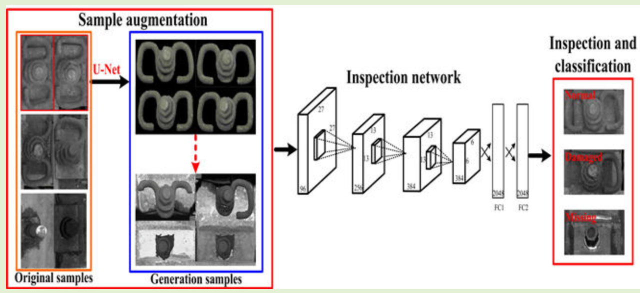
A Fastener Inspection Method Based on Defective Sample Generation and Deep Convolutional Neural Network

Jianwei Liu, Yun Teng, Xuefeng Ni, and Hongli Liu

***Abstract*—For the safety of railways, well-trained workers are required to check the fastener constantly, which shows the disadvantage of large time cost, huge labor cost and might being dangerous to workers. To address this and achieve automatic detection, an inspection model based on deep convolutional neural network (DCNN) is adopted in this paper. However, the inspection model suffering from the unbalanced training samples of defective vs normal due to defective fasteners are far less than normal fasteners in real railways. To tackle this problem, a novel sample generation method is proposed to generate defective fastener samples using the normal fasteners to realize sample augmentation. The comprehensive experiments are conducted on the collected real fastener samples and generated samples. The experimental results show that our method has good performance for fastener inspection on unbalanced samples and outperforms other state-of-the-art methods.**



***Index Terms*— Fastener inspection, sample generation, classification model, deep learning.**

I. Introduction

RAILWAY fastener is an important component of railway system, which is used to fix rail to the sleeper. Nevertheless, fastener will generate defects such as damaged and missing due to long-term rail vibration and temperature change. Thus, fastener needs to be detected periodically in order to ensure the railway safety. Traditionally, this work is operated by trained workers, but which faces the disadvantages of slow, huge labor cost and even dangerous.

In view of the disadvantages of manual inspection, in recent years, vision-based inspection technology has become the main mean of fastener inspection [1]–[3] because it can not only provide reliable inspection, but also decrease the cost of manual maintenance. As shown in Fig.2, the inspection system mainly includes two parts: image acquisition subsystem (IAS) and image processing subsystem (IPS). The former is used for capturing railway images and the latter is used to realize fastener inspection task.

A. Related Works in Existing Literatures

In the past decade, many traditional vision-based methods have been proposed to detect defective fastener. Yang *et al.* [4] extracted direction field features and then realize fastener inspection by template matching. Feng *et al.* [5] applied the probabilistic topic model based on Haar-like feature to detect fastener states, including normal, damaged and missing. Similarly, Ou *et al.* [6] proposed a Bayesian hierarchical model which combines the latent Dirichlet allocation and conditional random field to classify fastener states. Liu *et al.* [7] first generated the symmetry image and then adopted improved sparse representation method to realize fastener inspection. Fan *et al.* [8] proposed line local binary pattern (LLBP) method to detect the abnormal fasteners.

Although the above traditional vision-based methods achieve good performance for detecting the defective fastener, almost all the methods [5]–[8] are based on premise that the number of normal fasteners and defective ones is equal in the training set. As for the situation that training samples are imbalance, these methods are not mentioned.

In recent years, deep convolution neural network (DCNN) has been widely used in railway inspection. In literature [9], Kang *et al* proposed a multi-task learning framework to detect

Manuscript received January 16, 2021; accepted February 15, 2021. Date of publication February 24, 2021; date of current version April 16, 2021. This work was supported in part by the National Natural Science Foundation of China under Grant 61771191, in part by the Hunan Provincial Natural Science Foundation of China under Grant 2020JJ4213, and in part by the Changsha City Science and Technology Department Funds under Grant KQ2004007. The associate editor coordinating the review of this article and approving it for publication was Dr. Amitava Chatterjee. *(Corresponding author: Hongli Liu.)*

The authors are with the College of Electrical and Information Engineering, Hunan University, Changsha 410082, China (e-mail: ljw1990@hnu.edu.cn; tengyun@hnu.edu.cn; nixuefeng@hnu.edu.cn; hongliliu@hnu.edu.cn).

Digital Object Identifier 10.1109/JSEN.2021.3062021

the railway insulator surface defects. Xiao *et al.* [10] proposed hierarchical features model based on deep residual neural network for freight train defect detection. Jin *et al.* [11] proposed a deep multi-model to detect the rail surface defects. For fastener inspection task, some DCNN-based methods have also been proposed. Gibert *et al.* [12] proposed a multi-task learning framework to detect the defective fasteners. Wei *et al* used Faster R-CNN [13] and improved YOLO-V3 model [14] to detect the fastener states respectively. The states include normal, damaged and missing. These methods also do not mention the problem of imbalanced samples. However, in the experiment, they trained inspection model on training set expanded by the way of flip, rotation and scale transformation etc. rather than directly trained on the training set with sample imbalance. This indirectly reflects that sample imbalance will affect the performance of inspection model. Thus, the problem of imbalanced fastener samples needs to be solved.

In literature [3], Liu *et al* utilized Siamese network to solve the problem of imbalanced fastener samples. Meanwhile, the experimental results show that the fastener detection accuracy from 80.82% increased to 85.92% after the problem of sample imbalance is alleviated. Thus, this method can solve the problem of sample imbalance to some extent. However, the number of defective fastener samples required by this method is still large. In the case of the number of defective fastener samples is extremely small (there are only dozens or even several defective fastener samples), this method cannot achieve the good performance for fastener inspection task.

