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TW-YOLO: High-precision Steel Wire Rope Detection Algorithm Based on Triplet Attention

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Abstract

Addressing the issue of insufficient accuracy in detecting small target defects in steel wire ropes in scenarios such as construction sites and elevators, this paper proposes a steel wire rope defect detection method called TW-YOLO, based on the YOLOv8 network model. Firstly, a Triplet Attention mechanism is introduced after the SPPF module layer of the backbone network to enhance the robustness of the model and its detection accuracy for small defects. Then, the damage function of the original model is replaced with WIOU to further improve the model's detection capability for small targets. In ablation experiments, compared to the original YOLOv8, the TW-YOLO model achieved a 4.45% improvement in detection accuracy for the break category of steel wire ropes and a 3.3% increase in mAP. In comparative experiments, TW-YOLO demonstrated high accuracy and low computational complexity.

Keywords

Target detection; Triplet Attention; WIoU

1. Introduction

Steel wire ropes are crucial load-bearing components in the industrial production sector, widely utilized in mining, port transportation, high-rise elevators, and other domains [1]. During operation, steel wire ropes frequently endure external forces like stretching and squeezing, and may also be corroded by rainwater and dust [2], resulting in defects like broken wires and wear [3]. Failure to promptly detect and replace these defects can lead to safety accidents, thereby affecting safe production. Hence, conducting research on steel wire defect detection holds immense significance.

The detection of steel wire rope defects was initially carried out manually. This method is not only inefficient but also relies heavily on the experience of the monitoring personnel for accuracy, making it difficult to meet the high-precision requirements in industrial production. To overcome the limitations of manual detection, experts and scholars at home and abroad have explored a series of detection methods based on physical sensors, such as electromagnetic detection technology [4], ultrasonic detection technology [5], and acoustic emission detection technology [6]. These technologies utilize different physical principles to obtain defect characteristics of steel wire ropes through sensors, thereby achieving defect detection. Although these methods have been applied in practice to some extent, they still face challenges such as difficulty in distinguishing between certain types of steel wire rope defects, low detection accuracy, and high cost. With the development of digital image processing technology, scholars have begun to study extracting features from steel wire rope surface images for detection. Tang Qi et al. [7] improved the feature extraction method and introduced Histogram of Oriented Gradients (HOG) [8] and edge detection technology to extract the surface texture of steel wire ropes and achieve high-precision defect classification.

The development of deep learning technology has provided new insights for steel wire rope defect detection. Many scholars have applied object detection technology to industrial defect detection and achieved some progress. Liu et al. [9] achieved rapid detection of fabric defects by optimizing the SPP structure of the YOLOv4 model. Zhou et al. [10] improved the detection accuracy and speed of the model for metal surfaces by using a global attention mechanism on the YOLOv5 model. Hu et al. [11] improved the detection accuracy of the model for insulator defects by using a contextual converter network and an EMA attention mechanism based on YOLOv7. Utilizing deep learning technology to solve industrial defect detection problems has become a trend for future development.

The surface of steel wire ropes exhibits distinct texture features, and the metal surface reflects light. Additionally, most defects are minor, making it challenging to extract their features. Furthermore, in practical industrial applications, cost considerations necessitate that detection algorithms can be deployed on low-computational-power edge devices. Therefore, this paper proposes an improved YOLOv8 algorithm, TW-YOLO. By optimizing the network structure, it effectively enhances the detection accuracy of steel wire rope defects.

2. Design of the TW-YOLO model

YOLOv8 is currently one of the most outstanding object detection algorithms [12]. Compared to the previous YOLOv5, it has optimized the C3 module and retained the idea of the feature pyramid, making the YOLOv8 algorithm excel in object detection tasks. YOLOv8n is the lightest model among YOLOv8. To meet the lightweight requirement, this paper chooses YOLOv8n as the base model for improvement. The improved TW-YOLO network structure is shown in Figure 1. The improvements in this paper are mainly in two aspects: Firstly, the Triplet Attention [13] mechanism is introduced after the SPPF module of the backbone network to enhance the accuracy and robustness of the model for defect detection. Then, the original loss function is replaced with the WIOU loss function [14] to alleviate the impact of low-quality samples in object detection tasks, further improving the detection accuracy of the network.

