Missing Rail Fastener Detection Based on Machine Vision Method

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Abstract: Rail fastener missing detection is an important part of railway daily inspection, according to the need of modern railway automatic detection, a method of rail fastener missing detection based on template matching is proposed in this paper. Firstly, in order to deal with the interference of environmental light, according to the basic principle of machine vision, a simple rail inspection car is designed for image acquisition. Secondly, according to the characteristics of the track image, the rail fastener area is located by using the mutation information of the image. Then, through the establishment of template, test images are matched with the template image, when the matching degree between test images and template images is low, it is need to detect the occlusion area of the test image and if there is a occlusion in the test image, remove the occlusion area from the test image and sample images to obtain new sample images and test image. Finally, the minimum distance classifier is used to detect the missing rail fastener. Simulation results show that the correct detection rate of this algorithm is 93.7% and the average detection time of each image is 385.74 ms, providing a reference for real-time detection of railway line.

1 INTRODUCTION

With the rapid development of high-speed railway, how to ensure the safe operation of the train has attracted more and more attention of the public. Track fastener is an important component for connecting rail and track sleeper, playing an important role of holding on the track gauge and preventing the rail from vertically and horizontally moving relative to the track sleeper, once be lost will bring security risks to the safe operation of the train(Gibert, et al, 2017).

In recent years, many domestic and foreign scholars have done a lot of research on the detection of missing track fastener and have obtained some achievements. Among them, Wang L *et al*.(2011) use principal component analysis (PCA) algorithm to extract the feature vector of the rail fastener nut and use the minimum distance classifier to detect the fastener. Yang J *et al*. (2011) use the orientation field algorithm and the template matching method to detect the state of the rail fastener. Jia L H(2014) carries on processing to the image edge by using mathematical morphology, intercepts the sub module from the test images to match with the standard rail fastener image and uses the support vector machine (SVM) method to detect the missing fastener. Yan F(2014) extracts the edge feature of the fastener image, and then respectively use the BP neural network and fuzzy C mean clustering method to identify the missing fastener.

The existing researches mainly focuses on the case that the track fastener image is not be occluded. In that case, the local characteristics of rail fastener is not interfered by the external environment and can be easily extracted. However, the track fasteners may be obscured by such as fallen leaves or food bags et al. in the actual railway lines, causing some of local features of track fastener be split and cannot be accurately extracted.

Taking into account the situation that rail fastener may be obscured by some occlusions, a method based on machine vision method for the detection of missing rail fastener is proposed in this paper. Firstly, the rail fastener area is located by using the position relationship among components of the track image. Then, select a track image that contains rail fastener a track image lacking of track fastener as the sample images, and the test image is compared with the sample images. When there is a high matching degree between the test image and the sample images, the

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result can be obtained directly, while the difference between test images and sample images is large, it's needed to consider the influence of the may existing occlusion on the matching result, therefore, it is necessary to firstly detect the occlusion of the test image, if there is a occlusion in the test image, removing the occlusion area to obtain new samples and test image to minimize the impact of the occlusion on the detection results. Using the minimum distance classifier to get the final detection result. The detection flow of the algorithm is shown in figure 1.

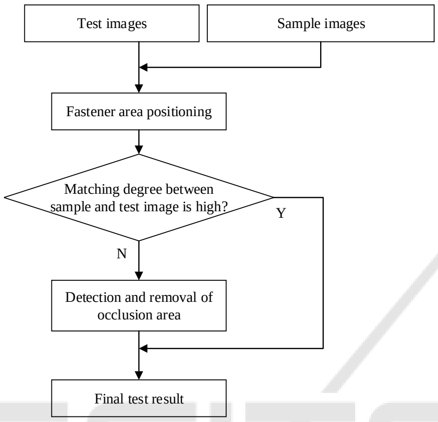


Figure 1: Schematic diagram of algorithm detection process.

2 IMAGE ACQUISITION

If track images are collected directly in natural environment, they may be affected by natural light, making the illumination of images is inconsistent and the algorithm will be difficult to carry out a unified process to images (Li, et al, 2010). In order to avoid the influence of the external light, a rail fastener detection system is designed and is shown in figure 2.

