A novel visual inspection system for rail surface spalling detection

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Abstract. Railway transportation plays an important role in economic development since it can transport large volumes of passengers and cargo through great distances. Therefore, monitoring the condition of the railroad is essential to ensure train safety. With the development of computer vision, the railway non-destructive inspection systems have become possible. However, these methods have been still challenged by so many obstacles from ambient light on the rail surface and defects themselves. Defects appear on the rail surface are variety, in which spalling type is usually in heterogeneous shape and size. In this paper, a visual inspection system for rail surface spalling detection is proposed. The track image is first segmented by a novel rail track extractor. Then the rail surface spalling can be coarsely detected based on histogram curves in the longitudinal direction of the track image. Finally, a fusion technique is performed to eliminate all the false detected defects in the resulting image. Experimental results demonstrate that the proposed method achieves the precision and recall of 97.48% and 95.74%, respectively, and shows good robustness under nonuniform illumination and various rail surface conditions.

1. Introduction

As abovementioned, the railway inspection is essential to ensure train safety. Traditionally, one well-trained person has to walk along the railroad to evaluate the rail condition. However, this kind of inspection has many crucial disadvantages such as waste of human resources, time-consuming, subjective evaluation, and the performance of a worker may be degraded within one day and serious mistakes can be made. Thus, automatic inspection systems are required for an objective, fast, and reliable quality assessment of railways.

To handle this goal, a lot of paper that differ in either inspected objects or approach methods have been developed, including Fiber Bragg Grating sensors [1-3], ultrasonic inspection [4], eddy current [5], MEMS gyroscope sensors [6], and visual inspection system (VIS) [7]. Especially, VIS with its advantages has been developing and become more and more accurate. For instance, Mandriota et al. [8] performed three filtering approaches based on texture analysis and chose the Gabor texture feature for rail surface images, and then apply the k-nearest neighbor (KNN) method to identify the possible defects. In [9], the geometrical features (i.e., area, centroid, filled area, and perimeter) of the defected regions based on maximally stable extremal region technique are extracted. Li et al. [10] proposed the method of LN+DLBP for real-time discrete defects inspection using the local normalization (LN) method, which is nonlinear and illumination independent then applied the defect localization based on projection profile (DLBP) algorithm to identify possible defects. In [11], a new inverse Perona-Malik (PM) diffusion model is presented for image enhancement and, subsequently, an adaptive threshold binarization can easily find out the desired defects. Although these approaches have achieved certain effectiveness in detecting several types of defects none of them aim to inspect spalling with extreme various appearances.
and dynamic backgrounds due to heavy random noise caused by complex rail track conditions and camera quality.

This paper presents two scientific contributions: an accurate rail track extractor and rail surface spalling detection method for the railway inspection system.

Accurate extraction of ray surface image plays an important role in detecting defects on the rail surface. However, this problem has not been completely solved by the previous studies, so it is only possible to extract the rail images under certain assumptions. In this study, we carefully analyze rail imaging conditions such as railroad background, ambient light, and contrast in each acquired image, therefore it is easy to accurately extract rail surface image.

To overcome the challenges of detecting spalling on the rail surface, our approach takes two main steps:

1) Determine longitudinal defect according to the maximum gray value in each column of rail image individually.

2) Combine with a complete adaptive threshold image for eliminating false defects in longitudinal consideration.

The remains of this paper are organized as follows. After our system is introduced in Section 2, an accurate rail track extractor is presented in Section 3. Then Section 4 describes a method for detecting spalling on the rail surface. The experiment results are shown in Section 5, followed by our conclusions in Section 6.

2. System overview

This paper proposes a real-time visual inspection system (VIS) for spalling detection on the rail surface and produces an accurate rail track extractor. VIS consists of the image acquisition subsystem (IAS) and the image processing subsystem (IPS). The basic component of IAS is a Dalsa Spyder 2 line-scan camera with a resolution of 1024 x 1024 pixels and a maximum line rate of 65 000 lines/s. A PC-CamLink frame grabber is utilized to capture rail images based on the camera link protocol. An illumination setup equipped with two LED light sources is installed to reduce the effect of ambient light. Moreover, the line-scan camera is triggered by a wheel encoder to synchronize data acquisition.

![Figure. 1 Our system configuration](image)

Our system configuration (Figure 1) has some advantages as follows:

+ Reflection property of rail surfaces in the longitudinal direction is pretty homogeneous.
+ An auspicious installation to detect rail track longitudinal defects.
+ Easy for the operator to install and adjust.