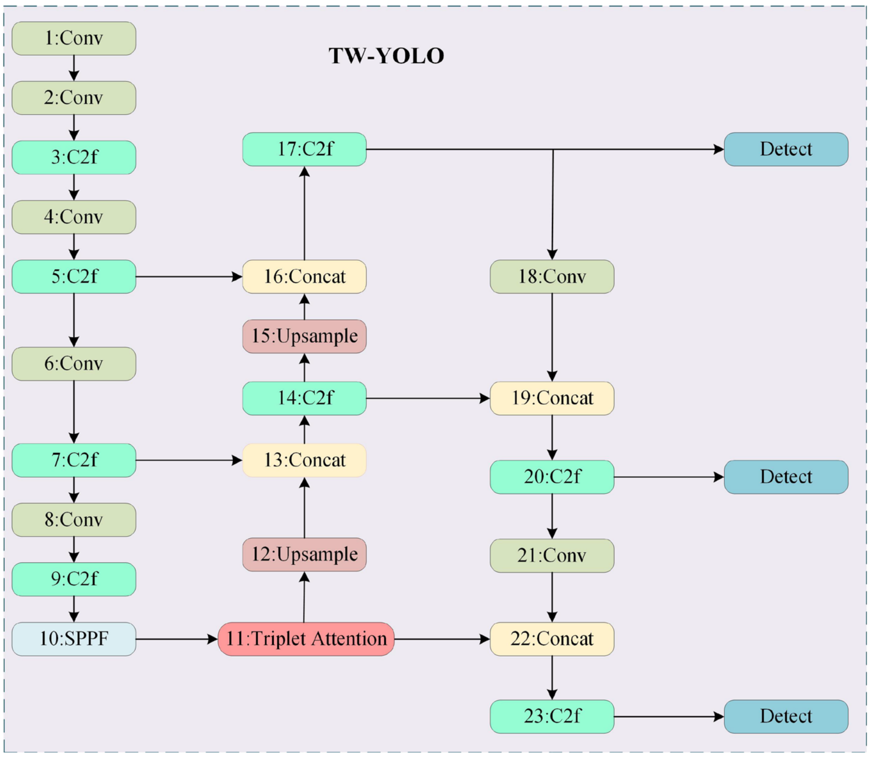

Figure 1. Overall network structure of TW-YOLO.

2.1 Attention optimization design based on Triplet Attention

The elevator is dimly lit and dusty, and the contrast between the steel wire rope and the surrounding environment is low, making it prone to missed inspections [15]. To address this issue, this paper introduces Triplet Attention into the

YOLOv8n model. By applying attention mechanisms in three dimensions: horizontal, vertical, and depth, the model's performance is enhanced, thereby improving its ability to recognize and process features. The Triplet Attention network structure is shown in Figure 2. It mainly enhances the feature learning ability of the deep learning network through a three-branch structure. Two branches are used to capture cross-channel interactions between the channel dimension (channel count C) and the spatial dimension (width W, height H), allowing the model to deeply understand and process the complex relationships of input data. The third branch continues to perform traditional spatial attention weight calculation, thereby enhancing the model's sensitivity and accuracy in processing spatial information.

In this paper, the Triplet Attention mechanism is incorporated into the SPPF module of the backbone network to enhance the network's detection accuracy for steel wire rope defects. The feature heatmap is illustrated in Figure 3.