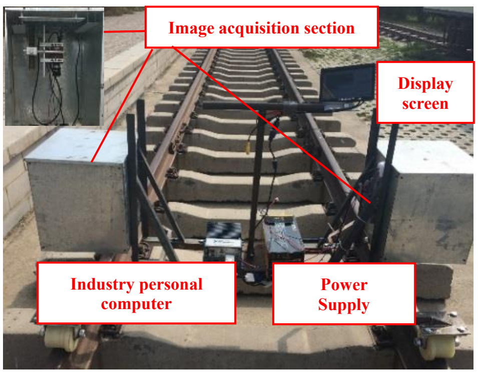


Figure 2: Rail fastener missing detection system.

A CCD camera is used to meet the requirement of the system on the acquisition speed and an 8mm lens is installed to coordinate with the camera. An industrial control computer and a display screen are equipped in the rail inspection car to display and process the images.

3 AREA POSITIONING

The relationship between the track fastener, rail and track sleeper in a track image is that the track sleeper and rail intersect vertically, the track fastener is located on the track sleeper and distributed on two sides of the rail(Liu J J, et al,2015). The positional relation of a track image is shown in figure 3. Therefore, according to the position relation in the track image, the rail and the sleeper area can be located firstly, and then the fastener region will be positioned.

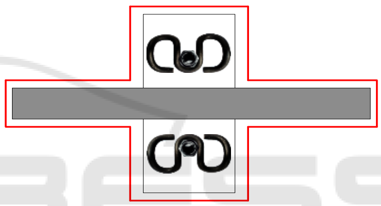


Figure 3: Sketch map of track area structure.

In a track image, there are a lot of edges in the stone ballast area for a large number of stone ballast exist in this area, while the rail and track sleeper area are smoother and have only a small number of edges. Defined the marker number of gray mutation between adjacent pixels is as n_q :

$$n_q = \begin{cases} 1, h^*|f(i,j) - f(i,j+1)| + v|f(i,j) - f(i+1,j)| \geq T \\ 0, h^*|f(i,j) - f(i,j+1)| + v|f(i,j) - f(i+1,j)| < T \end{cases} \quad (1)$$

The gray value of (i, j) is $f(i,j)$ and T is a threshold. In this paper, we set the value of T as 2/3 of the average gray value of image, when we calculate the gray mutation in the horizontal direction, take h=0, v=1, while calculate the gray mutation in the vertical direction, take h=1, v=0.

The statistical value of the gray mutation of k-th row and k-th column can respectively be obtained by formula (2) or formula (3):

$$N_{Hi} = \sum_{j=1}^{J} n_{i,j}, i = k \quad (2)$$

$$N_{Vj} = \sum_{i=1}^{I} n_{i,j}, j = k \quad (3)$$

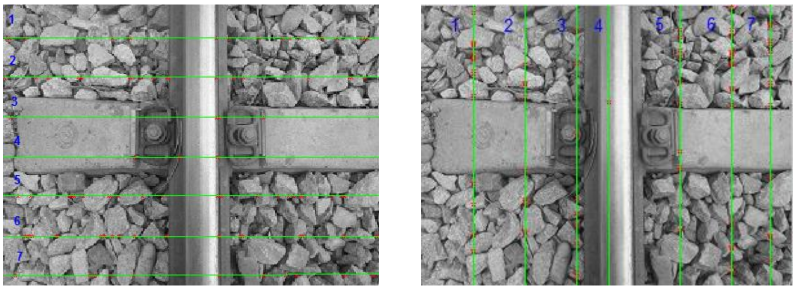
I is the row number of image while J is the column number. k represents the k-th row or the k-th column.

