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Pointer-type instrument identification based on YOLOv5s-MG

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ABSTRACT:In recent years, traditional industries are facing the choice of upgrading and digital transformation. For the oil and gas industry and the power industry, regular inspection, inspection and maintenance of equipment safety is a top priority. Oil, natural gas, power plants have a lot of power equipment and pressure vessels. The main observation indicators of these devices are current, voltage, pressure and so on. Pointer tools account for a large proportion of existing industrial tools. Therefore, it is of great practical significance to study the intelligent reading of pointer instrument. Aiming at the fuzzy, fuzzy and difficult recognition problems of instrument images in complex dynamic environment, object detection model YOLOv5s based on deep learning was adopted to study the recognition and positioning of pointer instruments. First, the YOLOv5s model is improved and trained by using the self-made instrument data set, custom anchoring framework and GAM attention mechanism, and the trained model Yolov5s-MG is used to predict the image. Under the condition of guaranteeing the recognition speed, the recognition accuracy is improved by 3.2% compared with YOLOv5s, which has certain optimization effect for the recognition of pointer instrument.

KEYWORDS:YOLOv5s; GAM attention; Custom anchors; Pointer-type instrument

I. INTRODUCTION

At present, there are two ways to locate the instrument: one is the traditional target detection method; One is object detection algorithm based on deep learning. The main traditional target detection[4] algorithms include template matching method and SIFT algorithm. Among them, template matching method is one of the most basic and original pattern recognition methods, which is to study the pattern of a certain object located in the position of the detected image, and then identify the object, which is a matching problem. However, template matching also has some limitations, specifically, it can only move in parallel, if the detected object rotation and size transformation, template matching[2] will be invalid. The other SIFT algorithm (scale invariant feature transform) is based on the principle that key points can be detected in the image. It is a local feature descriptor, which is used to detect the local features of the image and match the feature points[3]. It can solve the problem of image rotation and size transformation, but it can not remove the problem of background and object edge recognition. At present, object detection algorithms based on deep learning are mainly divided into two categories: one is single-stage object detection algorithm; One is two-stage object detection algorithm. Two-phase target detection uses the region proposal method to create a region of interest (ROI) for target detection. In selective search (SS), each pixel is first considered as a group. Then, the texture of each group is calculated and the two closest groups are combined. Therefore, it has a good recognition accuracy rate, but the recognition speed is relatively slow. As pointer instrument belongs to small target recognition, it has certain requirements on real-time performance and recognition speed. However, the single-stage end-to-end target detection does not require the generation of candidate frames, and directly converts the problem of target frame positioning into a Regression problem. YOLOv5 is a single-stage target detection algorithm, which adds some new improvement ideas on the basis of YOLOv4, and greatly improves its speed and accuracy. The YOLOv5 algorithm[6][7] has four versions, including YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x. The network structure of these four versions is similar, but the difference lies in the depth of the backbone network. The volume of the four versions increases from small to large. In

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order to ensure a certain accuracy, they have a good recognition speed. Therefore, the object detection algorithm based on YOLOv5s is adopted in this paper to identify and locate the pointer instrument data set. The research content of this paper is mainly divided into two parts: It Bottleneck improves the recognition accuracy of target models by using a custom anchor frame and improving the Bottleneck module.

1. Self-made pointer instrument data set[1] with a total of 3125 images, and labelImg tool was used to annotate the data set and save it in YOLO format.
2. Combining with small targets in the pointer instrument data set, the method of user-defined anchor frames and a modified Bottleneck module are used to improve the recognition accuracy of the target model.

II. METHODOLOGY

In this section, we will introduce YOLOv5s-MG network structure, K mean mean clustering algorithm, and Bottleneck-M and C3-MG module

A. Custom anchors frame

When the initial target detection model is used to test the image test set of pointer instrument, it is found that there is a certain gap between the real box and the predicted box, and the confidence is low. Then it is found that the preset anchorage[7] threshold of yolov5 model is 4.0, which is for coco data set and is not suitable for the current data set. Therefore, the K-means clustering algorithm is used to recalculate the data cluster to obtain the appropriate aspect ratio. K-Means algorithm[5] is a cluster analysis algorithm, which is mainly used to calculate the data aggregation algorithm, mainly by constantly taking the nearest mean value from the seed point algorithm. By calculating the data set of the pointer instrument, it is found that the best width-height ratio is 3.2, so the threshold is set at 3.2. Predefined anchor box values [81,82, 113,101, 145,143], [147,181, 185,167, 228,216], [270,263, 324,296, 416,318] are generated by clustering algorithm code.The specific anchor box pair ratios are shown in Table 1.

Table 1. Comparison table of cluster values

Original value	Clustering value
[10,13, 16,30, 33,23]	[81,82,113,101, 145,143]
[30,61,62,45,59,119]	[147,181,185,167 ,228,216]
[116,90,156,198, 373,326]	[270,263,324,296 , 416,318]

B. Bottleneck-CG residual element

The network structure of YOLOv5s is mainly composed of Conv layer downsampling of basic module, deep feature extraction of C3 module[9], and fusion feature of SPPF module. In order to enhance the fusion ability of network features and enable the target model to pick characteristics at different levels[8], it is Bottleneck improved on the component of the C3 module, and fuses F1(x) characteristics when it bottleneck operation, which improves the average accuracy of the final network model to a certain extent[17]. A Bottleneck summary is shown in Figure 1.