Our system installation specification also remains some disadvantages, such as some small bright or dark regions probably appear on the rail surface image or the shadow of rail track exists in the acquired image. However, the proposed method overcomes these obstacles easily. For example, the solid dark region evaluating can be applied on both sides of the rail image for finding the rail shadow. And since the brightness intensity is homogeneous on the rail surface in the rail track longitudinal orientation, thus the abnormal solid bright regions (shown in Figure 6g bottom right) would be eliminated by performing an image fusion ceremony of defects detected rail images in both longitudinal and transversal direction.
3. Rail track extractor

In the past few years, various texture analysis approaches have been proposed, which are widely applied in many applications such as classification, inspection, and segmentation of image based on the histogram gray value curve (Rail localization based on Projection Profile (RLPP) [10], Rail Localization based on Weighted projection Profile (RLWP) [12], Geometrical defect Locating method based on Gray-level Histogram Curve (HGLHC) [13]) of the original image or Hough transformation. These methods only perform well with some certain assumptions of the rail image, such as the maximum deviation of the gray value of the pixels in each column in the rail image is not too large, and the rail surface region is the brightest. However, as we can see in Figure 2, such assumptions are often broken by illumination inequality and the variation of reflection property of rail surfaces and ballast or concrete background.

![Two samples of rail image in our data set. (a) Rail image with a concrete background. (b) Rail image with ballast background](image)

**Figure. 2** Two samples of rail image in our data set. (a) Rail image with a concrete background. (b) Rail image with ballast background

On the other hand, some disadvantage conditions challenge the methods based on Hough transformation such as lots of strikes or lines that appeared on the original image beside the rail track (Figure 3a). Moreover, it is difficult to exactly localize the rail track region if serious defects exit on the rail surface or rail track shadow cast alongside the rail track because their features are always variable throughout the images. To decrease the impact of these, a series of transformations need to apply, but they complicate the algorithm and cost processing time.

As we all know, rail images obtained in reality are influenced by the imaging conditions as well as the quality of the rail surface. So if just relying on some assumptions like such as the gray value of the pixels on the rail surface is relatively homogeneous and larger than the gray value of other areas in the image or the rail track is in the middle position of the image obtained from the imaging system ... will be unable to accurately extract the rail track images. To overcome these obstacles, we perform the following steps:
1) Identify the background of the rail image (ballast or concrete) based on the average gray value deviations in each column of the whole image. In our experiments, the background is ballast as that value is larger than 1500.

2) The shadow of a rail track in the image always has the nearly smallest gray value in the whole image. Therefore, it can be determined as the largest region in the longitudinal direction of the binary image with a small threshold value (Figure 3b).

3) By accurately localizing the shadow of the rail track, the image of the rail surface will be determined by comparing the two adjacent areas of the shadow. If the background is a ballast, the rail track image will be the area with the larger average gray value deviations in each column (the gray value of the pixels in the rail surface region is more uniform than the ones in the background region). If the background is concrete, the rail track image will be the region with the larger average gray value in each column (rail surface is brighter than the concrete surface).

4) Use a rectangle with exactly rail track dimensions to extract the rail track image.

![Figure 3](image)

**Figure. 3** Illustration of rail track extracting procedure. (a) Original image. (b) Binary image with a small threshold. (c) Extracted rail track image.

4. Rail surface spalling detection

Defects are easy to be hidden or confused in rail images because of illumination inequality and the variation of reflection property of rail surfaces, so contrast enhancement is a necessary procedure to highlight defects from their background. Different from [14], the proposed method aims to detect spalling on the rail surface image of which gray value is larger than adjacent regions in the longitudinal and transversal direction respectively. Some of the main reasons are as follows:

- Defect’s features (shape, size, gray value) always change from image to image and challenge the visual inspection systems. The defect region may be very small with a size less than 20 pixels or even very large with a size greater than 10000 pixels, which spread though over the image in the longitudinal direction. Consequently, it is unreliable to evaluate the maximum deviation of the gray value in the longitudinal direction because some large defects could be omitted (Figure 4).
Figure 4 Gray value Histogram curvature of a rail sample image (a) in longitudinal (b) and transversal direction (c)

- Generally, the spalling is brighter than the background. However, this order can be changed because of variations of illumination and reflection property or some small lighter or darker regions.
- Furthermore, numerous objective noises caused by visual inspection systems establishing and operating processes significantly affect the quality and performance of acquired images. The noticeable ones are time, weather, place of inspection, natural light, quality of the image acquisition subsystem (IAS), the velocity, and the shake of the moving test train. All of them need to be particularly considered for cancellation in pre-processing.

