Non-Contact Bolt Detection Based on YOLOv5-Ganomaly Algorithm and UAV

Haibo Xie[1,*], Qianyu Liao[1], ShiXiang Yang[2], Junwei Zhu[1]

[1]School of Civil Engineering, Changsha University of Science and Technology, Changsha, Hunan, China
[2]Hunan Zhongnan Bridge Installation Engineering Co., Ltd., Changsha, Hunan, China

*Corresponding author's e-mail: bridgexhb@126.com

Abstract. High-strength bolt loosening detection is an important part of steel bridge inspection. The automatic detection methods based on machine vision and UAV have the characteristics of fast speed and high efficiency, and have been widely used to replace manual inspection. However, it is difficult to realize the automatic inspection based on vision due to the high height of the position where high-strength bolts are located, the small target, the loosening characteristics are not obvious, and the large number of characteristics. This paper proposes non-contact bolt detection to get the bolt image information, and then combine YOLOv5 and Ganomaly algorithm, propose YOLOv5-Ganomaly semi-supervised learning model bolt detection algorithm. Firstly, locate the bolt target area through YOLOv5-CT model, and automatically screen the un-lost bolts; then pre-process the un-lost bolt images, and finally detect the anomaly looseness of the pre-processed images through Ganomaly algorithm, and automatically determine the looseness of the bolts by the given threshold value. The test results show that the detection accuracy of lost bolt loosening reaches 98.3% and the accuracy of bolt loosening detection can reach 85%.

Keywords: YOLOv5; Ganomaly; High-strength bolt; Anomaly detection; Non-contact detection; UAV.

1 Introduction

High-strength bolted have been widely used in bridge engineering, becoming one of the main connection forms for steel and steel-composite bridges [1]. When stress corrosion damage occurs in high-strength bolt members, resulting in a significant decrease in their preload, fatigue loosening is prone to occur. High-strength bolts looseness directly affect the safety of traffic, the local stability of the bridge structure will also be greatly affected, so the scientific and efficient detection of a large number of bolts is particularly important.

The commonly used bolt detection methods are generally manual exclusion [2], ultrasonic detection [3,4], piezoelectric resistive detection [5], etc. With the development of computer vision, image - based and deep learning - based non - contact bolt detection

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methods have been proposed. Park et al. [6] proposed a bolt detection method based on image segmentation, which involves comparing the deviation angles between the bolt and the splice plate to determine the presence of bolt loosening. Huang et al. [7] employed white light speckle patterns on washers as optical sensors, using image information to measure the strain on the washers and subsequently analyze the bolt's tightness based on force analysis. Image-based methods offer advantages such as low cost and convenient data acquisition, enabling non-destructive bolt detection. However, the analysis and processing of image data entail a significant computational burden, resulting in slower detection and analysis speeds, which may compromise the expected efficiency of detection outcomes within specified time frames.

Deep learning has emerged as a solution to alleviate the challenges associated with manual analysis of large datasets, thereby ensuring objective data analysis and detection accuracy. Current machine vision and deep learning detection methods commonly adopt a two-step approach involving "Positioning" and "Detection". The team of Zhenbing Zhao [8], Longfu Luo [9] and Yincheng Qi [10] all utilized improved detection algorithms to enhance bolt detection accuracy.

Based on UAV and deep learning technology, it improves the bolt detection method, enhances the detection efficiency and precision, reduces the cost, and realizes the automatic detection of bolts. In practice, it is difficult to identify loose bolt, resulting in a small number of samples, the supervised learning model is prone to overfitting, and the detection accuracy is hard to improve [11]. Aiming at the problems such as small bolt target, difficult positioning and fewer samples, this paper proposes a non-contact measurement of bolts based on the YOLOv5-Ganomaly algorithm, which requires only a small number of loose bolt samples, and automatically completes the bolt positioning, loss, and loosening identification. The bolt detection algorithm steps are shown in Figure 1.