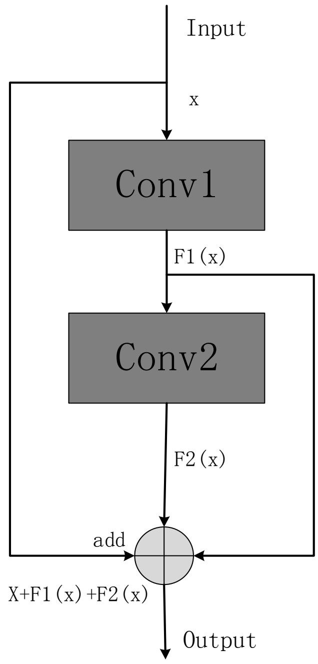

Figure. 1Bottelneck module structure

C. GAM attention mechanism

By introducing the GAM attention mechanism[16], the problem of information overload can be solved and the efficiency and accuracy of task processing can be improved by focusing on the information that is more critical to the current task, reducing the attention to other information, and even filtering out irrelevant information. This is similar to the human visual attention mechanism, by scanning the global image, to obtain the target area to focus on, and then devote more attention resources to this area, to obtain more details related to the target, while ignoring other

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irrelevant information.The GAM structure diagram is shown in Figure 2.

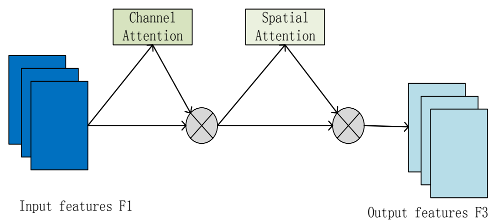

Figure. 2GAM attention mechanism

D. C3-MG module

C3 module, an important component of YOLOv5, is located in the backbone and head part of the network structure, and is used to extract the deep features of images. In this paper, the GAM attention[16] mechanism and residual network structure are used to improve the C3 module to improve the performance of the network model. The C3 structure diagram is shown in Figure 3.

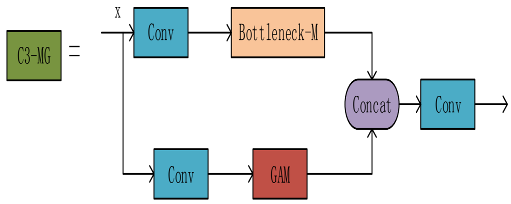

Figure. 3C3-MG module

E. YOLOv5s-MG

The object detection model code of YOLOv5s consists of two main trunk structures and header structures. The backbone network is mainly used to extract the depth information of the image, and the head structure is mainly used to classify the feature maps of different levels by comparing features. The object model is improved by replacing the structure in the original model with C3-MG module. The YOLOv5s-MG object detection framework is shown in Figure 4. The main reason for choosing YOLOv5s[6] this time is that the model is light in weight and has good recognition accuracy under certain speed conditions. It is a relatively mainstream target detection model at present. This paper will use it to identify and locate the instruments in the target data set.