B. Challenges to Solve the Problem of Unbalanced Samples

Aiming at the problem of sample imbalance, many methods have been proposed, such as unsupervised methods and few shot learning methods. However, there are two shortcomings to solve the problem of imbalanced fastener samples and realize fastener inspection by these methods.

1) Unsuitability of Few Shot Methods: The few shot learning methods can solve the problem of imbalanced samples, such as Siamese network [15], prototypical network [16], matching network [17] and learning to learn [18]. However, due to the change of the railway lines or environment, fastener inspection model needs to be fine-tuned periodically using the new collected fastener samples to ensure the inspection performance. Thus, from the practical perspective, the inspection model must have simple training step and high detection accuracy. Unfortunately, these networks need to be retrained when transferring to the new railway line. And more, they cannot achieve the high detection accuracy. Therefore, they are not suitable for fastener inspection task. Furthermore, some researchers [19] used generative adversarial network (GAN) to generate the defective samples. However, GAN is difficult to train and easy to collapse. Moreover, it requires a large number of training samples. Unfortunately, the defective fastener is insufficient in real railway. Therefore, GAN is not suitable for generating defective fastener samples to solve the problem of sample imbalance.

2) Poor Robustness of Unsupervised Methods: In the previous works, unsupervised methods can also solve the problem of imbalanced samples. However, these methods cannot learn the fastener features independently, and the extracted features are hand-engineered features (direction fields feature [4] and Haar-like feature [5]). Whether feature selection and design is appropriate or not will have a significant impact on the fastener inspection. Therefore, these methods have poor robustness and generalization to the fastener inspection task.

Fig. 1. The defective fasteners.

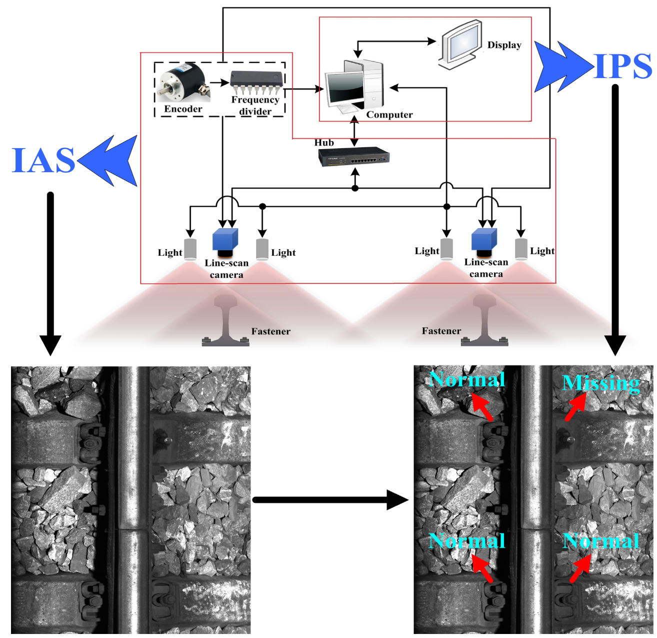


Fig. 2. Schematic diagram of fastener visual inspection system.

C. Outline of Our Works

In order to solve the problems of previous works, this paper proposes a novel approach that employs defect sample generation and DCNN for fastener inspection. The contributions of our works are as follows:

1) A novel defect sample generation method based on U-Net is proposed and a large number of defective fastener samples can be generated by this method. Niyogi *et al.* [20] demonstrated that the generated samples can provide the effective information in the same way as real samples. Thus, we generate defective samples to equalize the quantity of normal and defective fasteners and it is more benefit for training a robust inspection model.

2) A CNN-based model is constructed for fastener inspection. First of all, the model is pre-trained on the large number of generated defect samples and real normal samples. Then, we only need a small number of new collected fastener samples to fine-tune the pre-trained model when transferring

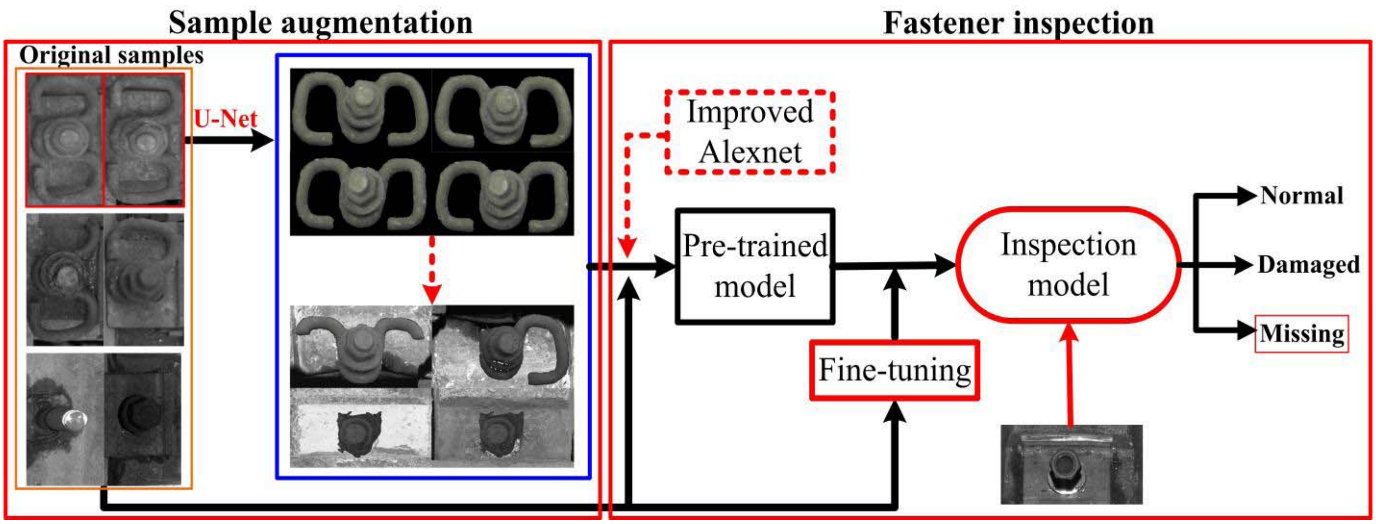


Fig. 3. Overall diagram of the proposed fastener inspection method.

to the real railway line, which can achieve better inspection performance.