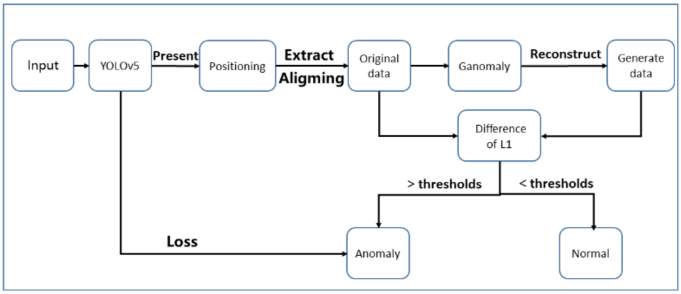


Fig. 1. Algorithm Framework of Bolt Detection Model

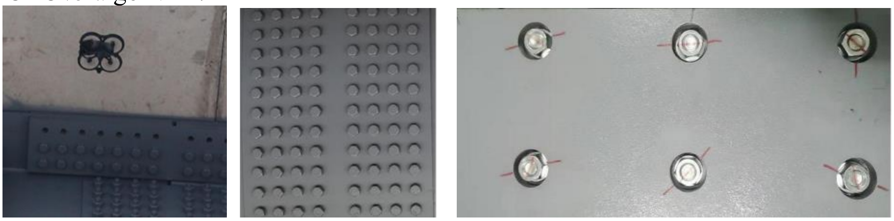
2 Method Discussion

2.1 Data Collection

In this paper, we propose to utilize DJI Avata to achieve non-contact acquisition to bridge high strength bolt images. To clearly indicate the presence of bolt loosening, red lines are drawn on the surface of high-strength bridge bolts. If the red line on the bolt surface does not align with the red line on the steel panel, it is determined that the bolt has experienced loosening. As shown in Figure 2-a- c.

2.2 Target detection: YOLOv5-CT model for bolt positioning

YOLOv5, as a typical algorithm of target detection, has fast detection speed and high accuracy. The model structure includes: Backbone (Feature extraction backbone network), Neck (Feature fusion layer) and Head (Prediction layer), where the Focus in the Backbone network is an interlaced sampling and splicing structure, which slices the input image to reduce the number of parameters of the model and thus improve the detection speed; The C3 module is a residual network structure containing three standard convolutional layers as well as a Bottleneck module for feature extraction. To improve the detection accuracy of the classic YOLOv5 model and better utilize underlying feature information for small target bolts, the following modifications are made to the YOLOv5 algorithm:



a) b) c)

Fig. 2. Data Collection for Bolts(a) DJI Avata;(b) Bolt Images;(c) High Strength Bolts

1. The Convolutional Block Attention Module (CBAM) attention mechanism is added to the last convolution module of the first three C3 modules of the Backbone layer.

2. In the feature extraction layer, the Bottleneck module in the last C3 module is replaced with a Transformer module, as shown in Figure 3.

In YOLOV5, the detection head performs detection on the bridge high-strength bolt image to predict the location of the bounding box, object category, etc., and then uses a set of predefined anchor frames to predict the location and category of the bolt bounding box, followed by post-processing steps such as non-maximum suppression (NMS) to obtain the final object detection results, while multiple loss functions work together to optimize the model parameters.

2.3 Image Processing

In order to improve the generalization ability of the model and ensure the clarity of the reconstructed image, it is necessary to preprocess the captured image before the training and testing of the anomaly detection model. First the red lines are extracted by using the HSV (Hue, Saturation, Value) color space [12], and the HSV threshold is set to [0, 43, 46]-[10, 255, 255], and the Mask image is obtained. The linear fitting of white pixels in the Mask image is shown in Figure 4. Then rotate the image declination Angle α according to the slope to achieve horizontal alignment as shown in Figure 5.

2.4 Anomaly Detection: Ganomaly-based Loose Bolt Anomaly Detection

Generative Adversarial Networks (GAN) are a type of machine learning architecture that has been utilized in the expansion and enhancement of dataset samples[13] through the reconstruction of images. As the capabilities of GANs have progressed, the reconstruction speed and quality of images has improved. Ganomaly infers abnormalities by comparing the L1 difference between the original image and the hidden features of the reconstructed image space. The added abstraction helps to increase the model's resistance to noise. The structure of the Ganomaly model is depicted in Figure 6.

