A Fine-Grained Method for Detecting Defects of Track Fasteners Using RGB-D Image

Xuanyu Ge[1,2,3], Yong Qin[1,3](✉), Zhiwei Cao[1,2,3], Yang Gao[1,2,3], Lirong Lian[1,2,3], Jie Bai[1,2,3], and Hang Yu[1,2,3]

[1] State Key Laboratory of Advanced Rail Autonomous Operation, Beijing Jiaotong University, Beijing 100044, China
{gexuanyu,yqin,zhiwei,gaoyang_,lianlirong,baijie, yuhang_}@bjtu.edu.cn

[2] School of Traffic and Transportation, Beijing Jiaotong University, Beijing 100044, China

[3] Key Laboratory of Railway Industry of Proactive Safety and Risk Control, Beijing 100044, China

Abstract. To ensure the safety of railway transportation, it is necessary to promote the defect detection of track fasteners. However, most current inspections focus on coarse-grained detection of defects, while neglecting the potential fine-grained defects, such as looseness and subtle deformation. To solve this problem, this paper proposes a method for fine-grained defect detection of track fasteners using RGB-D images. The proposed method is divided into two stages: coarse-grained detection, which detects defects such as missing or loose elastic strips, and fine-grained detection, which detects potential defects such as loose fasteners. By combining coarse-grained detection and fine-grained detection, more excellent defect detection of track fasteners has been achieved The proposed method achieves 99.6% accuracy of coarse-grained detection and 90.6% accuracy of fine-grained detection at 23.3 FPS.

Keywords: RGB-D images · Defects detection · Fine-grained detection · Structured light

1 Introduction

Active security in the railway system is necessary [1]. Fasteners are an important component of railway tracks, which can effectively maintain the reliable connection between the steel rails and sleepers, prevent longitudinal and transverse displacement of the steel rails, and reduce the impact of trains on the track. Manual detection of fastener defects is time-consuming, labor-intensive, with low accuracy and potential safety hazards. At present, China's railway departments are actively using railway inspection vehicles equipped with high-definition cameras and deep learning algorithms to replace the manual inspection. However, the current inspection mainly focuses on the detection of coarse-grained defects such as loose or missing elastic strips, ignoring the potential fine-grained defects such as looseness and subtle deformation. The potential defects are the

M. Gong et al. (Eds.): EITRT 2023, LNEE 1138, pp. 37–44, 2024.
https://doi.org/10.1007/978-981-99-9319-2_5

most fatal, as accidents are unpredictable. To adress this problem, a structured light camera is used instead of a camera. As shown in Fig. 1, a structured light camera mounted on a railway inspection vehicle captures RGB-D images for fine-grained detection on top of coarse-grained detection.

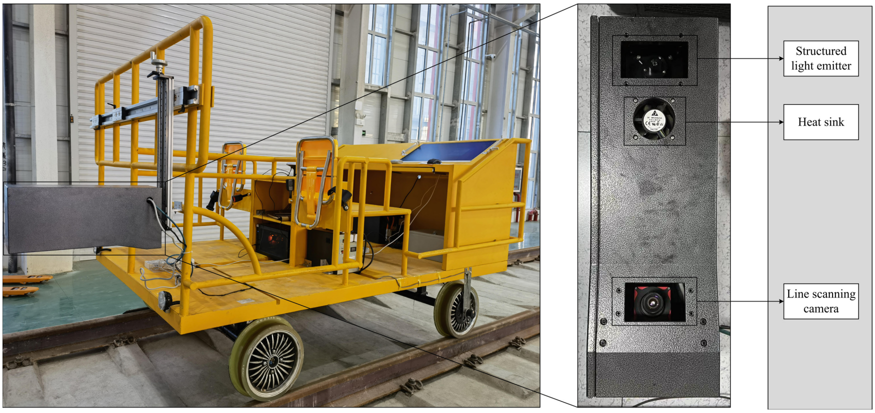

Fig. 1. Railway inspection vehicle with structured light camera

In this paper, based on the detection of coarse-grained fastener defects, we use depth images for fine-grained detection. The detection process is shown in Fig. 2. The main contributions of this paper are as follows:

(1) A fine-grained detection method of track fastener defects based on RGB-D images is proposed. The method consists of two parts: coarse-grained detection and fine-grained detection of fastener defects.
(2) Using structured light depth image to detect whether the fastener is loose, solves the problem that visual images are difficult to detect fastener loosening.
(3) The proposed method is tested using the Mask R-CNN algorithm and achieved 99.6% fastener defect detection accuracy and 90.6% fastener loosening detection accuracy with a detection speed of 23.3 FPS.