The rest of this paper is organized as follows. Section II describes the overview of proposed fastener inspection method. The defective sample generation method is described in Section III. Section IV introduces the constructed CNN-based inspection model. Experimental results and analysis are presented in Section V. At last, we provide conclusion in Section VI.

II. Overview of Fastener Inspection Method

In this paper, a novel method is proposed to realize fastener inspection on imbalanced samples. The proposed method contains two stages: One is to generate defective fastener samples by proposed sample generation method and the other is to realize fastener inspection by the constructed CNN model. The diagram of the proposed approach is shown in Fig. 3.

A. Defective Fastener Sample Generation

In the railway, the defective fasteners are far less than normal ones. Thus, a fastener inspection model is trained on such unbalanced samples, which apparently hinders the stability and robustness of the obtained model. To solve this problem, it is necessary to increase the defective fastener samples to equalize the number of normal and defective fasteners. Based on this analysis, we propose a U-Net-based method to generate defective fastener samples. In this way, normal and defective fastener samples can be equalized and it is benefit for training a robust inspection model.

B. Fastener Inspection Model

In this stage, a CNN-based model is constructed for fastener inspection. We first pre-train the model on the large number of fastener samples (defective fasteners are the generated samples and normal fasteners are the real samples) to obtain the powerful feature representation ability of fastener. And then, we transfer the pre-trained model to the real railway line to recognize the defective fastener. It should be noted that only a small number of new collected fastener samples are needed to fine-tune the pre-trained model when transferring to the real railway line, which can achieve good detection performance.

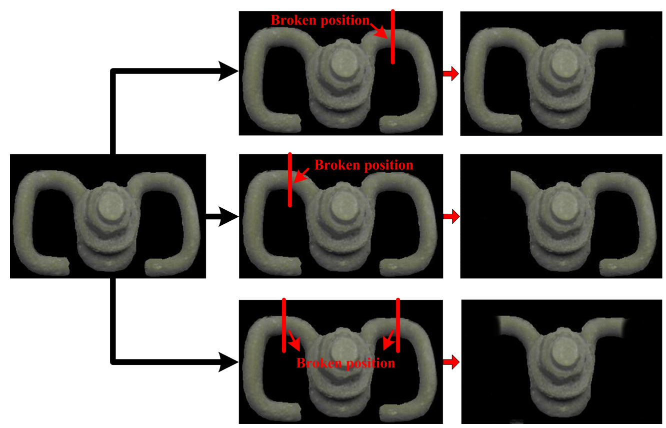


Fig. 4. Schematic diagram of the relationship between the elastic rod removal region and broken position.

III. Sample Generation of Defective Fastener

In this section, a U-Net-based defect image generation method is proposed to solve the problem of imbalanced fastener samples. Firstly, we obtain the foreground image of fastener region through image segmentation. Here, the segmentation network is U-Net. Then, we randomly remove partial or entire elastic rod region to obtain the foreground image of defective fastener. Finally, the defective fastener image is generated by combining the foreground image of defective fastener and the background image of fastener region. The specific flow chart of defective fastener image generation is shown in Fig. 5.

A. Fastener Foreground Image Segmentation

In order to generate defective fastener sample, we first need segment the foreground image of fastener region.

