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Detecting Defects of Railway Tracks by Using Computer Vision Methodology

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Abstract

Maintaining railway tracks in healthy conditions is critical to ensuring the safe operation of railroad transportation. According to the Federal Railroad Administration (FRA), nearly 23% of train accidents that occurred between 2015 to 2020 were due to the defects of the tracks. In an effort to prevent such accidents, railway companies regularly inspect tracks to detect and fix defects of track systems. This research proposes an innovative method for conducting railroad track inspection to enhance the maintenance operation. The proposed approach aims to overcome the existing inspection practices based on human observation that is costly, time-consuming, and error prone. To this end, the proposed method utilizes computer vision methodologies to achieve high-level automation and accuracy of defect detection through the analysis of digital images. The outcome of this study is envisioned to help railway companies perform predictive maintenance more effectively and, thereby, reduce the risk of train accidents and increase the resiliency of their assets.

Keywords
Rail Defects, Convolutional Neutral Network, Visual Inspection, Computer Vision.

1. Introduction

There is a worldwide trend towards increasing axle loads, traffic density, and speed to decrease operating costs and increase railway efficiency. Axle loads worldwide have risen from 22.5 to 32.5 tons in the last ten years [1]. Under the circumstances, the effective and efficient port operation requires the safe and healthy condition of the railroad operation, considering the critical role of railroad freight transportation in the port operation. Unhealthy railroads often contributed to severe train accidents, such as the derailment of trains in operation. For instance, approximately 45% of the derailments in the recent ten years were caused by defective tracks [2]. Such accidents typically result in fatalities, injuries, environmental pollution, and damages to the infrastructure and other properties. To this end, railroad companies regularly inspect tracks to avoid such detrimental events. BNSF, a private railroad company, claims that their maintenance crews perform an inspection on every foot of track twice a week [3]. The railroad track system comprises a few components—rails, rail sleepers, rail fishplates and bolts, rail fasteners, tie plates, spikes, and ballast. The deterioration or missing of these components undermines the structural integrity of tracks leading to rail misalignment—a critical reason for a train derailment. While detecting such defects is essential to preventing severe system failures and dangerous accidents, inspecting a vast railroad network is a highly challenging operation.

The current inspection practices have a few critical limitations—heavily involving human operations, costly and time-consuming processes, and error-prone results. It is especially worth noting that the widely applied practices are significantly affected by weather conditions such as extreme temperatures and challenging to implement to inspect railroads located distantly from populated places [3]. To overcome these limitations, we applied advanced information technologies for data collection and artificial intelligence for analyzing the collected data. An experimental approach was adopted to develop, test, and validate the proposed data collection system and AI-based analytical algorithms.

FRA retains the detailed reports of accidents or incidents associated with railroad operations. The FRA guidelines prescribe minimum safety requirements for railroad track that is part of the general railroad transportation system. The present study analyzed the FRA data from 2015 to 2020 to identify minimum safety requirements. The dataset is classified into five major groups, which are then sub-classified into other cause groups. According to the FRA database, between 2015 to 2020, nearly 23% of train accidents occur due to irregularity in track, roadbed, and structures each year, in which 71.5% of accidents occur due to faults in track geometry, rail, joint bar, and rail anchoring each year [2]. This paper mainly focused on identifying faults in track geometry, rail, joint bar, and rail anchoring.

2. Research Methodology

2.1. Vison System Setup

Figure 1 shows the setup and data collection system, including cameras and sensors, to monitor and assess the health condition of railroad tracks. Railroad track defects can be captured by cameras, and the track alignment can be measured by gyroscope sensors. Three cameras, one Sony RX-100 IV and two GoPro HERO8, were selected for video recording. In addition, Adafruit FT232H Breakout and Adafruit LSM6DSOX microchips were used to collect acceleration and gyroscope information, which is combined with video signals to create a multi-source inspection system. As Fig. 2 shows, the Sony RX-100 IV camera focuses on the track surface, sleepers, the inner side of the tracks, and the railway components between two tracks. The left and right GoPro cameras focus on the track surface, the outer side of the tracks, and the railway component outside the tracks. An onboard computer and two microchips collect real-time acceleration and gyroscope information.