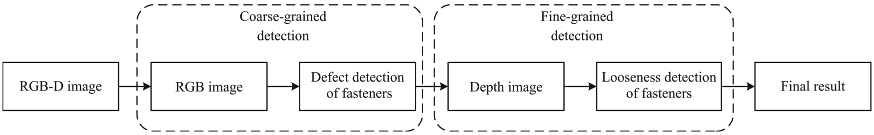

Fig. 2. The detection process

2 Related Work

2.1 Defects Detection of Track Fastener Based on Visual Images

Visual image-based methods generally analyze images captured by on-board cameras through deep learning or traditional image processing techniques. Bojarczak and Nowakowski [2] describes an algorithm that can detect fasteners distributed on four types of sleepers. Chandran et al. [3] proposes an image processing method to remove redundant information from fastener images to improve the positioning accuracy of fasteners. Wei et al. [4] proposes a fastener defect detection method based on dense SIFT features. Peng et al. [5] proposes a method for locating the center of hexagonal nuts in railway fasteners suitable for automatic nut replacement. In addition, some researchers have conducted relevant research on foreign objects in railway. Chen et al. [6] proposes a semi-supervised foreign object detection method for track board. Cao et al. [7] focuses on foreign object intrusion detection along the railway line to prevent foreign objects from entering and causing traffic accidents on unattended railway lines.

2.2 Defects Detection of Track Fastener Based on Structured Light

Although visual images have been widely used in detecting scenes, there are many insurmountable problems with visual images. To solve these problems, some researchers have done relevant research based on structured light depth image. Dai et al. [8] proposes a fastener detection method based on 3D laser scanning imaging to address the significant impact of light and unstable detection results in traditional detection methods. Zhan et al. [9] proposes an efficient structure based on convolutional neural network to detect fastener defects on 3D track. Experimental results show that the proposed method can successfully identify defected and missing fasteners. Mao et al. [10] designs a complex cylindrical surface center extraction method based on normal vectors, which is used to extract the centerline of the elastic strip of the fastener to evaluate the degree of looseness of the fastener.

3 Methodology

We use the Mask R-CNN [11] algorithm as the baseline model for the detection framework. When the coarse-grained detection is complete, we use the depth images for fine-grained detection.

3.1 Coarse-Grained Detection

The structure of the Mask R-CNN algorithm is shown in Fig. 3. The Mask R-CNN algorithm is an instance segmentation model that can detect and segment objects simultaneously, achieving good fine-grained detection. As shown in Fig. 3, the Mask R-CNN algorithm mainly consists of a backbone feature extraction network, a feature pyramid network, a region proposal network, and a ROI-Align network. During detection, the hierarchical scale features of the input images are extracted by a backbone feature extraction network, followed by a feature pyramid network to fuse the features at different scales. Then the rough region proposals are generated by the region proposal network on each scale feature, followed by the projection of all region proposals to the ROI-Align network. In the ROI-Align network, the region proposals are paired with the image features. Finally the image features are extracted based on the region proposals and fed into the ROI head for classification and regression, while a pixel-level mask is generated by the FCN network.

3.2 Fine-Grained Detection

After the coarse-grained detection is complete, we use the structural light depth image to detect the looseness of fasteners. In the component parts of fasteners, the height of bolt is essentially fixed. The looseness of the fastener is mainly caused by the loosening of the nut. Therefore, to determine the looseness of fasteners, only the height of the nut and bolt needs to be determined. The looseness detection process of the nut is shown in Fig. 4. A depth image is an image in which the distance from the image collector to each point in the scene is used as the pixel value. However, depth images often have large pixel values, reading and processing such large pixel values requires a lot of computing power and time. Therefore, the depth image is normalized before being read, making it is easier to be processed. Once the position of the nut is obtained, it is mapped to the normalized depth image, and this portion of the pixel information in the depth image reflects the height information of the nut and bolt. By statistically calculating the mean value of this pixel information and comparing it with a set threshold value, the looseness of the fastener can be determined.