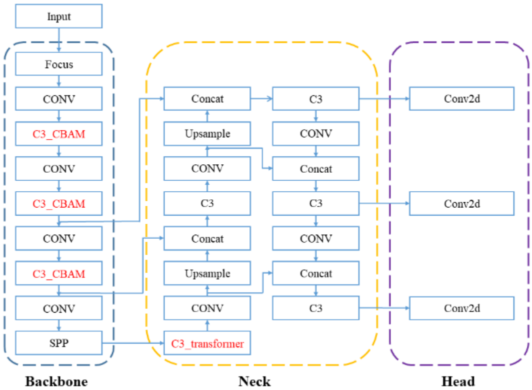


Fig. 3. Structure Diagram of YOLOv5-CT

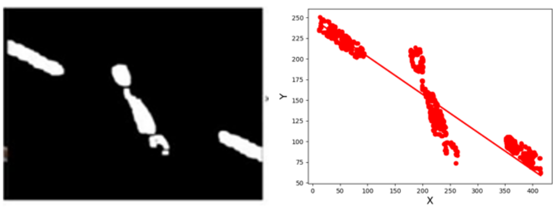


Fig. 4. Linear Fitting

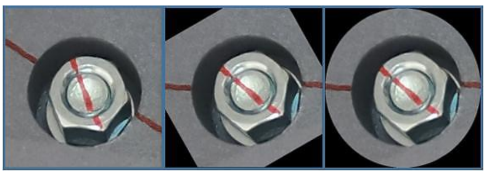


Fig. 5. Data Alignment

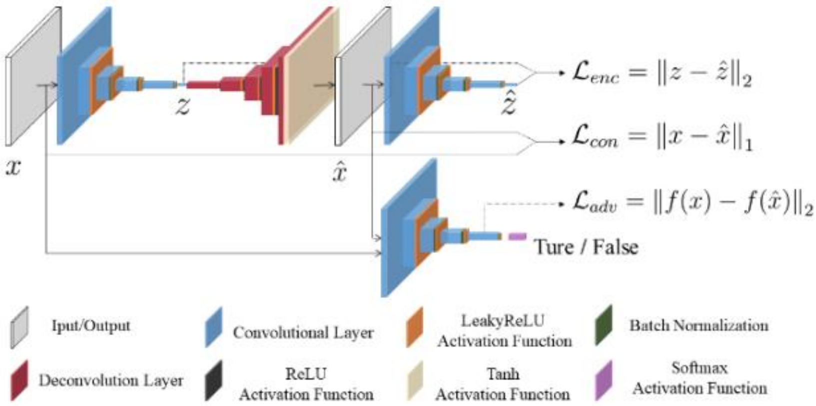


Fig. 6. Structure Diagram of Ganomaly

The anomaly detection process of the Ganomaly model is as follows: First, the input bolt is fed into the generator network model for encoding, resulting in a hidden feature vector, z. The reconstructed image is obtained by decoding the hidden feature vector. Then, the reconstructed image is encoded to obtain the hidden feature of the reconstructed image, $\hat{z}$. For an input bolt image x, its anomaly score is defined as follows:

$$A(x) = \| z - \hat{z} \|_1 \tag{1}$$

By using a given discrimination threshold φ, if anomaly score A(x) > φ, it indicates that the input bolt image is an anomalous bolt image. Due to the displacement between the red lines on the surface of a loose bolt and the red lines on the steel panel, there is a clear difference between abnormal bolt samples and normal ones. Therefore, Ganomaly is unable to reconstruct the shifted lines of anomalous bolts, resulting in an anomaly score higher than the threshold φ, thereby identifying the bolt as an anomalous one.

3 Experimental Setup and Evaluation Criteria

3.1 Experimental Environment and Dataset

The graphics card used for the experiment was NVIDIA GeForce RTX 3060, and the programming environment was python 3.8, pytorch 1.9.0, and CUDA11.1 was used for GPU acceleration. In the experiment, DJI Avata was used to obtain high-strength bolt images and construct target dataset sets, as shown in Tables 1 and 2:

Table 1. Bolt Positioning Dataset

Bolt Positioning Dataset	Training set	Validation set	Test set
Number	1811	363	481

Table 2. Bolt Anomaly Detection Dataset

Bolt anomaly detection data set	Training set	Positive verification set	Positive verification set	Positive verification set	Negative test set
Number	9863	89	89	1056	1224

3.2 Target detection and evaluation

The target detection evaluation metrics used in this experiment are: P is the precision of detection (Precision), R is the recall rate (Recall), AP (average precision), mAP (mean average precision):

$$P=\frac{TP}{TP+FP};\ R=\frac{TP}{TP+FN};\ \mathrm{AP}=\int_0^1 P_i(R_i)dR;\ mAP=\frac{\sum_{i=1}^{Nc}\int_0^1 P_i(R_i)dR}{N_c}$$

Where: TP, TN, FP, and FN denote true positive, false positive, true negative, and false negative predictions, respectively; P_i *and* R_i respectively represent the accurate value and recall rate of Class i detection, N_c indicates the total number of detected categories.