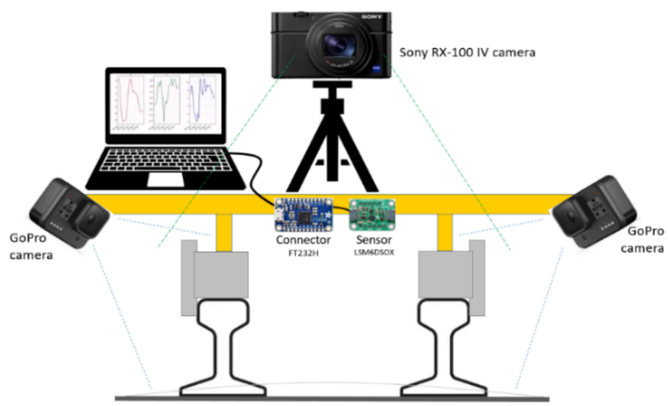


Figure 1: System architecture

The railway track videos captured by high-speed cameras were saved in a compressed format and decoded into frames. Among the frames, only the keyframes storing the complete image information in the data stream were used for track segmentation and analysis to reduce the processing time. The tracks appearing in the in-between frames were detected based on the detection outputs obtained from the keyframes.

2.2. The Proposed Computer Vison-based Railway Inspection

Literature shows that the computer vision-based inspection methods for railroad tracks mainly use edge and color extracted from images and deep learning neural networks. Rizvi et al. [4] applied histogram equalization to enhance the images after a median filtering and detected tracks using binarized regions' connectivity. Jiang et al. [5] used Canny edge detection and Hough Transform to detect and locate track edges in a polar coordinate system. Bo et al. [6] presented a method that combines image features extracted from both spatial and frequency domains to detect cracks based on a neural network classifier. Mubarak [7] applied mean-shift clustering, Hough Transform, region growing, and Scale Invariant Feature Transform (SIFT) for track segmentation, fastener detection, and object tracking. Stella et al. [8] preprocessed railway track images by wavelet transform and then classified track components. Feng et al. [9] used a probabilistic structure topic model to detect worn and missing fasteners with different orientations and illuminations. Mandriota et al. [10] analyzed the texture features of the railway track surface for defect detection. Resendiz et al. [11] adopted a multiple signal classification and Gabor transformation to detect and segment the periodically occurring track. Marino et al. [12] used a digital line-scan camera and two perceptron neural classifiers to detect visible and missing bolts from railway track videos. De Ruvo et al. [13] detected the presence/absence of the fastening bolts by principal component analysis and a shallow network. Deep convolutional neural network (CNN) models were also applied to railway track defect detection. Faghih-Roohi et al. [14] compared three CNNs with different sizes and activation functions for track surface defect detection. In the study proposed by Santur et al. [15], a 3D laser camera was used to collect 3D data, and a CNN was applied to classify healthy and faulty rail profiles. Gibert et al. [16] combined multiple detectors within a multitask learning framework for detecting defects on railway ties and fasteners. A 5-layer CNN was developed to detect different components of the railway. Recently, two survey papers reviewed sensors and devices that can be used for inspecting railway infrastructure [17] and machine learning methods in rack maintenance [18].