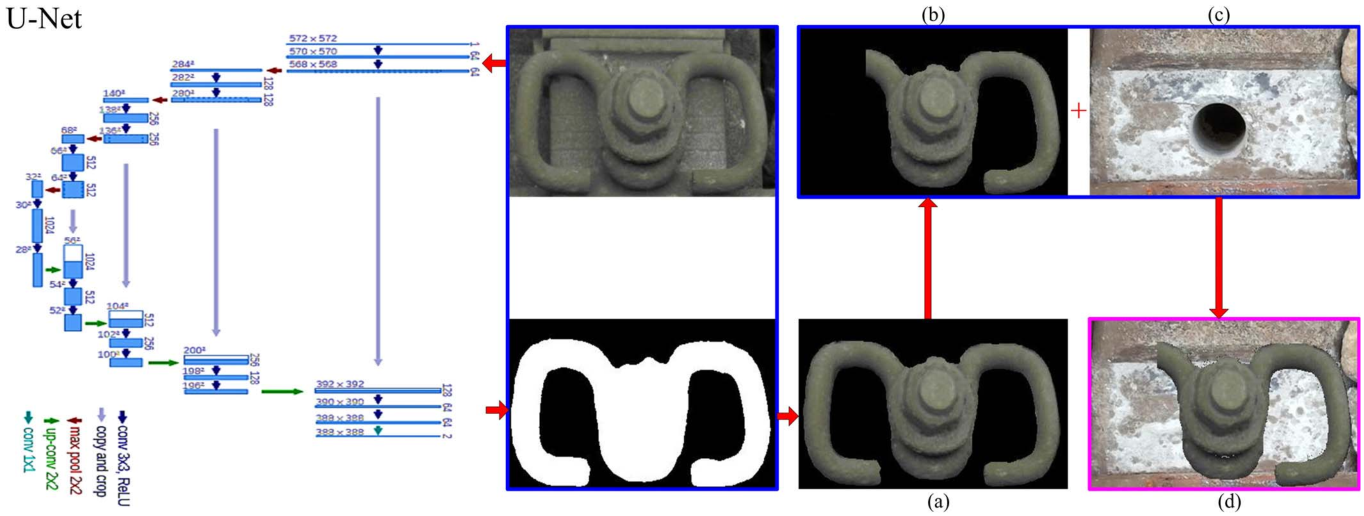


Fig. 5. Flowchart of the defective fastener image generation. (a) Foreground image of fastener region. (b) Foreground image of defective fastener. (c) Background image of fastener region. (d) Generated defective fastener sample.

Since U-Net [21] can achieve good segmentation effect only needs a small number of training samples and the training is simple and fast, it is adopted for segmenting the foreground image of fastener region. U-Net contains a contracting path and an expansive path. The total number of convolutional layer is 23. The contracting path is a typical convolutional network. It consists of repeated application of two 3×3 convolutions, each convolution followed by a RELU and a 2×2 max pooling with stride 2. In expansive path, an up-sampling of the feature map is performed after each 2×2 convolution and the obtained feature map concatenation with the corresponding cropped feature map from the contracting path. Finally, each 64 dimension feature vector is mapped to the desired number of classes by a 1×1 convolution. The network architecture is shown in Fig. 5.

B. Defective Fastener Sample Generation

After obtaining the foreground image of fastener region, we randomly remove partial or entire elastic rod region to obtain the foreground image of defective fastener. Finally, defective fastener image is generated by combining the foreground image of defective fastener and the background image of fastener region. The specific process of defective fastener image generation is as follows:

1) Randomly select the broken position of elastic rod.

2) Remove the corresponding elastic rod region based on the selected broken position. As shown in Fig. 4. In this way, the foreground image of defective fastener is obtained.

3) According to formula (1.1), combine the foreground image of defective fastener and the background image to generate the defective fastener image. Here, we use the fastener completely missing image as the background image.

$$D_{img} = \begin{cases} B_{img}\,(x, y) & if\ \ DF_{img}\,(x, y) < 0 \\ DF_{img}\,(x, y) & if\ \ DF_{img}\,(x, y) > 0 \end{cases} \tag{1}$$

Here, D_{img} is the generated defective fastener image, B_{img} is the background image, DF_{img} is the foreground image of defective fastener.

IV. Fastener Inspection Model

In this section, we construct a CNN-based model to realize fastener inspection. Firstly, network architecture of the proposed model is introduced. Then, the implementation details of the model are given.

A. Network Structure of the Inspection Model

In recent years, deep convolutional neural network (DCNN) has achieved great success in image classification. For fastener inspection task, DCNN can improve the inspection performance of the traditional methods. Therefore, we construct a CNN-based model to detect the defective fastener. Specially, the constructed inspection model has good mobility and can be easily applied to the fastener inspection task in the new railway line only by fine-tuning the model with the new collected fastener samples.

Fig.6 shows the network architecture of the proposed fastener inspection model. In detail, we build our inspection model based on AlexNet [22]. Considering the foreground and background of the fastener region are more distinguishable and only three types of states need to be detected, we reserve the first four convolutional layers and remove the fifth convolutional layer of AlexNet. Meanwhile, the channel number of the first two fully connected is reduced from 4096 to 2048. It should be noted that our proposed model without Local Response Normalization (LRN) due to it increases computation costs but only slightly improves the performance.

B. Implementation Details

1) Loss Function: For fastener inspection task, the cross entropy loss function is used for training the proposed

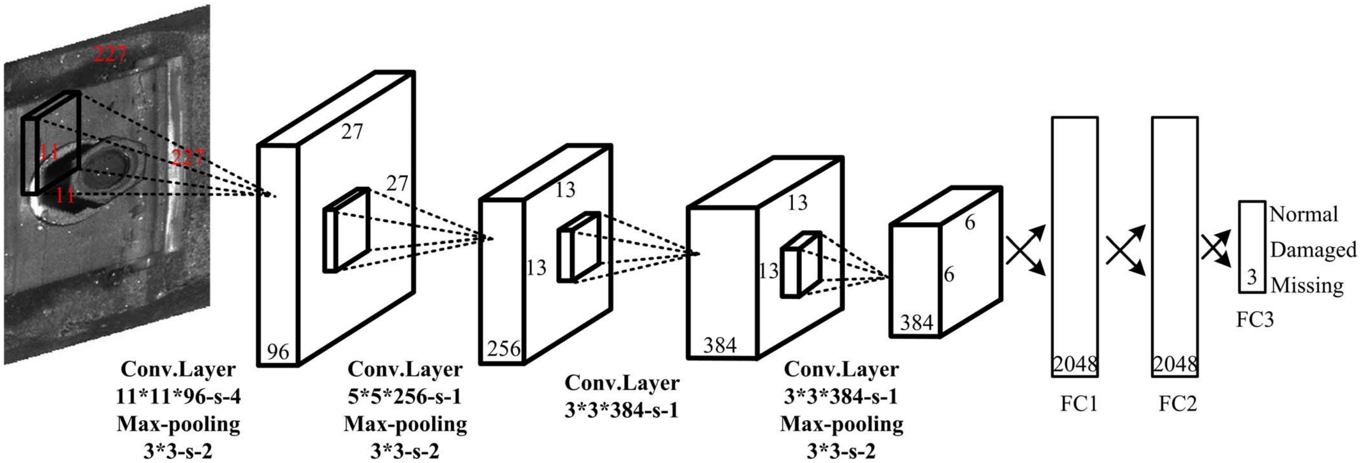
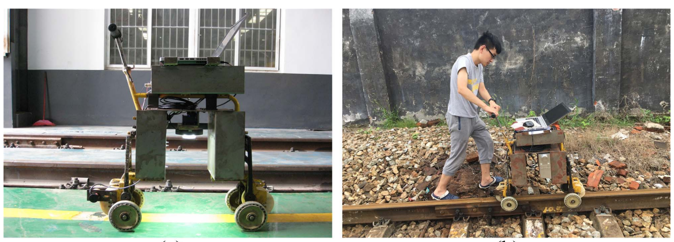