The number of gray change points in horizontal and vertical directions of the image respectively is:

$$N_H = \sum_{i=1}^{I} N_{Hi} \tag{4}$$

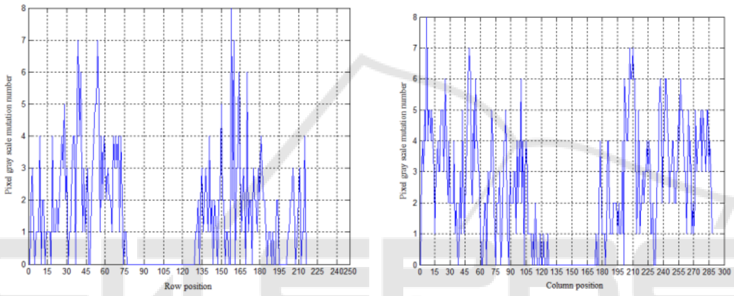
$$N_V = \sum_{j=1}^{J} N_{Vj} \tag{5}$$

According to the formula (1)-(5), the gray change point mark map and the statistical graph are respectively shown in figure 4 and figure 5.



(a) Horizontal direction (b) vertical direction

Figure 4: Gray change point mark map.



(a) Horizontal direction (b) vertical direction

Figure 5: Statistical graph of image gray mutation.

From figure 4 we can see, the number of gray change points in the straight line that through the stone ballast area is more than that in the through the track sleeper area or rail area straight lines. Because there are fewer gray abrupt points in the areas of track sleeper or rail, the bottom is formed in the statistical chart as shown in figure 5.

The location to the track sleeper area and rail area can be completed by searching the bottom position in figure 5, and then the fastener region is positioned by the position relation in a track image expressed in figure 3. The coarse positioning diagram of rail fastener image is shown in figure 6.

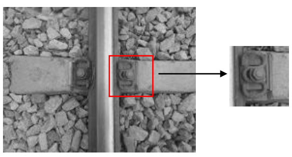


Figure 6: Fastener region location and segmentation.

4 DELETION DETECTION

4.1 Image registration

In order to get the difference image between test images and sample images, it is necessary to register test images and sample images firstly. Due to test images may missing rail fastener as well as may be blocked by occlusion, therefore, in this paper, the edges of rail and track sleeper are selected as the image registration features. Even in some occlusion conditions that shown in figure 7, we can detect at least one edge line (as shown in figure 8), which is helpful for us to register the test images and sample images. Select images shown in figure 9 as sample images of this paper.

Figure 7: Some of occluded rail fastener images.

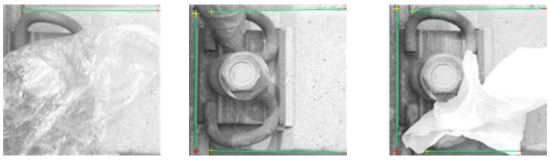
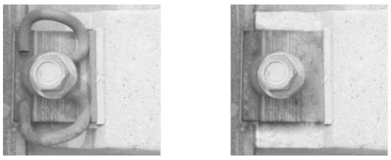


Figure 8: Line detection results.



(a) Containing fastener (b)Missing out fastener

Figure 9: Sample images.

4.2 Occluded area detection and removal

The detection and removal of the occlusion areas is an important part of the rail fastener detection. Once the test image is an occluded image, the occlusion will interfere with the extraction of the fastener features. The key to the occluded image detection is to find an effective method to reduce the influence of occlusion area. This paper presents an improved rail fastener detection method based on removing occlusion area. The implementation of this method is divided into two stages: in the first stage, judging and detecting the occlusion area in the test image. In the second stage, carrying out unified treatment on the occlusion area in the test image and the region that corresponding to the occlusion area in the sample images. The specific steps are as follows: ① According to the comparison result between the test image and the sample images, get the difference image between the test image and the corresponding sample image. ② Compare the gray value of the difference image with the threshold *Y*, when the pixel gray value is larger than the threshold value *Y*, set the value of these pixels to 255, otherwise set these pixels gray value to 0, in this way, we get a new difference image. ③ Get the removed occlusion images by subtracting the difference image from the test image and the sample images respectively.

5 MINIMUM DISTANCE CLASSIFIER

Compared with the K nearest neighbor method and the neural network method, the speed of the minimum distance classifier is faster, therefore, minimum distance classifier is often chosen for real-time on-line inspection systems(Liu, 2009). The specific process of using the minimum distance classifier to complete the defect detection of rail fastener is as follow.

Define the modulus of image *I* as:

$$|I| = \sum_{x=1}^{n}\sum_{y=1}^{m} I(x,y) \tag{6}$$

Where *n* and *m* are image size of *I*, $I(x,y)$ is the gray value at (*x*, *y*).