We have developed a railroad track inspection method by integrating advanced computer vision and a gyroscope sensor to identify defects and determine the rail alignment. The adopted research methodology comprises the following four steps:

- Step 1 – Texton filter bank and convolution-based segmentation of railway track and spike: Texton filter bank [8] contains a set of filters defined using Gaussian and Laplacian of Gaussian functions at multiple scales and orientations. After performing a convolution operation with the selected image, each filter in the bank yields a convolutional response showing the matching levels between the filter and local image patches. The filters that produce maximum responses can capture the characteristics of local image information efficiently for texture and shape description. Because the tracks and sleepers have different orientations and sizes, they can be segmented from the image by detecting their maximum responses using the filters with similar orientation and size. After that, a postprocessing step is applied to remove the regions that are too small or do not satisfy the geometric relationship between tracks and sleepers (i.e., the sleepers are in between two parallel tracks) are removed. The remaining regions are marked as regions of interest (ROIs) and are analyzed for defect detection in the next step.
- Step 2 – Detect defects by gradient and color information: The defects in the ROIs can cause image feature changes, which can be detected by analyzing gradient and color information. The research team applied Laplacian filter and mean shift clustering method to localize defects on the tracks and sleepers. Laplacian filter can efficiently enhance the fine details in the ROIs and highlight the intensity, shape, or texture changes caused by the defect. The mean shift clustering method can detect color changes on the tracks in an unsupervised manner and is robust in different illumination conditions.
- Step 3 – Measuring the track alignment by gyroscope sensor: The online gyroscope sensor extracts the 3D gyroscope information (i.e., the rotation in x, y, and z dimensions) in real-time and stores the sensor data as time-series data in the computer. By analyzing the saved sensor data and matching them with video data, the combined multi-source data can boost the system performance efficiently.
- Step 4 – Identifying cracks by the object tracking-based technique: It is necessary to assign each detected object a unique ID to avoid duplicate detection. Provided a video be captured at the speed of 30 miles per hour with a refresh rate of 60 frames per second, the distance interval between two consecutive frames is about 0.22 meters. In this case, the same defect may appear in more than one frame of video. Thus, object tracking was used to identify defects based on spatial constraints and motion direction.

3. Experiment Design

3.1 Fundamentals of Track System

The fundamental part of the railroad infrastructure is the track, which is the locomotive's steering base. The track consists of two steel rails, adjusted on crossties to keep the rails at a suitable distance apart and capable of supporting locomotive's weight. Track geometry and FRA minimum safety requirements are discussed below.

- Gage Distance: The distance between the rails is referred to as the gage distance. It is measured at a right angle to the rails, in a plane ⅝ inch (1.59 cm) below the top of the rail. The gauge distance must be at least 4 ft. 8 in feet and not more than 4 ft. 10 in. for class 1 tracks [3].
- Track Alignment: The projection of each rail's track geometry or the track centerline onto the horizontal plane is known as the track alignment. For class 1 tracks, alignment may not deviate from the mid-ordinate line may not be more than 5 in. out of a 62 ft. chord. For a curved track, the mid-ordinate deviation from a 62 ft. chord may not be more than five inches [3].
- Cross-level: The difference in height between opposing rails is known as cross-level. The track surface shall maintain the cross-level within limits as follows. (1) The deviation from zero cross-level at any point on a tangent

or reverse cross-level elevation on curves may not be more than three inches in class 1 tracks. (2) The cross-level difference between any two points less than 62 ft. apart may not be more than three inches in Class 1 tracks [3].

- Profile: The vertical surface as cross-level relates to the transverse plane in track elevation. Profile relates to elevation along the longitudinal axis, which is an adherence to an established grade and dips and humps incidence. The deviation from the uniform profile on either rail at the mid-ordinate of a 62 ft. chord may not be more than three inches in class1 tracks [3].

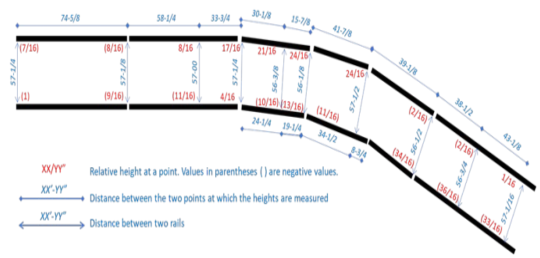
3.2 Defects of Track System

Rails are exposed to severe burdens from heavy traffic, high-speed, and the constant braking and acceleration of rail cars. Moreover, stresses become inevitable in various types of rail defects due to natural wear. The most frequently occurring rails defects are the horizontal split head, vertical split head, split web, bolt hole crack, and broken base. These defects were applied to the testbed for this study.