Fig. 6. Network framework of the proposed fastener inspection model.



(a) (b)

Fig. 7. Image acquisition and experiment platform. (a) Experimental platform. (b) Experimental site.

inspection model. The formulation is defined as follows:

$$L = -\frac{1}{N}[\sum_{i=1}^{N}\sum_{j=0}^{C} 1(Y^{(i)} = j) \log \frac{e^{W_j X^{(i)}}}{\sum_l^C e^{W_l X^{(i)}}} \tag{2}$$

where, N is the total number of training samples and C is the number of categories. $Y^{(i)}$ represents the class label of the ith sample. W is weight parameters matrix. **1** is the truth expression and it equals to 1 or 0 when the predict label is same as the truth label or not. In addition, Adaptive Moment Estimation (Adam) method is used to minimize the loss function L to update the weight parameters W.

2) Training Process: The training process of the proposed inspection model consists of two steps. The first step is to pre-train the model with a large number of generated fastener samples (defective fasteners) and real fastener samples (normal fasteners). In this way, the model can obtain the powerful feature representation ability of fastener. The second step is to fine-tune the pre-trained model by the new collected fastener sample on the real railway line. Specially, in the process of fine-tuning, the model can achieve good performance for fastener inspection only requires a small number of new collected fastener samples.

It should be noted that the weight parameters of all the convolutional layers and the first two fully connected are fixed when pre-training is completed. In the process of model fine-tuning, only the weight parameters of the last fully connected layer is updated.

TABLE I
THE DETAILED INFORMATION OF THE DATASET

Original dataset			Generated dataset	
Normal	Damaged	Missing	Damaged	Missing
35702	357	672	41040	37440

V. EXPERIMENT AND ANALYSIS

In this section, we first constructed the fastener dataset, which includes the real samples collected in several railway lines and the generated samples. Then, the experimental results and analysis are given.

In this paper, the experimental environment is as follows: TensorFlow1.14.0, Ubuntu 16.04 operating system, Intel Core i7-7820X CPU@3.50GHz×12 and a single NVIDIA RTX 2080Ti GPU with 11-GB memory.

A. Experimental Data

Since there is no a public dataset for fastener inspection task at present, we collected fastener images from several railway lines (Changsha-Shimen, Miluo and Guangzhou) and design a dataset used for fastener inspection task in this paper. The constructed dataset includes 35702 normal fasteners, 357 damaged fasteners and 672 missing fasteners. We named this dataset the original dataset.

In addition, we expand original dataset using the defective fastener images generated by our proposed image generation method. In detail, we generate 41040 damaged fasteners and 37440 missing fasteners. This dataset is named as generated dataset. The detailed information of the two datasets is summarized in Table I.

B. Sample Generation of Defective Fastener

For the fastener inspection task, the sample balance between normal and defective fasteners is the key to train a robust inspection model. However, in real railway, defective fasteners are far less than normal ones. It is difficult to train an inspection model with good robustness on such unbalanced fastener samples. Thus, generating defective

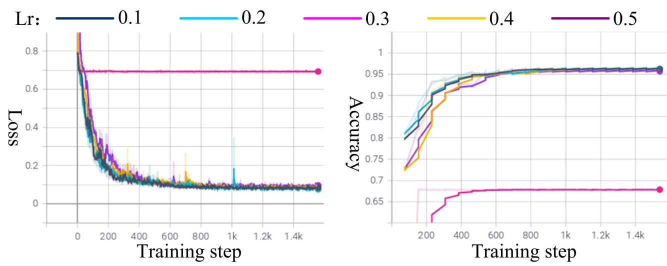


Fig. 8. The training process of coarse tuning of learning rate.

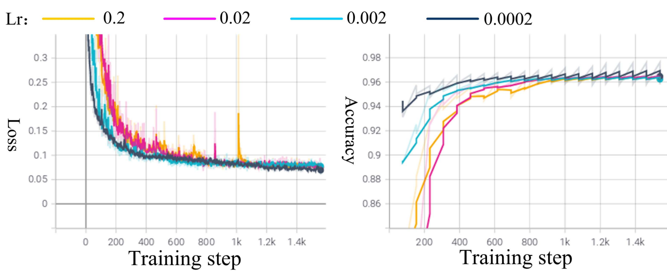


Fig. 9. The training process of fine tuning of learning rate.

fastener samples to achieve the fastener samples balance is very important to ensure the effectiveness of fastener inspection.