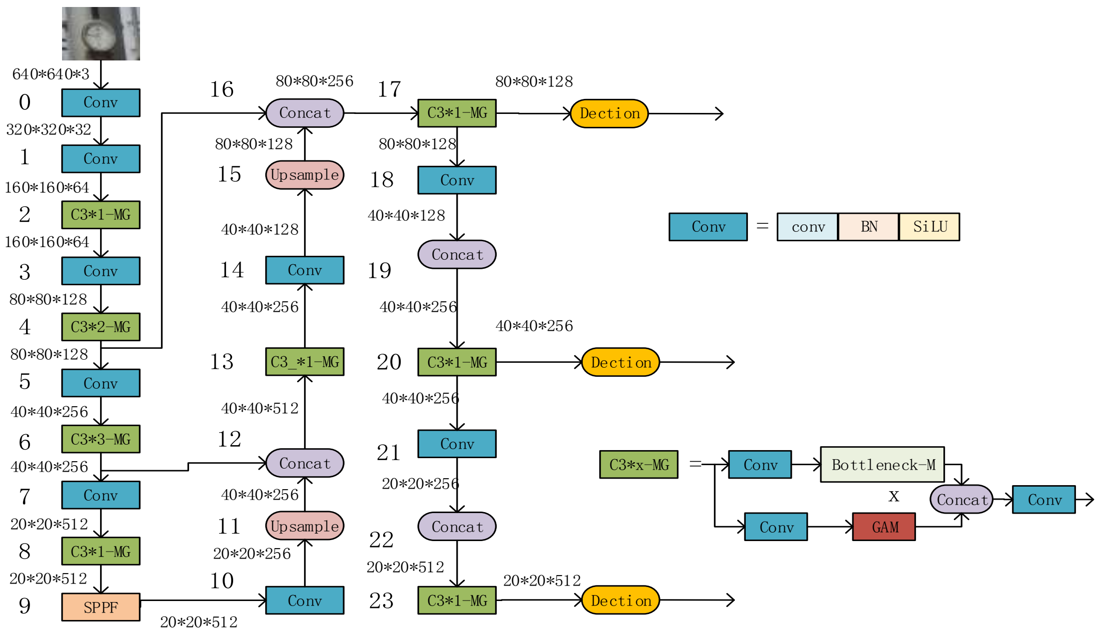

Figure. 4YOLOv5s-MG network structure

III. EXPERIMENTAL RESULTS AND ANALYSIS

A. Experimental environment

This chapter experiments in Windows10 professional edition system, intel-i5CPU, NVIDIA TITAN Xp, 16GRAM computer environment construction and experiment operation. The programming environment is based on python 3.6, pytorch 1.10.1, cudatoolkit 10.2.89, cudnn 7.6.5, torchvision 0.11.2, torchaudio 0.10.1 and other basic files. This experiment is mainly designed for the image of hydraulic meter, voltmeter and ammeter commonly used on inspection equipment in the intelligent inspection system of oil and gas. In this chapter, there are 3125 images in the pointer instrument data set, and then randomly divided according to training set: verification set: test set = 6:2:2. In the feature extraction section, epoch is 300, the learning rate is set to 0.001, the learning decay rate is set to 0.01, the optimizer is Adam[11], the loss function adopts the cross entropy loss function[10], the formula is shown in Equation (1), and the Swish function is used as the activation function, whose expression is as follows: , where the sigmod (x) function converts the input value to a value between 0 and 1, and makes the output closer to 0 and 1.

$$C=-\frac{1}{n}\sum_{x}\left[y\text{In}a+(1-y)\text{In}(1-a)\right] \quad (1)$$

x represents the sample, y represents the label, a represents the predicted output, and n represents the total sample.

B. Evaluation Metrics

YOLOv5sobject detection model often evaluates the performance of object detection system through accuracy rate, recall rate, PR curve, AP, mAP and other indicators[12]. The PR curve is composed of Recall as the abscissa and Precision as the ordinate. AP is the average accuracy, and mAP is the average AP of each type.Since the self-made data set is a single class of data set, Precision and Recall indexes are basically similar except mAP index, which is maintained above 95%, so mAP is finally adopted as a reference for this network model.

C. Datasets

The target detection algorithm adopted by pointer instrument positioning based on YOLOv5s has no publicly available pointer instrument data set[14] on the network at present, so this paper adopts self-made instrument data set for experimental analysis and verification. Considering the variability of the natural environment, the collected data sets are multi-condition[15] images of different periods, different illumination, different instrument states and different distances, so as to satisfy the diversity of the data sets and improve the robustness of the dynamic environment. The data set contains a total of 3125 pictures, which will be used as the pointer instrument data set for experiments in this chapter. Part of the collected data sets are shown in the figure 5. The following figure shows some meter images under different dynamic environments.

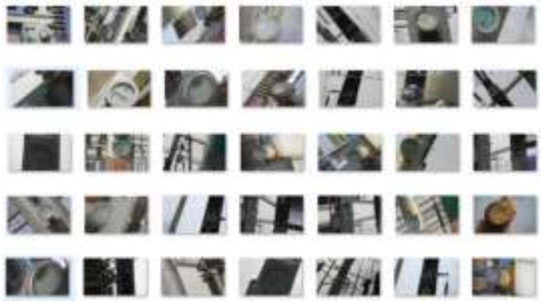

Figure. 5 Pointer-type meter image

d. Comparison experiment

In order to verify the experimental effect of the improved YOLOv5s model on the pointer instrument data set, this section will compare the original model, the improved model and other target detection algorithms, and compare the precision, recall rate and average accuracy. The results are shown in Table 2.

Table 2.Summary of comparison test results

Method	mAP
YOLOv5s	92.6%
YOLOv5s+custom anchors	93.4%
YOLOv5s+C3-MG	93.6%
Faster Rcnn	91.0%
YOLOv5s+customanchors+C3-MG（YOLOv5-MG）	95.8%

By comparing the mAP indexes of each network structure, it can be found that the YOLOv5-MG network model has a better effect on the average recognition accuracy than the network structure without improvement.

a. Relevant data and results display

In this section, the improved YOLOv5s-CM model is briefly used to predict the image of the pointer instrument, and the prediction results are shown in Figure 6,7.The two test plots show the target detection results in the distance, illumination and occlusion, and the red shadow font indicates the category and confidence of the meter respectively.

Figure. 6 Test Results Plot (a)

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Figure. 7 Test Results Plot (b)

CONLUSION

In this paper, we propose a target detection model based on YOLOv5s-CM to solve the current identification problem of pointer meters in the power oil industry. This paper improves the original YOLOv5 model for the images of long distance, illumination, and occlusion in the real environment. At the same time, compared with other traditional target detection algorithms, this method is simpler, lower cost and has better identification accuracy. In the future, the method can be lightweight, and can be applied to mobile devices[13].

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