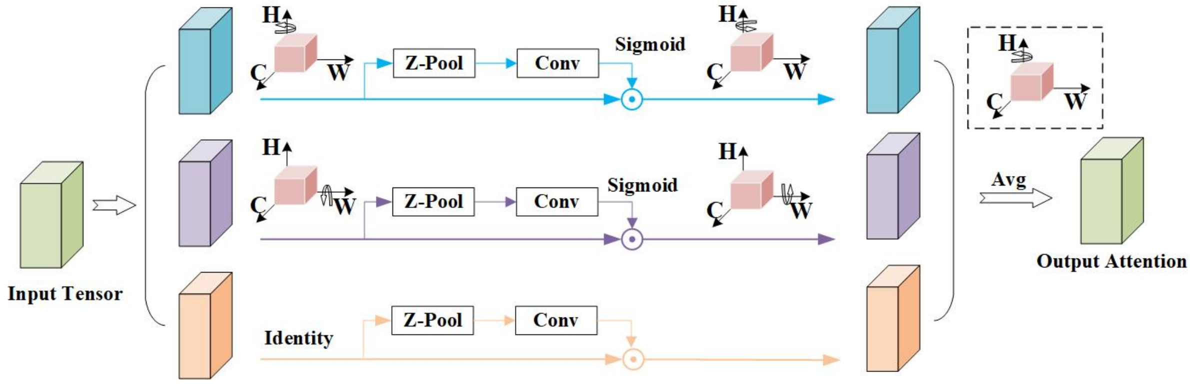

Figure 2. Triplet Attention network structure.

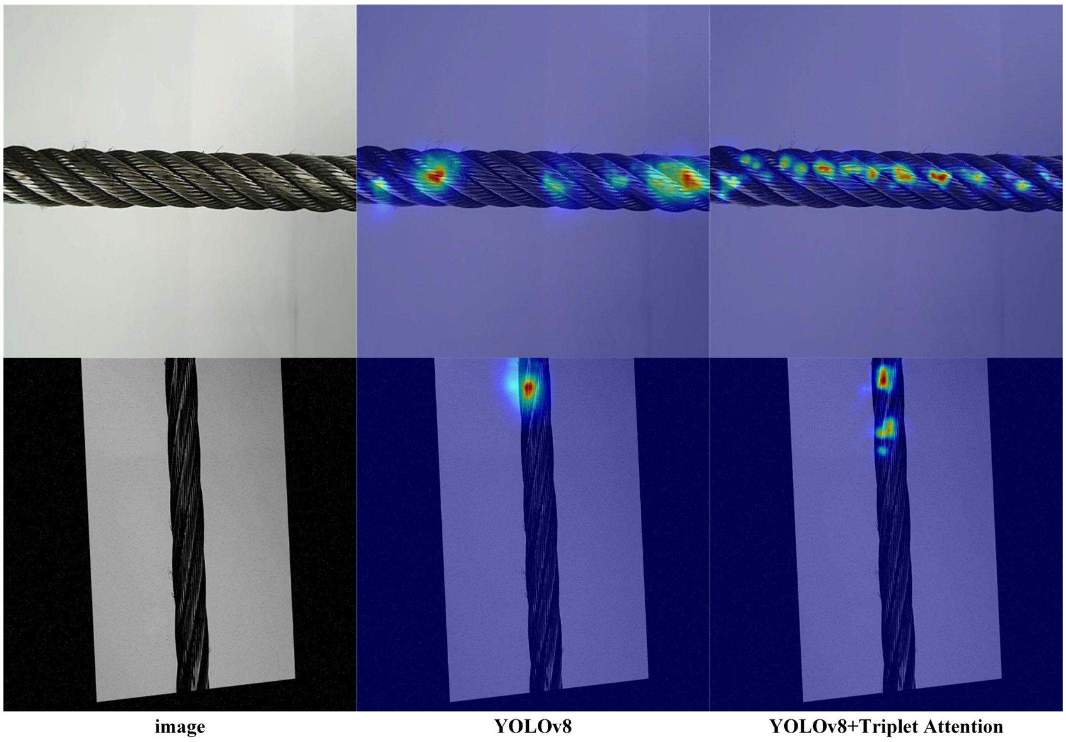

Figure 3. Feature heatmap.