According to the above analysis, the proposed method is based on the maximum gray value deviation in each column individually then associated with a complete adaptive threshold image in the result.

4.1. Pre-process
Firstly, the mean gray value of the whole rail image is calculated. After that, all the small regions which have too large a gray value while comparing with the mean gray value of the whole image are eliminated.

According to the mean gray value, the contrast of the rail image is adjusted. Then a boundary detecting method by evaluating the Gradient of pixels is performed.

Since the digital image is discrete signals so the partial differential equations are replaced by performing a convolution technique to get the linear approximation result.

Following the above analysis, a method of which advantage to eliminate the impact of random noises and keep the image detail simultaneously is applied (Equation (1)):

\[
R(x,y) = \alpha * f(x,y) + (1 - \alpha) * g(x,y)
\]

where \(x\) and \(y\) are the spatial coordinates of acquired raw image \(f(x,y)\), \(g(x,y)\) represents the smoothed image of \(f(x,y)\) by a median filter, \(R(x,y)\) denotes the output image. And \(\alpha(x,y)\) is the smoothing rate parameter which can be derived from Equation (2):

\[
\alpha(x,y) = \frac{\partial g(x,y)}{\partial x} \max\left( \frac{\partial g(x,y)}{\partial x} \right)
\]

4.2. Rail surface spalling detection method
As shown in Figure 5, the process of spalling detection is composed of the following main steps:

1) In each column of the image, find out the maximum and minimum gray value pixels, and calculate the mean gray value of the pixels in that column simultaneously. If the maximum deviation of the pixels in that column is larger than a threshold value then there are defects in that column. After that, the
contrast of these columns in the image is adjusted by performing a quadratic function \( y = k \cdot x^2 \), where \( k = 0.01 \). Meanwhile, all the pixels in other columns of the image are set to zero. Finally, an adaptive threshold is applied to the retrieved image to obtain a binary image with defects detected in the longitudinal direction.

2) Another binary image obtained by performing an adaptive threshold on the original rail image.

3) Combine the above two result images using a bit AND logical function to eliminate non-defect regions on both of them and reshape the derived defects simultaneously.

By performing a connected component detecting function with the 8-nearest neighbor parameter, the size of each defect can be determined. In accordance with that, exactly identify all the defects and their features, thenceforth evaluating the harmful of them to railway operating will be available.

![Flowchart](image)

**Figure. 5** Flowchart of rail surface spalling detection process.

5. **Experimental results and discussions**

Our experiments are conducted with the images collected in the actual railway of China by the abovementioned IAS and divided into two small data sets. One including 500 images with several abnormal illuminations and different types of defects on the rail surface which are arbitrarily chosen from a large image set is used for evaluation of rail track extractor. And the other contains 1108 images which consist of 556 typical spalling rails and 552 normal rails.

5.1 **Performance evaluation of rail track extractor**

In our experiments, the ray width in the images is a constant of 120 pixels. The difference of this method compared to the previous ones is that it ignores some assumptions such as the rail surface is brighter than the background, the gray level value of the pixels on the rail surface area is relatively homogeneous or the position of the rail track is at the center of the image. Our experiments show that those assumptions are broken easily for several reasons. For example, the vibration of the test train while running in curves makes the position of the rail track surely deviate from the center axis of the acquired image. For images with many large defects, the surface of the rails is so deformed that resulting in gray values of the pixels on the rail surface area in the longitudinal direction becomes inhomogeneous. Also, ambient light noise
such as contrast and brightness of the background can affect the image quality and make the rail surface region no longer brighter than the others.

It can be seen that the rail shadow is a homogeneous region in which the pixels have the smallest gray value in the image. Therefore, using our method, it can be detected easily based on the average gray curve in Figure 2. After that, the rail track image can be localized by comparing the two regions of which the width is equal to the width of the rail lying alongside the shadow. In that way, the proposed method can extract the rail track image at any position in the original image. Quantity statistics of experimental results show that the performance of the proposed rail track extractor reaches a value of 98.6%.

5.2 Performance evaluation of spalling detection method

As we can see in Figure 6, spalling appears on the rail surface in various shapes, colors, and sizes. They may be very small, scattered on the rail surface, but can also be large and spread along the entire length of the rail image. However, many traditional methods fail to detect the spalling of such large sizes by mistaking them for light noise on the rail surface and ignoring them.