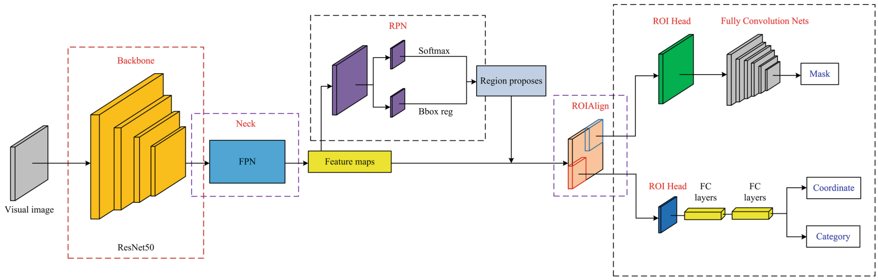

Fig. 3. The structure of mask R-CNN algorithm

4 Experiment

4.1 Dataset

We use the rail inspection car equipped with the structured light camera to collect data on the simulated railway line. The simulated railway line adopts the same standard as the current high-speed railway in China. The experimental scenario is shown in Fig. 1.

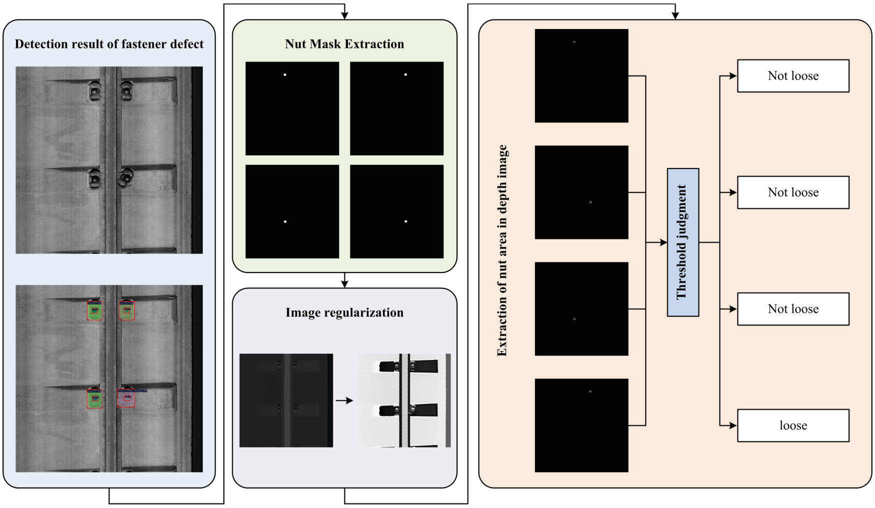

Fig. 4. The process of nut loosening detection

We collected a total of 2146 2D gray images with the size of 2048 $\times$ 2048 and their corresponding structured light images. The dataset consists of 8 categories: nuts, missing nuts, loose nuts, normal fasteners, missing baffles, loose elastic strips, missing elastic strips and foreign object intrusion. There are 1998 training sets and 148 testing sets in the dataset.

4.2 Experimental Parameters

Mask R-CNN is trained and tested on CPU (Intel (R) Core (TM) i9-10980XE) and GPU NVIDIA 3090Ti. The experiment is conducted on the open-source toolbox MMDetection [12]. The hyperparameter settings of the experiment are shown in Table 1. In the experiment, an SGD optimizer with a learning rate warm-up mechanism is used. The initial learning rate is 0.0001, and the upper limit learning rate is 0.02. We trained 20 epochs and reduced the learning rate by 10 times at 12 and 16 epochs, respectively.