3.3 Design and Construction of a Testbed

A testbed was designed and built for the lab experiment based on the literature review on the railroad track system. Figure 2(a) shows defects created, such as missing fasteners, damaged crossties, and rail damage defects. Rail damaged defects were the cracks created on the head, web, and base of the rail. The track geometry of the testbed was also monitored. Figure 2(b) shows the track geometry recorded, which were gauge distance, track alignment, cross-level, and profile. Multiple experiments were conducted using the testbed to create an automated data collection system, including testing, and calibrating individual equipment and the whole system. Various camera settings were examined to find the optimal camera angle, frame per second (fps), and resolution while varying the test car's speed under different weather conditions to perform robust tests.

(a) defects on the testbed



(b) track geometry of the testbed

Figure 2: Testbed and simulated defects

4. Experiment Results

Video stream was recorded for each run of the test car during the lab test. The average length of the video streams is about 7 seconds. The GoPro setting was 2160*3840 at 30 fps, and the Sony setting was 1920*1080 at 60 fps. For the videos captured by the Sony camera, the texton filter bank method and unsupervised color-based clustering method described in Section 2.2 were used to segment tracks and sleepers. Figure 3 illustrates the 1st frame of a captured video and its texton filtering results. It can be seen that the 32nd to 35th filters yield the maximum responses for right and left tracks because their scales and orientations match the properties of the track in the image. For the videos captured by the GoPro cameras, the color clustering method was used directly to segment tracks because the GoPro videos have a much smaller depth of fields and much fewer background objects compared with Sony videos. After that, a gradient-based method was applied to detect defects automatically based on the segmented track and sleeper regions.

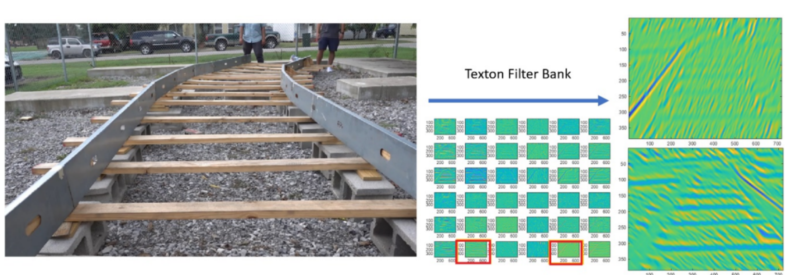


Figure 3: Texton filter bank for railroad track detection

Figure 4 shows the track and sleeper segmentation results of a Sony video captured at the testbed. The blue shaded regions are the segmented tracks, and the green shaded regions are segmented sleepers. Note that only tracks and sleepers that are close enough to the camera were segmented because they can provide clear and reliable image information. Figure 5 shows the track segmentation results of the left GoPro video and the right GoPro video at the testbed. The blue shaded regions are the segmented tracks. It can be seen that the proposed method worked well on the videos captured at the testbed. The tracks and sleepers were segmented efficiently. The defect detection results are shown in Figure 6. By combining the gradient information calculated from the images and the segmented track regions, the shape intensity changes can be detected as in the smooth track regions. All defects on the testbed were detected, and track geometry was measured accurately. The red boxes in Figure 6, highlighted two detected defects.