Suppose that I_{F} represents sample image contained with rail fastener and I_{M} represents sample image of missing rail fastener. The modulus of image I_{F} and I_{M} respectively are:

$$|I_{\mathrm{F}}| = \sum_{x=1}^{n}\sum_{y=1}^{m} I_{\mathrm{F}}(x,y) \tag{7}$$

$$|I_{\mathrm{M}}| = \sum_{x=1}^{n}\sum_{y=1}^{m} I_{\mathrm{M}}(x,y) \tag{8}$$

The modulus of the test image I_{T} is:

$$|I_{\mathrm{T}}| = \sum_{x=1}^{n}\sum_{y=1}^{m} I_{\mathrm{T}}(x,y) \tag{9}$$

Compare $|I_T|$ with $|I_F|$ and $|I_M|$ to obtain the final test results.

6 EXPERIMENTAL RESULTS AND ANALYSIS

We collected 480 rail fastener images on the spot. Among them, 467 rail fastener images contain fastener, 13 images lack of the track fastener. Due to the small number of the missing fastener images, we added 20 missing fastener images by using artificial synthesis method. In this way, the total number of experimental images is 500. At the same time, in order to increase the diversity of occluded images, we randomly selected 20 images from existing images and add occlusion into these images to obtain 20 occluded images (Cai, et al, 2010).

In order to verify the performance of the algorithm in different cases, we carried out three simulation experiments. In experiment 1, all the test images are all non occluded track images, and this is the most common experimental method used in fastener detection algorithms. In order to compare with experiment 1, in experiment 2, we used occluded images as the test images. In Experiment 3, the test image set contains both non occluded and occluded images, and this is the most consistent with the actual railway scene. The distribution of sample and test images of the three experiments are respectively shown in table 1, table 2 and table 3. It should be noted that in order to reduce the influence of occlusion on the test results, the occluded images are not included in the sample images, the test images and the sample images are randomly selected in different experiments. The results of the three experiments is shown in table 4.

Table 1: Distribution of sample and test images in experiment 1.

Category	Non occluded image with fastener	Non occluded image missing fastener	Occluded image with fastener	Occluded image Missing fastener
Sample images	20	10	0	0
Test images	432	17	0	0

Table 2: Distribution of sample and test images in experiment 2.

Category	Non occluded image with fastener	Non occluded image missing fastener	Occluded image with fastener	Occluded image Missing fastener
Sample images	20	10	0	0
Test images	0	0	15	6

Table 3: Distribution of sample and test images in experiment 3.

Category	Non occluded image with fastener	Non occluded image missing fastener	Occluded image with fastener	Occluded image Missing fastener
Sample images	20	10	0	0
Test images	432	17	15	6

Table 4: Detection result.

Category	Experiment 1	Experiment 2	Experiment 3
Correct detection rate	94.6%	87.5%	93.7%
Per frame Image detection time	367.21 ms	425.58 ms	385.74 ms

It can be seen from the experimental data of table 4 that the detection of occluded images takes a longer time than that of non occluded images, this is because there is a process of removing occlusion when processing occluded images. But in actual scenes, the proportion of occluded images to the total image is unlikely to be so high, so, the overall speed of this algorithm is good, just like the result of experiment 3. The experimental data also show that the correct detection rate is less affected by occluded images.

7 CONCLUSION

In view of the possible occlusion problem in defect detection of rail fastener, this paper propose a method based on machine vision. The fastener area is positioned firstly and the template images are established. The test images are directly matched with the sample image, accelerating the detection speed of the algorithm. When the difference between the test images and the template images is large, by detecting the occlusion area in the test image and removing the region corresponding to the occlusion area from the sample images as well as the test image, the influence of the occlusion area on the detection can be effectively reduced and the accuracy of the detection algorithm is improved. The algorithm proposed in this paper has higher recognition rate and strong robustness, it can be used for reference in the detection of similar occlusions. But the sample image and the test images used in this paper contains no track images that acquired in the rain or under strong sunlight condition, therefore, the sample set is still failure to fully reflect the actual situation on the rail line. So, the detection of missing track fasteners for different weather will be the focus of the next study.

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