Research and Optimization of Tubular Column Joint Identification Technology for Intelligent Drilling Platforms

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Abstract. An improved target detection algorithm based on YOLOv5s is proposed to be applied to identify and localize tubular column joints in The improved SC-YOLOv5s model is obtained by combining SPPF, CBAM and the improved multi-scale feature fusion network BiFPN. The improved SC-YOLOv5s model is obtained by combining SPPF, CBAM and the improved multi-scale feature fusion network BiFPN. The SPPF structure introduces spatial pyramid pooling in the network, which can effectively capture the features of the target at different scales and improve detection precision. different scales and improve the detection precision and recall of the target, while the CBAM attention mechanism can adaptively learn the target's spatial and channel feature relationships. s spatial and channel feature relationships, improving the model's ability to distinguish between targets and anti-interference ability The improved multi-scale feature fusion network BiFPN combines Bottom-up and Top-down feature transfer mechanisms, which can better fuse feature information at different levels, making the model's ability to distinguish between targets and anti-interference ability. information at different levels, making the model better adapted to detection tasks in various complex environments. The experimental results show that the improved algorithm achieves the following results that the improved algorithm achieves significant performance improvement in the pipe-column joint detection task, with a mAP value of 99.44%, a frame rate of 136 FPS, and an accuracy of 98.4%, which is 6.6% higher than the original model. The algorithm also improves sensing capability, accuracy and robustness, and outperforms the original model. The algorithm also improves sensing capability, accuracy and robustness, and outperforms other mainstream models in terms of precision. This provides a reference for automatic processing of tubular columns in intelligent oil rigs.

Keywords: yolov5s; pipe-column joints; target detection; SC-YOLOv5s; algorithm optimization.

1. Introduction

Drilling is key to the development of oil and gas resources and is usually the most costly step in upstream operations. With the increase in available data and the rapid development of artificial intelligence (AI) technology, a large number of machine learning studies have been conducted in different drilling applications.[2] Data-driven models based on machine learning methods can provide greater advantages than traditional analytical or numerical models, such as flexible model inputs, better prediction accuracy, and the ability to discover hidden patterns.[3] At this stage, the automation level of oil drilling in China is low. On the drilling platform, most of the operation process still needs to be completed manually, so the personnel demand is high and there are obvious efficiency problems and safety problems. Therefore, it is of great significance to develop automation technology for oil drilling to reduce the consumption of manpower, lighten the work intensity, improve the operation efficiency, shorten the operation cycle, and stabilize the operation quality.[4]1.5 Improved target detection model for lightweight drill pipe

Based on the traditional YOLOv5s module, an improved multi-scale feature fusion network BiFPN architecture is used to replace the SPP module of the Neck structure with the SPPF module, and then the CBAM attention module is introduced, with the aim of improving the robustness of the model, reducing the parameters and the amount of computation and improving the model's ability to extract the features and the model's detection accuracy. The structure of the improved lightweight YOLOv5s model is as follows The structure of the improved lightweight YOLOv5s model is shown in Fig. 6. The improved algorithm is referred to as SC-YOLOv5s algorithm in the following text. The introduction of SPPF can pool the feature maps in a multi-scale manner to better capture the information at different scales. This helps to enhance the model's ability to perceive pipe-column joints of different sizes and improve the accuracy and robustness of detection. Second, applying the CBAM module enables the model to learn the importance and adaptive weights of features adaptively. Through the channel attention and spatial attention mechanisms, the model can better focus on important feature channels and spatial locations, which improves the sensitivity and accuracy of the detection; the introduction of the improved multi-scale feature fusion network BiFPN in the model further strengthens the cross-layer connectivity of the feature map and the information transfer. It effectively fuses the features of different scales to enhance the model's ability to recognize pipe-column joints at different scales, and also effectively alleviates the problem of information loss in the feature pyramid.