In the process of defective fastener images generation, it is the key to obtain foreground image of fastener region by U-Net segmentation network. Thus, we first train the U-Net to obtain fastener segmentation model. Here, we randomly choose 800 normal fasteners from original dataset as training set and validation set and the ratio is 4:1. The optimizer Adam is used to optimize the model. Through trial calculation, the U-Net model has converged after the training reaches the 11th epoch. Thus, the training period is set to 20 epochs. Due to the limitation of GPU memory, the batch size is set to 8. As for the initial learning rate, it is determined by two steps: coarse tuning and fine tuning.

Coarse tuning: The learning rate is set to 0.1, 0.2, 0.3, 0.4 and 0.5, and then train the model respectively. Fig. 8 shows the training results. According to the result, the learning rate is roughly set to 0.2.

Fine tuning: On the basis of the above preliminary determination of the learning rate, we carry out further fine tuning. The learning rate is set to 0.2, 0.02, 0.002 and 0.0002, and then trains the model respectively. Fig. 9 shows the training results. According to the result, the learning rate is finally set to 0.0002.

Fig.10 shows some generated defective fastener images. We can intuitively see that these generated defective fastener images are close to the real ones in the railway environment.

C. Effectiveness Verification of the Proposed Method

In this experiment, we evaluate the effectiveness of the proposed method for fastener inspection task. The evaluation indicators are *precision*, *recall* and $F1$ score. They are defined

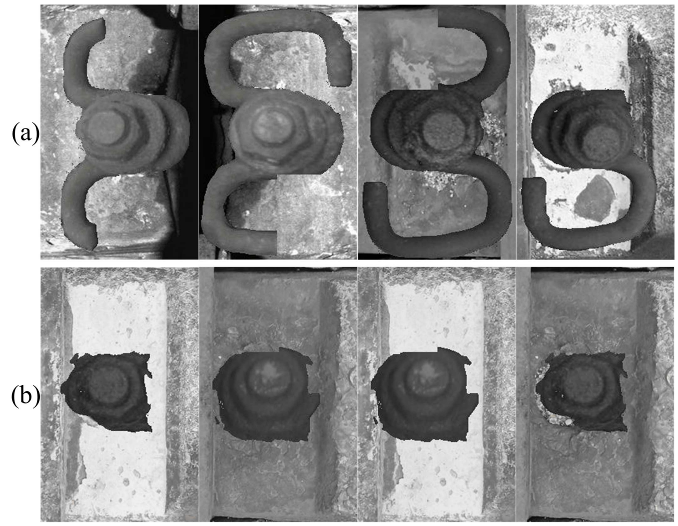


Fig. 10. The generated defective fastener images. (a) Damaged fastener. (b) Missing fastener.

as follows:

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

$$F_1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{5}$$

Here, TP is the number of correctly classified samples for a class, FP is the number of false positives, FN is the number of false negatives.

Firstly, we pre-train our inspection model with the batch size of 64, momentum of 0.9 and weight decay of 5×10^{-4}. The initial learning is set to 0.001 and then tuned to 0.0001 after 10 epochs. The total training period is 30 epochs. The pre-training dataset includes 30000 normal fasteners, 30000 damaged fasteners and 30000 missing fasteners. In which the training set and validation set are divided according to the ratio of 4:1. Specially, the normal fasteners are from original dataset and the defective fasteners are from generated dataset.

After the pre-training is completed, we need to transfer the pre-trained model to the real railway for testing. Here, we choose 100 normal fasteners, 100 damaged fasteners and 100 missing fasteners from the original dataset to fine-tune the pre-trained model. The batch size is 16. The learning rate is 0.0001 and the training period is 10 epochs.

We evaluate the performance of the proposed method for fastener inspection on test set and which contains 2000 normal fasteners, 257 damaged fasteners and 572 missing fasteners. The results are shown in Fig.11. From the confusion matrix, it can be seen that the precision of missing fasteners and recall of normal fasteners can reach 100%. Specially, the precision of damaged fasteners is the lowest, but it reaches 93%. Based on these numbers, it can be concluded that our proposed method has a good effect on fastener inspection.

D. Ablation Test

In this paper, our proposed fastener inspection method includes two modules. One is U-Net-based defective fastener

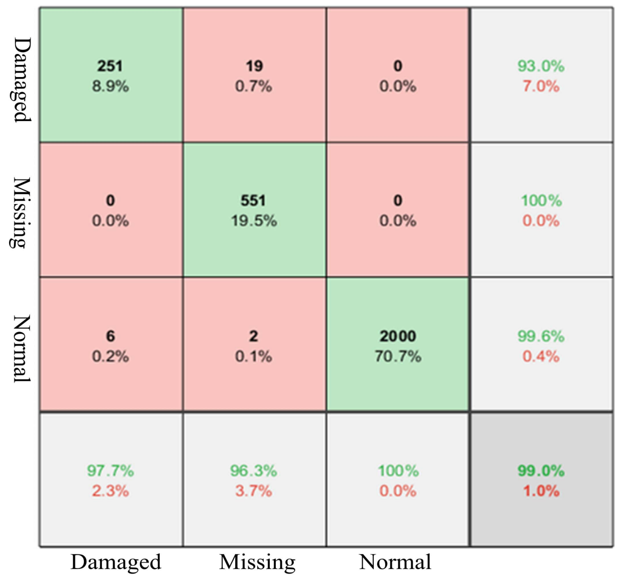


Fig. 11. The inspection result of the proposed method.