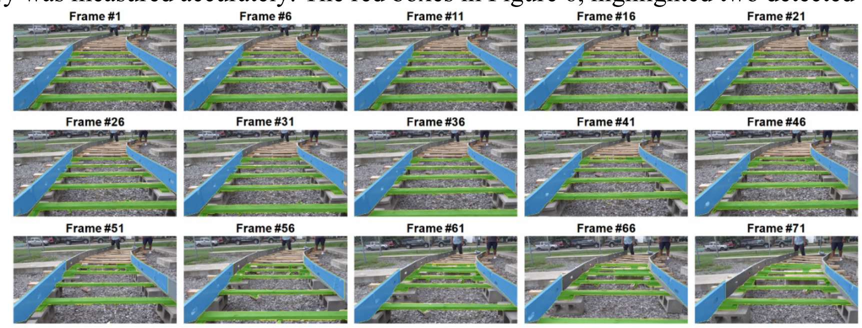
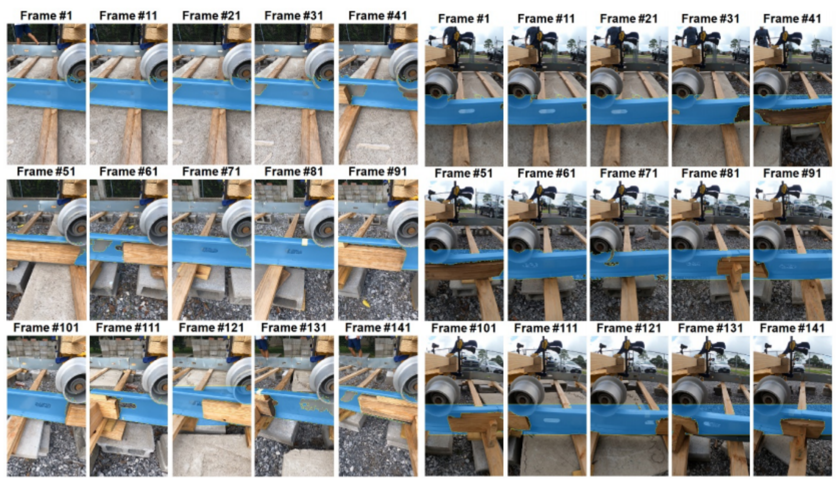


Figure 4: Track and sleeper segmentation based on the video captured by the Sony camera



(a) left rail (b) right rail

Figure 5: Track and sleeper segmentation based on the video captured by GoPro cameras

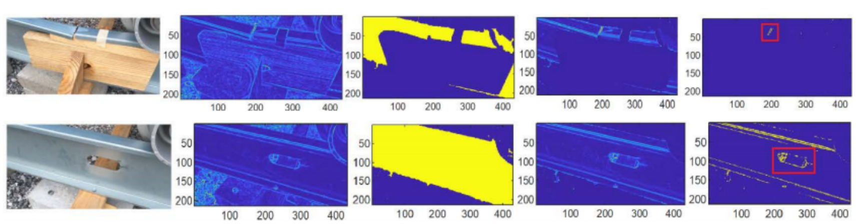


Figure 6: Gradient-based defect detection

5. Discussions and Conclusions

Healthy and resilient tracks are essential to the safe operation of railroad transportation. This present research proposed an AI-based method for detecting defects of railroad tracks. The present paper reported the early-stage results of an ongoing study, primarily discussing the ability of the proposed method in terms of detecting the targeted defects. The test results show that the developed method has the potential for enhancing the existing inspection practices by increasing the automation in detecting the targeted defects that can incur train derailments, such as rail damages, missing fasteners, and deteriorated crossties. The enhanced capacity for monitoring and inspecting tracks is expected to improve railroad maintenance and ultimately increase railway resiliency. The authors are currently undertaking additional analysis on the accuracy of measurement of the detected defect. Meanwhile, the need for further investigation in a few areas was recognized, including examination and analysis of the influence of dust and grease stains covering the track on detecting defects and reducing the interference of weather effect on the accuracy of video-based detection.