2.2 Description of the study area

The original YOLOv8 model employs the CIoU loss function, but this function fails to account for the imbalance in sample quality, resulting in poor regression performance for low-quality samples and small bounding boxes, thereby weakening the model's generalization ability. This paper introduces the dynamic non-monotonic focus mechanism (wise intersection over union, WIoU) loss function to replace the original loss function. The dynamic non-monotonic and gradient allocation strategies of the WIoU loss function can balance sample quality, thereby enhancing the model's generalization performance. The calculation formula for WIoU is as follows:

$$L_{WIoUv3} = \gamma R_{WIOU} \cdot L_{IOU} \tag{1}$$

$$R_{WIoU} = exp\left(\left(\left(x - x_{gt}\right)^2 + \left(y - y_{gt}\right)^2\right) / \left(W_g^2 + H_g^2\right)\right) \tag{2}$$

$$\gamma = \beta / \left(\delta \alpha^{\beta - \delta}\right) \tag{3}$$

$$\beta = L_{IoU}^{*} / L_{IoU} \tag{4}$$

In the formula: L_{WIoUv3} represents the non-monotonic focal loss function of the prediction box; γ denotes the non-monotonic focal coefficient; R_{WIOU} signifies the normalized distance between the center point of the prediction box and the center point of the ground truth box; L_{IOU} indicates the overlap degree between the prediction box and the ground truth box; x, y stand for the width and height of the anchor box, respectively; x_{gt}, y_{gt} represent the width and height of the minimum enclosing box, respectively; β is the outlier degree; δ and α are adjustable hyperparameters; L_{IoU}^{*} is the monotonic focal coefficient. As the number of training rounds changes, a dynamic non-monotonic focusing mechanism and gradient allocation strategy can be achieved.

3. Experimental results and analysis

3.1 Experimental environment, parameters, dataset, and evaluation metrics

The operating system used in this experiment is Windows 10, with a GPU model of NVIDIA GeForce RTX 2080Ti and 11GB of VRAM. The model does not use pre-trained weights and is trained using the SGD optimizer. Detailed experimental environment and configuration information is presented in Table 1.

The steel wire rope dataset used in this paper is sourced from the Roboflow website. Available from: kanaaat Object Detection Dataset by st.hedgehog.yusupov@gmail.com. The defects of steel wire ropes are categorized into three types: break, thunderbolt, and wear, with a total of 3850 images. The ratio of training set, test set, and validation set in the dataset is 7:2:1.

The evaluation metrics used in this experiment include various types of average precision (AP), mean average precision (mAP), parameter count (Params), model weight (Weight), and frames per second (FPS).

Table 1. Experimental Environment and Parameters

Experimental configuration	Version parameters
Operating system	Windows10
Display memory	11GB
CPU	Intel(R) Core(TM) i9-9900KF
GPU	NVIDIA GeForce RTX 2080 Ti
CUDA	11.6
Python version	Python3.8
Pytorch version	Pytorch1.13.1
Epochs	300
Initial learning rate	0.01
Weight decay	0.0005
Image size	640×640

3.2 Ablation experiment

To conduct a detailed comparison of the enhancement effects of various modules on steel wire rope defect detection, ablation experiments were conducted in this paper, and the experimental results are presented in Table 2.

Table 2. Ablation experimental results

Model	Triplet Attention	WIOU	AP			mAP	Weights	Params (M)	FPS
			Break	Thunderbolt	Wear				
1			72.58	91.52	49.14	71.13	6.3	3.011	112.8
2	√		78.92	92.03	48.69	73.21	6.3	3.011	113.2
3		√	78.02	94.26	47.65	73.34	6.3	3.011	99.1
4	√	√	77.03	93.52	52.71	74.43	6.3	3.011	103.6

As can be seen from Table 2, after the introduction of the Triplet Attention module alone, the detection accuracy of the model for break category defects increased from 72.58% to 78.92%, and the average detection accuracy also improved by 2.08%. This indicates the effectiveness of the Triplet Attention module in enhancing the model's ability to focus on key information. After replacing the WIOU loss function alone, the detection accuracy of the model for both break and thunderbolt categories significantly improved by 5.44% and 2.74%, respectively. Meanwhile, the average detection accuracy also reached 73.34%, but the detection speed decreased.