TABLE II
THE RESULTS OF ABLATION TEST

Fixed method	Comparison method	Acc / %
U-Net	AlexNet	95.4
	VGG-16	95.6
	Improved AlexNet	97.6
Improved AlexNet	FCN	85.2
	DeepLab_v3	89.1
	U-Net	97.6

image generation module and the other is the CNN-based defective fastener recognize module. To investigate the influence of every module on fastener inspection, we conduct the ablation test. First, we fixed the inspection module and test the effect of image generation module. In detail, we compared U-Net with FCN and DeepLab_v3. Then, we fixed the image generation module and show the effect of inspection module. Here, we compared proposed improved AlexNet with original AlexNet and VGG-16 [23]. The training set contains 1500 normal fasteners, 100 damaged fasteners and 100 missing fasteners. Specially, the number of training samples used for segmentation network is 600. The test set is same as verification experiment. Meanwhile, detection *Accuracy* (Acc) acts as the evaluation index of all the experiments.

The test results are shown in Table II. From the Table, it can be seen that image generation module has a greater influence on the detection effect of fastener. In the case of generated samples are with good quality and rich diversity, the detection effect of model based on different networks almost same. However, once the generated samples are with low quality and diversity, it will have a great impact on the detection effect. In addition, the results also demonstrate that our proposed method can effectively improve the detection effect of fastener and solve the problem of imbalanced fastener samples.

TABLE III
COMPARATIVE RESULTS OF FASTENER INSPECTION USING DIFFERENT METHODS

Approach		Performance P/%	R/%	F_1	FPS
KNN-FTL [24]	Normal	92.0	97.2	0.9452	6
	Damaged	67.1	87.2	0.7584	
	Missing	83.1	87.4	0.8519	
STM [5]	Normal	97.8	97.3	0.9754	14
	Damaged	82.9	80.0	0.8142	
	Missing	82.7	87.7	0.8512	
Improved YOLO-v3 [14]	Normal	99.3	98.6	0.9894	137
	Damaged	83.7	85.8	0.8473	
	Missing	86.4	88.5	0.8743	
Similarity-based [3]	Normal	97.7	97.5	0.9759	196
	Damaged	89.2	93.3	0.9120	
	Missing	92.0	90.9	0.9144	
Proposed method (ours)	Normal	99.6	100	0.9979	188
	Damaged	93.0	97.7	0.9529	
	Missing	100	96.3	0.9811	

E. Comparison With the Methods in the Literatures

In order to further illustrate the effectiveness of the proposed method that employs defect image generation and DCNN for fastener inspection, we compare our method with the related methods in literatures [3], [5], [14], [24]. These methods include traditional supervised method (KNN with fixed template library, named KNN-FTL) [24], unsupervised method (new probabilistic structure topic model, named STM) [5] and deep learning-based method [3], [14].

We choose 100 normal, 100 damaged and 100 missing fasteners from original dataset as the template library and training set for the methods in literatures [5], [24]. Meanwhile, we choose 30100 normal, 100 damaged and 100 missing fasteners from original dataset as the training set for the method in literature [3], [14] and our method. The test set is same as the verification experiment.

Table III shows the comparative results of fastener inspection with different methods. It can be clearly seen that our method achieves best performance. In detail, the deep learning-based methods (our method, similarity-based and improved YOLO-v3) outperform the traditional methods (KNN-FTL and STM), which strongly demonstrates that deep learning-based method has powerful classification and detection ability. In addition, our method is superior to the similarity-based method and improved YOLO-v3 model. There are two reasons for this result. One is similarity-based method expanded the number of training samples by building the fastener sample pair. However, the quantity of defective fastener is too small. Although the number of training samples is increased, this method only can learn the characteristics of limited defective fasteners. Thus, it cannot obtain the powerful feature representation ability of fastener and achieve the best performance. The other is improved YOLO-v3 cannot solve the problem of sample imbalance. In the case of sample imbalance, its detection performance will be decreased. For our method, it can generate a large number of defective fastener images using a small number of normal fastener images. In this way,

TABLE IV
COMPARATIVE RESULTS BEFORE AND AFTER DEFECTIVE SAMPLE EXPANSION

Dataset		Performance P/%	R/%	F1
Without augmentation	Normal	84.3	100	0.9148
	Damaged	88.5	11.5	0.2036
	Missing	49.5	16.7	0.2497
Augmentation (Copy)	Normal	97.4	97.0	0.9719
	Damaged	39.2	76.0	0.5172
	Missing	50.4	20.0	0.2864
Augmentation (Histogram matching, rotation etc.)	Normal	99.5	94.0	0.9667
	Damaged	64.5	92.5	0.7600
	Missing	74.7	80.7	0.7758
Augmentation (Generated samples)	Normal	99.7	99.8	0.9974
	Damaged	97.0	97.5	0.9724
	Missing	98.3	97.7	0.9799

the training set is balanced and it is benefit for training a robust inspection model. Therefore, our method achieves the best performance.

In addition, the detection speed of our proposed method can reach 188 fps. Therefore, it is a better alterative for practical application.

F. Further Analysis

1) Improvement by Adding the Generated Defective Samples: As above mentioned, in real railway, defective fasteners are far less than normal ones and it is difficult to train a robust inspection model on such imbalanced samples. Thus, we generate defective fastener images to achieve a balance of normal and defective fastener samples. In order to evaluate the effectiveness of the generated defect images for training a robust fastener inspection model, we compare the detection results of the model trained on the dataset before and after expansion. The dataset expansion includes three ways: One is to expand dataset by the way of copy; the other is to expand dataset by the way of histogram matching, rotation and scale transformation *etc*. The last is to expand dataset by our proposed sample generation method. In detail, the unexpanded training set contains 30100 normal fasteners, 100 damaged fasteners and 100 missing fasteners. The expanded training set is same as the verification experiment. The test set is from original dataset and which contains 2000 normal fasteners, 200 damaged fasteners and 300 missing fasteners.