![Figure 6](image-url)

Figure 6 Some samples and the results derived with our method. (a) Original rail image; (b) Image after pre-processing. (c) Longitudinal contrast adjusting. (d) Binary image with an adaptive threshold. (e) Fusion image. (f) Connected components localization. (g) Spalling detection.

With the proposed method, every location with a large gray level variation in each column of the rail image can be a suspect area. Then the contrast in the corresponding columns will be raised while the gray level of the pixels in the remaining columns of the rail image are set to 0. From that, defects can be coarsely detected in the longitudinal direction of the rail image. Some defects that might be false
detection in the image with defects detected in the longitudinal direction can be eliminated by combining this image with a binary image obtained from the original image with an adaptive threshold.

To quantitatively evaluate the proposed method, we use criteria of precision (pre) and recall (rec) which are defined as equations (3) and (4):

\[
\text{pre} = \frac{TP}{TP + FP},
\]

\[
\text{rec} = \frac{TP}{TP + FN},
\]

where TP indicates the number of correctly detected spalling images, FN means the number of missed spalling images, and FP refers to the number of misjudged spalling images.

Experimental results demonstrate that the proposed method achieves the precision and recall of 97.48% and 95.74%, respectively, and shows good robustness under nonuniform illumination and various rail surface conditions.

6. Conclusion

This paper has proposed a method for detecting spalling appearing on rail surface mainly based on the histogram gray level curvature in both longitudinal and transversal direction. The results of experiments conducted on 1108 rail images shown that the proposed method could easily overcome the challenges such as ambient light inequality, the vibration of the testing-car while moving, the inhomogeneous reflection property of the rail surface, defect distribution on rail images, ... Since then, the proposed method has been demonstrated to be robust to noise and efficient performance, and consequently be conveniently applied to the railway visual inspection system. Besides, this paper also produces an accurate rail track extractor with better efficiency in reality applications comparing with the conventional methods. With the detection method for the spalling defect on a rail surface, relevant railroad period maintenance planning would be made. This result also contributes a significant data source for the complete railway visual inspection system based on deep learning in future work.

Reference

[1] Filograno M L 2012 Real-time monitoring of railway traffic using fiber Bragg grating sensors *IEEE Sensors Journal* 12 85-92
[2] Wei C L 2010 A fiber Bragg grating sensor system for train axle counting *IEEE Sensors Journal* 10 1905–1912
[3] Filograno M L, Corredera P, Rodriguez-Plaza M, Andrés-Alguacil A, and Gonzalez-Herráez M 2013 Wheel flat detection in high-speed railway systems using fiber Bragg gratings *IEEE Sensors Journal* 13 4808–4816
[4] Li Y, Trinh H, Haas N, Otto C and Pankanti S 2014 Rail component detection, optimization, and assessment for automatic rail track inspection *IEEE Transactions on Intelligent Transportation Systems* 15 760-770
[5] Gao B, Bai L, Woo W L, Tian G Y, and Cheng Y 2014 Automatic defect identification of eddy current pulsed thermography using single channel blind source separation *IEEE Transactions on Instrumentation and Measurement* 63 913–922
[6] Broquetas A 2012 Track detection in railway sidings based on MEMS gyroscope sensors *Sensors* 12 16228-16249
[7] Li Q and Ren S 2012 A visual detection system for rail surface defects *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)* 42 1531-1542
[8] Mandriota C, Nitti M, Ancona N, Stella E and Distante A 2004 Filter based feature selection for rail defect detection *Machine Vision and Applications* 15 179–185
[9] Dubey A K and Jaffery Z A 2016 Maximally stable extremal region marking-based railway track surface defect sensing *IEEE Sensors Journal* 16 9047-9052
[10] Li Q and Ren S 2012 A real-time visual inspection system for discrete surface defects of rail heads *IEEE Transactions on Instrumentation and Measurement* 61 2189-2199
[11] He Z, Wang Y, Yin F and Liu J 2016 Surface defect detection for high speed rails using an inverse PM diffusion model *Sensor Review* 36 86–97
[12] Li Q, Shi Z, Zhang H, Tan Y, Ren S, Dai P and Li W 2018 A cyber-enabled visual inspection system for rail corrugation *Future Generation Computer Systems* **79** 374-382

[13] Lin J, Luo S, Li Q, Zhang H and Ren S 2009 Real-time rail head surface defect detection: A geometrical approach *IEEE International Symposium on Industrial Electronics* **Seoul** 769-774

[14] Hu Z, Zhu H, Hu M and Ma Y 2018 Rail surface spalling detection based on visual saliency *IEEJ Transactions on Electrical and Electronic Engineering* **13** 505-509