4 Experimental Results and Analysis

4.1 Bolt positioning experiment and result analysis

The YOLOv5-CT model is used to iteratively train the labeled training set. In the training simulation, the target bolt label is set as "Bolt", the bolt loss target label is set as "Lose", the initial weight learning rate is 0.01, the weight decay rate is 0.0005, and the batchsize is 8. The number of iterations is 300. 0.01, weight decay rate is 0.0005, batch size is 8, and the number of iterations is 300.

To validate the effectiveness of the improved backbone network, the YOLOv5-CT model is compared with current state-of-the-art object detection algorithms. Furthermore, ablation experiments are conducted to evaluate the impact of the proposed enhancements. The experimental results are summarized in Table 3.

According to the data in the table, it can be concluded that Faster-RCNN has higher accuracy under the same input dimension, but due to the limitation of model inference speed, it fails to meet real-time detection requirements. The YOLOv5-CT model improves the detection speed and accuracy over the YOLOv5 model, and the mAP value of target detection in the proposed method can reach 98.33%, which is 1.2% higher than the YOLOv5 model, and the FPS reaches 65.54, which is capable of real-time bolt detection. The YOLOv5-CT model mAP value is improved by 0.2% compared to Faster-RCNN.

As can be seen from the detection results in Figure 7 and Figure 8, the YOLOv5-CT model improves the capture of the underlying features and can accurately detect the loss of bolts and reduce the false detection rate.

Table 3. Comparative experiment of different model structures

Model	Inputsize	FPS	mAP(%)
Faster-RCNN	640x640	3.6	98.10
YOLOv5	640x640	62.48	97.01
YOLOv5+CBAM	640x640	66.22	97.54
YOLOv5+Transformer	640x640	**68.81**	97.16
YOLOv5-CT	640x640	65.54	**98.33**

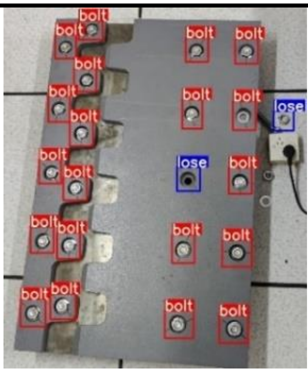


Fig. 7. YOLOv5 Model Results

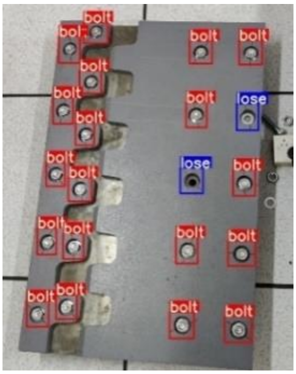


Fig. 8. YOLOv5-CT model Results

4.2 Anomaly detection experiments of bolts and analysis of results

The images containing the normal bolt regions within the detection boxes from section 4.1 are aligned and then fed into the Ganomaly anomaly detection model for training. Each bolt image has a size of 128x128 pixels. The training parameters are set as follows: learning rate of 0.0002, Batchsize of 16, and 1200 iterations, γ being the balance coefficient for the adversarial loss set to 1, α being the balance coefficient for the reconstruction loss set to 50, and β being the balance coefficient for the encoding loss set to 1.

The anomaly score,0.295, of the test data is obtained by evaluating the L1 difference of the test set data through Equation (1), which means abnormal values above 0.295 are recognized as abnormal bolts and then realize the detection of abnormal loosening of bolts. The experimental results are shown in Table 4.

Table 4. Abnormal Bolt Detection Results

Detection Result	TP	TN	FP	FN
Number	896	1036	160	188

The P of detection was calculated to be 85% and the R was 83%, and the experiment confirmed the effectiveness of the model for abnormal bolt loosening detection. In summary, the Ganomaly algorithm model can effectively discriminate between normal bolt images and abnormal loose bolt images with high accuracy, providing an effective algorithmic tool for the detection of high strength bolts in bridges.

5 Conclusion

Aiming at the problems of high strength bolt loosening detection in bridges, such as large workload, small target, many anomalies and difficult to obtain, this paper proposes a semi-supervised deep learning model for non-contact bolt detection, which can obtain the bolt loosening detection model with a small number of negative samples, and solves the problem of imbalance in the model training samples. The YOLOv5-CT model achieved 98.33% accuracy for bolt target detection. By preprocessing the bolt data, the reconstruction ability of the Ganomaly model for bolt images was improved. The AUC of the model is highest when the hidden space vector value is 100, and the model has the best discriminative performance. In the model testing stage, the abnormal score threshold is set to 0.295, and the accuracy of the calculation model for abnormal loosening detection of high-strength bolts can reach more than 85% to achieve the purpose of automatic identification and detection of the bolt.

Acknowledgments

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