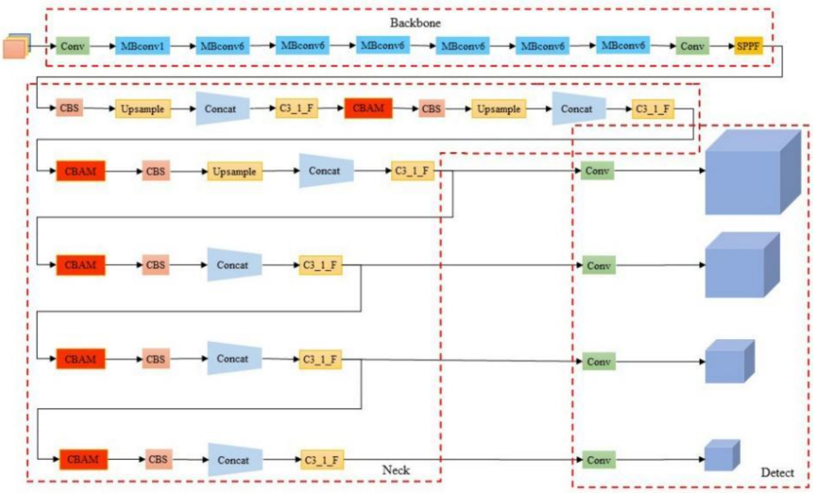

Fig. 1 Improved YOLOv5s network structure

2. Experimental equipment and data

2.1 Image data processing and environment settings

The experimental validation of this study was conducted under the Windows 10 operating system with Intel(R) Core(TM) i7-9700 CPU @ 3. 0GHz, 64-bit operating system, NVIDIA GeForce GTX 1060 6GB for GPU, 32GB of host computer RAM, Pytorch Deep Learning Framework, Pycharm Integrated Development environment, software environment for CUDA10.2, torch version 1.8.1, Python3.8 programming language to run. Determine the size of the image during training to be 640×640, the number of iterations to be 500, the batch size to be 128, and the learning rate to be 0.001.

2.2 Data set construction

Because there are fewer images of drill pipes and there are no publicly available related datasets, this study uses a self-constructed drill pipe dataset. The image data of the drill pipe was collected in Lanzhou City, Gansu Province, Lan Shi Petroleum Equipment Engineering Co. Ltd. The images of the drill pipe in different environments were captured with a cell phone under natural light, which included various situations such as smooth light, backlight, near distance, far distance, pitch angle, elevation angle, etc., and the acquired images were saved in .jpg format. To make the dataset more diverse, data enhancement preprocessing such as image mirroring, image noise, brightness enhancement, contrast comparison, and image rotation are performed on the acquired image set as shown in Fig. This can effectively avoid the overfitting problem to better extract image features, improve the overall generalization ability of the model, and avoid the problem of insufficient training due to too few sample images. Finally, a total of 2009 images were obtained, with a resolution of 4032×3024. The image processing schematic is shown in Figure 2 The schematic diagram of image processing is shown in Fig. 7.

Fig. 2 Image processing diagram

Label the 2009 drill pipe images in the dataset using the Labeling annotation software, using horizontal rectangular boxes to label the drill pipes in the images individually. Save the labeling information in text format. Finally, the dataset images are randomly divided into training set 1406 and validation set 603 according to the ratio of 7:3.

2.3 Evaluation indicators

In the target detection process, the model outputs several prediction frames after computing the input image, and these prediction frames can be categorized into four classes, TruePositive(TP), FalsePositive(FP), FalseNegative(FN), TrueNegative(TN), according to their classification results [28], the corresponding evaluation index is calculated according to whether the prediction box is judged correctly or not. Where: TP indicates that the true target A is correctly predicted as target A, TN indicates that the true target B is correctly predicted as target B, FN indicates that the true target A is incorrectly predicted as target B, and FP indicates that the true target B is incorrectly predicted as target A.

Based on the above four categories of samples, various evaluation metrics of the model can be obtained such as Recall, Precision, Average Precision (AP), mean Average Precision (mAP), and Frame Rate (FPS).

3. Analysis and Evaluation of Experimental Results

3.1 Ablation experiments

To further analyze the characteristics of the improved model and assess the robustness of the model, the number of parameters, accuracy, recall, and mAP values of the model were validated using ablation experiments, respectively. The results are shown in Table 1 shows.

Table 1. Results of ablation experiments

Model	SPPF	CBAM	Efficient Net	Parameters/×10^6	Precision(%)	Recall(%)	Map (%)
YOLOv5s	×	×	×	7.0 66	91.8	80.8	82.5
YOLOv5s-SPPF	√	×	×	7.224	91.2	79.4	84.6
E- YOLOv5s	×	×	√	4.126	89.42	78.56	80.64
SE- YOLOv5s	√	×	√	4.442	91.1	76.2	81.2
ECS-YOLOv5s	√	√	√	4.482	92.0	76.9	81.5
SC-YOLOv5s (this article)	√	√	×	**7.025**	**98.4**	**98.8**	**99.4**

