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Detection of Rail Surface Defects based on Axle Box Acceleration Measurements: A Measurement Campaign in Sweden

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Abstract. This work presents the results of a measurement campaign to demonstrate the effectiveness of the axle box acceleration (ABA) technology for detecting rail defects. The measurements were conducted along the Iron Ore line between Sweden and Norway for the IN2TRACK3 project. This line is mostly single-track with passenger-freight mixed traffic and heavy axle load. Historical data and track information data were not considered in this study. By analyzing data acquired from the accelerometers in vertical and longitudinal directions, rail defects were detected in near real-time using big-data analytics. For our validated sections, 100% of rail defects (including squats) were detected using time-frequency analysis and an outlier detection approach. The methodology also allows for identifying priority locations, e.g., defective welds, joints, transition zones, etc., and its use for prescriptive maintenance recommendations is being explored in the framework of the IAM4RAIL project.

Keywords: Rail defect detection, Rail monitoring, Rail surface defects, Axle-box acceleration, Intelligent railway infrastructure.

1 Introduction

Rail surface defects require great maintenance efforts, typically rail grinding, repair welding, or rail replacement. For light defects, grinding with a sufficient depth has the potential to remove them completely from the rail surface [13]. For severe defects, rail replacement or repair welding is needed as multiple grinding passages might not entirely remove them, leading to the re-appearing of the defect due to residual damages. As grinding is more cost- and performance-effective than rail replacement and repair welding, the effective management of light defects (those that can completely be removed by grinding) is needed to reduce maintenance costs. Further, managing defects (particularly severe defects) is also required to keep safety at adequate levels. To achieve adequate management, having an effective technology that is capable of timely detecting and frequently monitoring rail defects is of the utmost importance [9].

Various measurement technologies have been used for the detection of rail defects. Most of these technologies are suitable for reactive maintenance because, for instance, they detect defects when their crack length is rather high. In this work, we focus on axle box acceleration (ABA) technology, which allows frequent monitoring of the infrastructure as it can be mounted on trains in operation (without the need for dedicated measurement vehicles) and has reported capabilities for early-stage defect detection [1, 3, 6, 8].

The ABA technology has been tested in various countries by different infra-managers. The system used in this paper has been successfully tested in The Netherlands, UK, and Romania by TU Delft to assess the conditions of various railway components, e.g., fasteners [1], rails [3, 6, 8, 2, 5, 10], insulated joints [7], transition zones [11], and crossings [12]. As the ABA system has increased its technology readiness level, at this stage of development, assessing the robustness through extensive measurement and validation campaigns in different locations and under different measurement conditions is crucial for evaluating, improving, and achieving its large-scale application in Europe and worldwide.

2 Measurement campaign for rail defect detection

The measurement campaign was conducted on the Iron Ore Line between Lulea in Sweden and Narvik in Norway, from which five locations were selected to conduct track inspections and validation for the detection of the ABA measurements. A total of approximately 400 km of tracks were measured and analyzed almost in real-time for rail defect detection. The line is (mostly) single-track with passenger-freight mixed traffic and heavy axle load (up to 31 t). The measurement train ran two round trips along the line. No prior information about the location of defects and the type and location of railway assets was required.

The ABA measurement system can be implemented on various types of vehicles, including passenger trains. New generation trains are already equipped with smart sensing technologies, so it is expected in the near future to have massive amounts of condition data for the monitoring of the whole infrastructure. Within the same train, a localized acquisition system is installed for storing monitoring data, including ABA signals and positioning information. And, a wired connection based on cables is used for the data transmission.

3 Methodology

This campaign used the ABA measurements from the vertical and longitudinal directions to detect rail defects (including squats). The basic principle is to use a train as a moving load that excites the infrastructure and to detect defects by evaluating the time-frequency characteristics of the dynamic response measured by accelerometers installed on axle boxes. As small defects in their early development stage generate a rather short-duration impact on the wheel-rail interface, their characteristics are related to high-frequency responses. The sampling frequency of ABA measurements considered in this work was 25.6 kHz. A higher

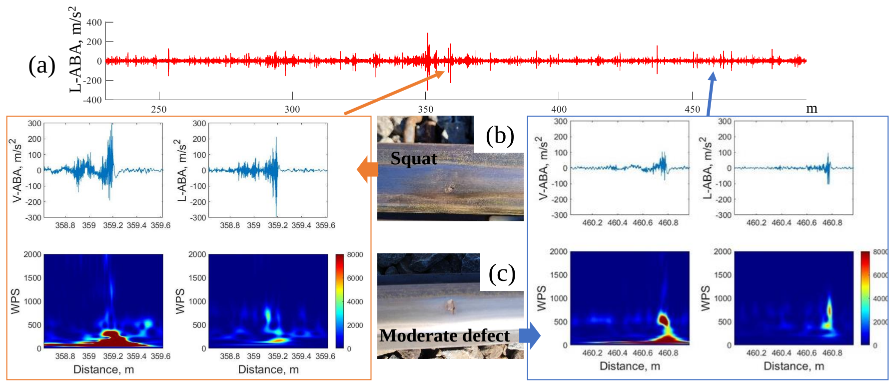

Fig. 1: Example of the ABA measurements of a rail portion from Location 1.

sampling rate is also needed because this is a moving sensor setup that requires a good set of data samples at each monitored location.