References

1. Kumar, Saurabh. “Study of rail breaks: associated risks and maintenance strategies.” Luleå Tekniska Universitet, 2006.
2. Liu, X., Saat, M. R., & Barkan, C. P. L. (2012). Analysis of causes of major train derailment and their effect on accident rates. Transportation Research Record, (2289), 154-163.
3. FRA Guide for Preparing Accident Incident Reports. FRA, U.S. Department of Transportation, 2011.
4. Rizvi, Aliza Raza, Pervez Rauf Khan, and Shafeeq Ahmad. "Crack Detection in Railway Track Using Image Processing." International Journal of Advance Research, Ideas and Innovations in Technology 3, no. 4 (2017): 489- 496.
5. Jiang, Junnan, Yu Zhou, Jie Zhang, and Shaofeng Wang. "Inspection Method for Track Components Defects based on Image Recognition in Subway System." In Challenges and Advances in Sustainable Transportation Systems, pp. 373-380. 2014.
6. Peng, Bo, Yang-sheng Jiang, and Yun Pu. "Review on automatic pavement crack image recognition algorithms." Journal of Highway and Transportation Research and Development (English Edition) 9, no. 2 (2015): 13-20.
7. Shah, Mubarak. "Automated visual inspection/detection of railroad track." Final Report, Computer Vision Lab, University of Central Florida (2010).
8. Stella, E., P. Mazzeo, M. Nitti, G. Cicirelli, A. Distante, and T. D'Orazio. "Visual recognition of missing fastening elements for railroad maintenance." In Proceedings. The IEEE 5th International Conference on Intelligent Transportation Systems, pp. 94-99. IEEE, 2002.
9. Feng, Hao, Zhiguo Jiang, Fengying Xie, Ping Yang, Jun Shi, and Long Chen. "Automatic fastener classification and defect detection in vision-based railway inspection systems." IEEE transactions on instrumentation and measurement 63, no. 4 (2013): 877-888.
10. Mandriota, Clelia, Massimiliano Nitti, Nicola Ancona, Ettore Stella, and Arcangelo Distante. "Filter-based feature selection for rail defect detection." Machine Vision and Applications 15, no. 4 (2004): 179-185.
11. Resendiz, Esther, John M. Hart, and Narendra Ahuja. "Automated visual inspection of railroad tracks." IEEE transactions on intelligent transportation systems 14, no. 2 (2013): 751-760.
12. Marino, Francescomaria, Arcangelo Distante, Pier Luigi Mazzeo, and Ettore Stella. "A real-time visual inspection system for railway maintenance: automatic hexagonal-headed bolts detection." IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews) 37, no. 3 (2007): 418-428.
13. De Ruvo, Pasquale, Arcangelo Distante, Ettore Stella, and Francescomaria Marino. "A GPU-based vision system for real time detection of fastening elements in railway inspection." In 2009 16th IEEE International Conference on Image Processing (ICIP), pp. 2333-2336. IEEE, 2009.
14. Faghih-Roohi, Shahrzad, Siamak Hajizadeh, Alfredo Núñez, Robert Babuska, and Bart De Schutter. "Deep convolutional neural networks for detection of rail surface defects." In 2016 International joint conference on neural networks (IJCNN), pp. 2584-2589. IEEE, 2016.
15. Santur, Yunus, Mehmet Karaköse, and Erhan Akin. "A new rail inspection method based on deep learning using laser cameras." In 2017 International Artificial Intelligence and Data Processing Symposium (IDAP), pp. 1-6. IEEE, 2017.
16. Gibert, Xavier, Vishal M. Patel, and Rama Chellappa. "Deep multitask learning for railway track inspection." IEEE transactions on intelligent transportation systems 18, no. 1 (2016): 153-164.
17. Falamarzi, Amir, Sara Moridpour, and Majidreza Nazem. "A review on existing sensors and devices for inspecting railway infrastructure." Jurnal Kejuruteraan 31, no. 1 (2019): 1-10.
18. Nakhaee, Muhammad Chenariyan, Djoerd Hiemstra, Mariëlle Stoelinga, and Martijn van Noort. "The recent applications of machine learning in rail track maintenance: A survey." In International Conference on Reliability, Safety, and Security of Railway Systems, pp. 91-105. Springer, Cham, 2019.