As can be seen from the ablation experiment data table, the improved model SC-YOLOv5 exceeds all other combinations in terms of accuracy, recall, and mAP values under the same conditions with different models, effectively improving the detection accuracy. In this paper, to improve the detection speed of the model, the EfficientNet lightweight network model is added on top of YOLOv5, and the detection results show that, although the number of parameters of the added model is greatly reduced, the recognition accuracy also decreases, and the reason for analyzing this is that the EfficientNet model usually adopts a shallow network structure and reduces the number of convolutional layers, which may reduce the generalization ability of the model, resulting in a decrease in the model accuracy and mAP value. The reason is that the EfficientNet model usually adopts a shallower network structure and reduces the number of convolutional layers, which may reduce the generalization ability of the model, leading to the loss of part of the representation ability of the model when dealing with complex tasks, thus affecting its ability to recognize the image features; after adding the SPPF network structure, the number of parameters is slightly increased, and the recognition accuracy is also improved accordingly, and the recognition accuracy is further improved by adding the attention mechanism of the CBAM, but the overall improvement is not very large, and the mapped value of ECS-YOLOv5s is only increased by less than 1 percentage point. only increased by less than 1 percentage point. The reason was analyzed as the relatively complex model with a small dataset was over-tuned during the training process, resulting in model overfitting. By comparing the ablation experiments, the number of parameters of the improved model with the introduction of feature fusion to form the SPPF based on the spatial pyramid pooling SPP, and then incorporating the CBAM attention mechanism is reduced by 0.41 percentage points compared to the original model, and then the accuracy and recall are improved by 6.6 and 18 percentage points, respectively, and there is a very large improvement in the mAP value, which is on average improved by 15 percentage points. The accuracy of the model in recognizing pipe-column joints is greatly improved.

3.2 Comparative Experiments

To compare the performance of the improved network model with other different algorithmic models and to analyze the superiority of the SC-YOLOv5 algorithm, the improved model is analyzed in a comparative experiment with the current mainstream target detection network models, including those of the SSD, Faster RCNN, and YOLO series. The experimental results are shown in Table 2 shows.

Table 2. Results of comparison experiments

Model	Parameters/×10 6	Computation/GFLOP s	Model size/MB	mAP (%)	FPS
YOLOv5s	7.066	15.9	14.4	82.5	156
Faster-RCNN	28.12	946.12	108.2	78.8	12
SSD	23.64	274.53	88.6	82.5	38
YOLOv6s	18.50	45.17	38.7	82.3	134
YOLOv7-tiny	6.01	**13.2**	**11.6**	86.2	105
YOLOv8s	**3.011**	28.6	21.5	85.5	**156.5**
SC-YOLOv5s (this article)	7.025	15.8	14.4	**99.4**	136

The conventional YOLOv5s model obtains good accuracy while having a smaller number of parameters and computation. This makes it a viable option for the application scenario of pipe-column joint detection. The Faster-RCNN network model has a larger number of parameters and computation and generates a larger weight file size. However, the mAP value is low, indicating that its detection accuracy is relatively poor; the SSD network model has a reduced number of parameters and computation and a slightly reduced weight size compared to Faster-RCNN. Meanwhile, the mAP score is improved to 82.5%, indicating a significant improvement in its detection accuracy. Nevertheless, the number of parameters and computation are still large and are not suitable for application in pipe-column joint recognition systems; YOLOv6s obtains a good accuracy but also improves the number of parameters and computation; the YOLOv7-tiny network model has a smaller number of parameters and the smallest computation, however, due to the smaller model capacity, the accuracy is poor and therefore not suitable for the recognition task.SC-YOLOv5s model has the highest recognition accuracy and optimal mAP, with a reduced number of parameters compared to YOLOv5s. In addition, the general real-time detection requires that the number of detected pictures per second is greater than 24, according to the data in the table, it can be seen that the improved network model SC-YOLOv5s detection speed is slightly lower than that of the original YOLOv5s model and YOLOv8s, which is much greater than the minimum requirement of 24 FPS, and is capable of accomplishing the task of real-time detection. In summary, different network models have different advantages and disadvantages in terms of the number of parameters, computation, weight size, and mAP. According to the requirements of the drill pipe application scenario, the SC-YOLOv5s network model can be selected to achieve the goal of balancing accuracy and computational efficiency.

3.3 Analysis of experimental results

A comparison of the PR graphs of the improved SC-YOLOv5s model and the initial YOLOv5s model is shown in Fig. 3.