The comparative results are shown in Table IV. Fig. 12 presents the confusion matrix. Based on these results, we can draw the following conclusions.

1) The inspection effect of the model trained on the expanded dataset is better than that of the model trained on the unexpanded dataset. It is not surprising for this result because normal and defective fasteners in the unexpanded dataset are seriously imbalanced. The inspection model trained on this dataset mainly learns the characteristics of normal fasteners and hardly learns the characteristics of defective fasteners. Thus, most defective fasteners are misclassified as normal fasteners and the inspection effect is worse.

Fig. 12. Confusion matrices of fastener inspection. (a) Without sample augmentation. (b) Sample augmentation by way of copy. (c) Sample augmentation by way of flip, rotation etc. (d) Sample augmentation by our generation method.

2) The generated defective fastener images are useful to train a robust inspection model. By comparing the inspection results before and after dataset expansion, we can see that the effect of the inspection model has been significantly improved. Especially for the defective fasteners, the recall increased from 11.5% and 16.7% to 97.5% and 97.7% respectively. Thus, we can conclude that the generated defective fastener images are obviously helpful to improve the performance of the inspection model.

3) Compared with other two sample augmentation methods, the samples generated by our proposed method has better effect for improving the performance of the inspection model. There are two reasons for this result: One is expanding the dataset by means of replication only increase the quantity of samples and not increase the diversity. The inspection model still learns the features of limited defect samples. The other is common data augmentation method (histogram matching, rotation etc.) can increase the diversity of samples. However, in essence, these expanded samples are still similar to the original ones so that the inspection model cannot fully learn the characteristics of defective fasteners.

2) Fastener Inspection in Different Railway Lines: For the actual fastener inspection task, the railway lines and environment are changing. Therefore, the proposed fastener inspection method should have good robustness and generalization. Here, we use the additional collected dataset to evaluate the robustness and generalization of the proposed fastener inspection method. The dataset is collected from Qiao Touyi Station of Changsha passenger Transport Section. A total number

TABLE V
ROBUSTNESS VERIFICATION RESULTS OF THE PROPOSED METHODS

Real class	Prediction class			Performance		
	Normal	Damaged	Missing	P/%	R/%	F_1
Normal	2940	0	3	100	99.89	0.9994
Damaged	0	5	0	100	100	1
Missing	0	0	4	57.14	100	0.7272

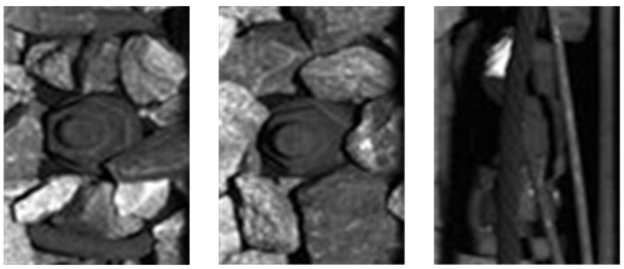


Fig. 13. The wrong inspection results due to fasteners are covered.

of 742 railway images were captured and which contains 2943 normal fasteners, 5 damaged fasteners and 4 missing fasteners. It should be noted that this dataset is not same as the dataset built in Section V-A.

The evaluation results are shown in Table V. It can be seen that our proposed method achieves good inspection effect. This result proves that our method has good robustness and generalization for fastener inspection in different railway lines. For the case of false inspection (three normal fasteners are misclassified as missing fasteners), the reason is that the fasteners are covered with stones and other sundries. For this special case, manual examination is still needed.

For the railway lines where the fastener inspection effect is not ideal, the inspection effect of our method can be improved by adding a small number of new samples to fine-tune the constructed inspection model. In this way, the better inspection performance can be achieved. This reflects the transfer generalization ability of our method once again.

VI. CONCLUSION

This paper presented a novel method that employs defect image generation technology and DCNN to detect the defective fasteners on the imbalanced samples. Firstly, the U-Net-based method is proposed to generate defective fastener images. In this way, normal and defective fastener samples can be equalized and the problem of imbalanced fastener samples can be solved. Then, a CNN-based model is constructed to recognize fastener states, which has good robustness and generalization to detect defective fasteners in different railway lines. We conduct comprehensive experiments on the constructed fastener dataset. The experimental results demonstrate that our proposed approach can effectively detect the defective fasteners in the case of imbalanced samples and has a superior performance over other state-of-the-art methods.

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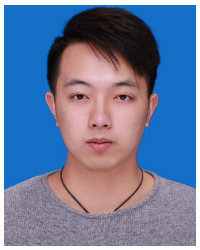
Jianwei Liu is currently pursuing the Ph.D. degree with Hunan University, Changsha, China.

He is also with the College of Electrical and Information Engineering, Hunan University. His research interests include machine vision, railway fastener inspection, and signal processing.

Xuefeng Ni is currently pursuing the Ph.D. degree with Hunan University, Changsha, China.

He is also with the College of Electrical and Information Engineering, Hunan University. His research interests include machine vision, railway defect inspection, and signal processing.



Yun Teng is currently pursuing the Ph.D. degree with Hunan University, Changsha, China.

He is also with the College of Electrical and Information Engineering, Hunan University. His research interests include machine vision, railway inspection, and signal processing.

Hongli Liu received the B.Sc. degree in electrical engineering and the Ph.D. degree in control theory and engineering from Hunan University, Changsha, China, in 1985 and 2000, respectively.

He is currently a Professor with the College of Electrical and Information Engineering, Hunan University. His current research interests include intelligent information processing and transmission technology.