region to realize the self-attention computation of inconsistent image window. Compared to the convolution process in convolutional neural network (CNN), Swin Transformer performs a convolution on each window to get a window's properties, while Swin Transformer performs a self-focusing calculation on each window, a new window is obtained, and then the new window is fused once, and then the fused window is fused once.

In this model, the traditional long-term attention mode (MSA) is transformed into a moving window mode. Swin converter consists of a sliding window-based Multilayer perceptron (MSA), which connects two different types of Multilayer perceptron (mlps) in series.

Instead of the Swin Transformer framework, the traditional Transformer framework needs to perform global self-attention computation on the image, which consumes a lot of computing resources, and it needs to divide the image into m × m non-overlapping blocks, on this basis, the computational complexity of global-based MSA and moving window-based W-sma are:

$$\Omega(MSA) = 4\mathrm{hwC}^2 + 2(hw)^2\mathrm{C} \tag{4}$$

$$\Omega(W - MSA) = 4\mathrm{hwC}^2 + 2\mathrm{MhwC} \tag{5}$$

From formula (4)(5) , we can see that the operation complexity of MSA is the square of the number of image blocks HW, the operation complexity of W-sma based on moving window is linear with the number of image blocks.

3 SUMMARY

With the wide application of deep learning and machine vision, transmission line inspection is changing from traditional manual inspection to intelligent inspection. In this paper, target detection and fault identification in transmission line inspection are studied, and the task of small target detection and fault identification in transmission line inspection is studied. On this basis, it is improved by using converter, sven converter, weighted bidirectional characteristic pyramid, and convolutional attention model, in this paper, we extend the defective samples by using saliency map, and adopt the method of enhanced feature pyramid and deep semantic embedding.

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