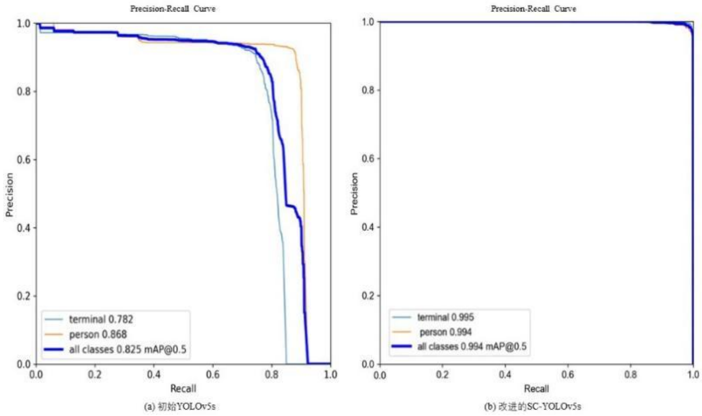

Fig. 3 Model PR curve comparison

The PR plot for YOLOv5s shows a faster decrease in precision as the recall increases. This may be because the initial model is not strong enough to detect between positive and negative examples, resulting in more erroneous positive examples at high recall. In addition, since the initial model has not been optimized and adjusted, there may be some problems, such as feature selection or selection of hyperparameters. The PR graph of the improved model shows relatively high precision under the same recall rate. This indicates that the improved model has better positive case detection and a lower error rate. The improved model has undergone feature optimization, model tuning, and re-optimization of the training process to improve its overall performance. In addition, the PR curves of the improved model may be smoother relative to those of the initial model, indicating that the improved model performs relatively well over the entire range of recall rates. It also achieves a better balance between the recall rate and precision rate, resulting in a significant improvement in the overall performance.

Using the trained weights to detect the randomly extracted images, the recognition effect of different target detection models on pipe-column joints is obtained as follows in Fig.4, Shown.

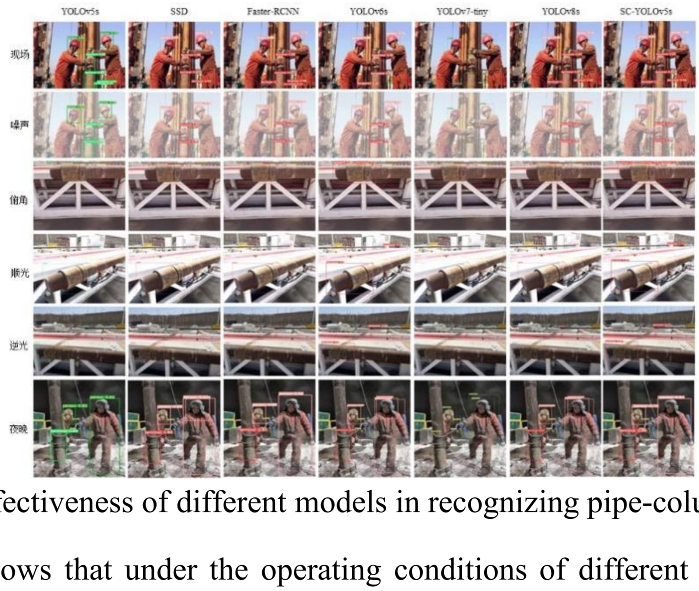

Fig. 4 Effectiveness of different models in recognizing pipe-column joints

The comparison shows that under the operating conditions of different environments, the SC-YOLOv5s model has the best recognition effect and can accurately identify the position of pipe-column joints and workers with higher confidence. the Faster-RCNN and SSD have a higher confidence and recognition accuracy, but their positioning accuracy is low, and the repeated detection of the worker targets increases the number of references, which affects the next step in the operation of the robotic arm; All YOLO series models can accurately identify pipe and column joints and workers, but YOLOv6s has the problem of missing detection of some joints.SC-YOLOv5s can accurately identify all joints and workers in complex operation sites, without repeated identification and missing detection and missing detection, and the detection speed meets the demand of real-time detection, with lower weights, which is more suitable for the deployment of industrial robots on the mobile side.

4. Conclusios

In this paper, we study the application of an improved target detection algorithm based on YOLOv5s to the automatic detection of tubular column joints in intelligent oil drilling platforms. The improved SC-YOLOv5s model is obtained by combining the SPPF structure, CBAM attention mechanism and the improved multi-scale feature fusion network BiFPN based on the YOLOv5s model. The experimental results show that the algorithm achieves significant performance improvement in the pipe-column joint detection task. In summary, by combining SPPF, CBAM and the improved multi-scale feature fusion network BiFPN, our algorithm achieves significant performance improvement in the detection task of pipe-column joints. These improvements lead to significant improvements in the model's perceptual ability, accuracy, and robustness, providing an effective solution for the pipe-column joint detection task. To improve the network's ability to detect dense targets, the study introduces an attention mechanism into the feature fusion network, which improves the loss of detection accuracy due to the effects of various complex environments, including various types of angles, distances, different lights, different orientations of the drill pipe, and different operating conditions, while improving the robustness of the model and reducing the parameters. The improved algorithm achieves a mAP value of 99.44% compared to the original model, a frame rate of 136 FPS, and a parameter count that is reduced by 0.041 compared to the initial YOLOv5s model; the accuracy is 98.4%, which is 6.6% higher than the initial model. The improved algorithm also exceeds all other mainstream models in terms of accuracy. The experimental results show that the algorithm's advantages of high efficiency and high accuracy for tubular column joints provide a reference for the research of automatic tubular column detection in intelligent oil drilling platforms.

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