4.3 Experimental Results

Results of the coarse-grained detection

The experimental results of coarse-grained detection are shown in Fig. 5. This method can detect all fastener defects with almost no false positives. The accuracy of this method for fastener defects reaches 99.6%. As shown in Fig. 5, in the first line, the proposed method has good ability on detecting the defects of losing baffle, missing elastic strips and loosening elastic strips. In the second line, the proposed method can effectively detect the intrusion of various foreign objects and the nut missing.

Table 1. Hyperparameter setting of model training

Define	Parameters	Annotation
IMAGE_MAX_DIM	1024	Picture size
IMAGE_MIN_DIM	1024	Picture size
LEARNING_RATE	0.0001	Learning rate
NUM_CLASSES	7	Category
RPN_ANCHOR_SCALES	8	Anchor box size
RPN_ANCHOR_RATIOS	[0.5, 1.0, 2.0]	Anchor box aspect ratio
STEPS_PER_EPOCH	20	Epoch
BATCH SIZE	4	Batch size
WEIGHT_DECAY	0.0001	Weight decay

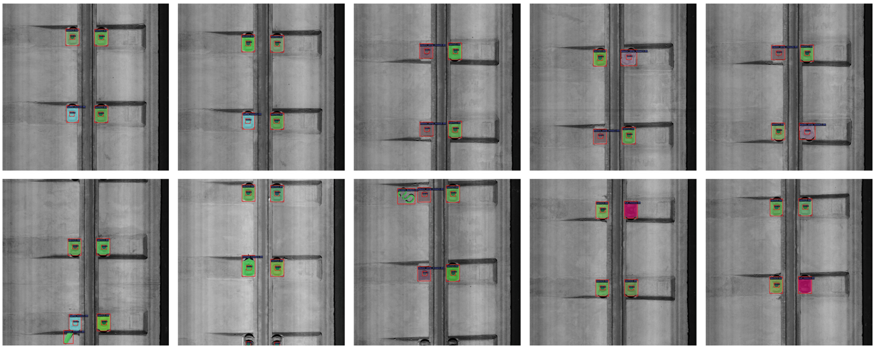

Fig. 5. The results of coarse-grained defect detection

Results of the fine-grained detection

Figure 6 shows the loosening detection of fasteners. The difference between the pixel histograms of loosened and unloosened nuts is large, and a good detection of loosened nuts can be achieved by calculating the average value and comparing it with the set threshold value. The proposed method finally achieves 90.6% of fastener loosening detection accuracy.