After simultaneously utilizing the Triplet Attention module and the WIOU loss function, the model's average detection accuracy has seen a new improvement, reaching 74.43%. This improvement is more significant in terms of detection speed compared to merely replacing the WIOU loss function. Overall, both improvements did not increase the model's parameter count, ensuring that the improved model maintains the parameter size of YOLOv8n, facilitating further algorithm deployment.

3.3 Algorithm comparison experiment

To evaluate the advantages of the TW-YOLO algorithm, this paper conducts an algorithm comparison experiment. The comparative algorithms in this experiment include two classic algorithms, namely Retinanet [16] and SSD [17], as well as lightweight algorithms based on the YOLO series, such as YOLOv3-tiny [18], YOLOv6 [19], YOLOv7-tiny [20], YOLOv11s [21], and YOLOv12s [22] models.

Table 3. Comparative experiments of different algorithms

Model	AP (%)			mAP (%)	Weights (MB)	Params (M)	FPS
	Break	Thunderbolt	Wear				
SSD	35.78	76.54	24.30	45.54	91.6	54.026	15.6
Retinanet	51.34	86.39	21.40	53.05	139	89.162	10.7
YOLOv3-tiny	76.52	93.61	62.68	72.08	17.4	8.671	120.3
YOLOv6	60.08	86.42	32.21	59.57	8.7	4.234	106.6
YOLOv7-tiny	64.42	90.87	41.69	65.63	12.3	6.02	108.3
YOLOv8n	72.59	91.52	49.91	71.13	6.3	3.011	112.8
YOLOv11s	69.06	91.17	42.92	67.68	19.2	9.414	72.3
YOLOv12s	67.72	86.91	40.58	65.11	18.9	9.232	50.4
TW-YOLO	77.03	93.52	52.71	74.43	6.3	3.011	103.6

As can be seen from Table 3, the detection accuracy and parameter count of SSD and Retinanet algorithms, as classic algorithms, have been surpassed by subsequent new algorithms. Since the algorithms compared to the YOLO series are all lightweight models, their performance in terms of parameter count is at a similar level. Although YOLOv3-tiny is a lightweight version based on the YOLOv3 algorithm, it outperforms many YOLO algorithms in detection accuracy, achieving a detection accuracy of 72.08% and a frame rate of 120.3 frames per second, making it an algorithm with excellent comprehensive performance. YOLOv6 is the worst-performing algorithm among the YOLO series compared in this experiment, mainly due to its low average detection accuracy of only 59.57%. YOLOv8n has been one of the most popular YOLO models since its release, achieving an average detection accuracy of 71.13 in this experiment, ranking second only to TW-YOLO and YOLOv3-tiny among the compared algorithms. YOLOv11s and YOLOv12s, as the latest generation of YOLO models, are close in detection accuracy and parameter count, but YOLOv11s has a faster detection speed than YOLOv12s.

The TW-YOLO algorithm proposed in this paper performs the best among all comparative algorithms. The model achieves an average detection accuracy of 74.41%, with a model size of 6.3MB and a detection speed of 103.6 frames per second. Comparative results on the Kanaaat dataset demonstrate that the WT-YOLO algorithm possesses high detection accuracy and commendable detection speed, facilitating subsequent deployment on mobile devices.

4. Conclusion

This paper proposes a TW-YOLO detection algorithm for detecting defects in steel wire ropes, which has been validated through the SteelWire Rope dataset. The TW-YOLO algorithm primarily enhances the model's performance in three dimensions by incorporating the Triplet Attention mechanism into the backbone network of YOLOv8n, thereby improving the model's accuracy in defect recognition. Additionally, the WIOU loss function is employed to enhance the model's generalization performance. Experimental results indicate that the comprehensive performance of the TW-YOLO algorithm is excellent.

Conflict of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.

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