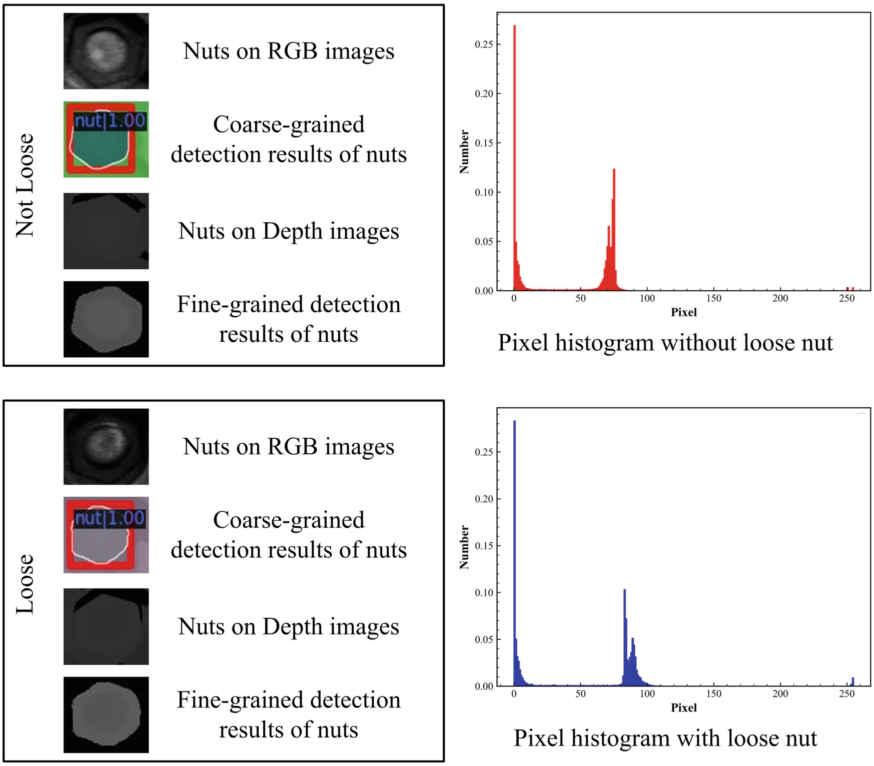

Fig. 6. The results of fine-grained defect detection

5 Conclusion

This paper proposes a method for fine-grained detection of fastener defects using RGB-D images, which can effectively detect various fastener defects and fastener looseness. There are three contributions. Firstly, a framework for fine-grained detection of fastener defects is proposed in which the algorithms are plug-and-play. Secondly, structured light images are used to detect fastener loosening. Finally, the proposed framework is tested using Mask R-CNN with 99.6% accuracy for fastener defects detection and 90.6% accuracy for nut loosening detection, and 23.3 FPS detection speed.

Acknowledgments. This work is supported by the National Key R&D Program of China (Contract No. 2022YFB4300601).

References

1. Qin, Y., et al.: Research on active safety methodologies for intelligent railway systems. Engineering (2022). https://doi.org/10.1016/j.eng.2022.06.025
2. Bojarczak, P., Nowakowski, W.: Application of deep learning networks to segmentation of surface of railway tracks. Sensors **21**(12), 4065 (2021)
3. Chandran, P., Asber, J., Thiery, F., Odelius, J., Rantatalo, M.: An investigation of railway fastener detection using image processing and augmented deep learning. Sustainability **13**(21), 12051 (2021)
4. Wei, X., Yang, Z., Liu, Y., Wei, D., Jia, L., Li, Y.: Railway track fastener defect detection based on image processing and deep learning techniques: a comparative study. Eng. Appl. Artif. Intell. **80**, 66–81 (2019)
5. Peng, Z., Wang, C., Ma, Z., Liu, H.: A Multifeature hierarchical locating algorithm for hexagon nut of railway fasteners. IEEE Trans. Instrum. Meas. **69**(3), 693–699 (2020)
6. Chen, Z., Wang, Q., Yu, T., Zhang, M., Liu, Q., Yao, J., Wu, Y., Wang, P., He, Q.: Foreign object detection for railway ballastless trackbeds: a semisupervised learning method. Measurement **190**(110757) (2022)
7. Cao, Z., Qin, Y., Xie, Z., Liu, Q., Zhang, E., Wu, Z., Yu, Z.: An effective railway intrusion detection method using dynamic intrusion region and lightweight neural network. Measurement **191**(110564) (2022)
8. Dai, X., Peng, Y., Wang, K., Yang, E., Li, J., Ding, S.: Railway fastener detection method based on 3D images. Railw Dev Oper Maint. 938–946 (2018)
9. Zhan, Y., Dai, X., Yang, E., Wang, K.: Convolutional neural network for detecting railway fastener defects using a developed 3D laser system. Int. J. Rail Transp. **9**(5), 424–444 (2020)
10. Mao, Q., Cui, H., Hu, Q., Ren, X.: A rigorous fastener inspection approach for high-speed railway from structured light sensors. ISPRS J. Photogramm. Remote Sens. **143**, 249–267 (2018)
11. He, K., Gkioxari, G., Dollar, P., Girshick, R.: Mask R-CNN. IEEE Trans. Pattern Anal. Mach. Intell. **142**(2), 386–397 (2020)
12. Chen, K., Wang, J., Pang, J., Cao, Y., Xiong, Y., Li, X., Sun, S., Feng, W., Liu, Z., Xu, J., Zhang, Z., Cheng, D., Zhu, C., Cheng, T., Zhao, Q., Li, B., Lu, X., Zhu, R., Wu, Y., Dai, J., Wang, J., Shi, J., Ouyang, W., Change Loy, C., Lin, D.: MMDetection: Open MMLab detection toolbox and benchmark. https://arxiv.org/abs/1906.07155 (2019)