Fig. 1 illustrates an example of the measurement of a rail portion from Location 1 in which relatively high energy is observed in the signal, from which Fig. 1(b) shows a location of a squat, while Fig. 1(c) shows that of a rail defect. The figure shows vertical (V-ABA) and longitudinal (L-ABA) ABA signals of the first axle on the left rails and their corresponding wavelet power spectrum (WPS) energy. The WPS is obtained from the time-frequency analysis using the Morlet wavelet function to extract characteristic frequency responses. For this work, the frequency responses considered are between 200 and 2000 Hz. Based on the obtained variations of the WPS energy, the location of defects is determined by the automated detection algorithm. This algorithm is an outlier detection approach detecting energy variations beyond local average values.

In the field inspections, various measurement techniques are used, including visual inspection using cameras and geometry profile measurements using RailProf. Other measurements were conducted for future analysis, such as impact hammer tests, falling weight tests, pass-by measurements of track vibrations, and geometry measurements using a 3D scanner. You can see the demonstration campaign and a webinar at https://youtu.be/1Hw5Nqmmc0Q and https://youtu.be/8a362ghI_5A.

4 Results

We evaluate the effectiveness of the ABA method by comparing the results of the field inspections to the ABA data. Results indicate that the ABA system detects all squats and other moderate and severe defects in the five validated locations, demonstrating the capability of ABA for the detection of rail defects. All insulated joints are also detected. Photographs of some of the rail defects can be seen in Fig. 2.

Fig. 2: Photos of some squats and other defects from validated locations.

In the first two locations, a total of eight rail defects were found over a length of over 2 km. At the last three locations, 51 rail defects were found over a length of approximately 1.5 km. These differences occurred because locations 1 and 2 were selected without prior analysis of the ABA measurements, whereas locations 3, 4, and 5 were selected based on the first round of ABA measurements. As the ABA detection method can indicate locations with an impact excitation energy higher than average values with a certain threshold, it detected all insulated joints and some locations of welds and small defects. Healthy welds ideally should remain undetected to the ABA system or exhibit a subtle response. Detected welds suggest an existing deteriorating condition that is typically associated with the presence of rail defects. Thus, to differentiate between faulty welds and rail defects themselves is not required. The ABA method can then be used as an indicator for weld quality control.

Fig. 3 illustrates an example of a small defect located within the running band. Due to the nature of the defect, the ABA signals obtained from four different wheelsets of the two measurement runs do not always show a pronounced energy content in the ABA responses. This presents us with a dual challenge. On the one hand, we can adjust the threshold to a lower setting in order to detect small defects like the one shown in Fig. 3. On the other hand, it is important to consider that these small defects may be of a benign nature, implying that some of them are likely to be naturally eliminated through natural wear [4]. Therefore, there is a trade-off between setting the threshold and the number of benign defects detected. Some small defects may be expected to wear away naturally over time, while others that are consistently detected over time can be indicated as defects that are becoming more severe.

After the first ABA measurement is conducted, new measurements of defects and track components will update their condition and allow for assessing their growth rate. Also, new measurements can indicate the presence of new defects

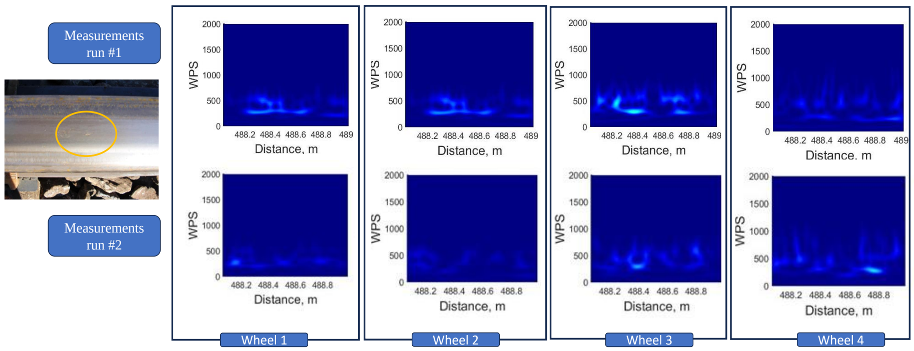

Fig. 3: Example of the ABA measurements at an undetected small defect, shown are the WPS obtained from the ABA signals in the vertical direction from all four wheelsets and two measurement runs.

or can be used to evaluate the effectiveness of maintenance actions, for instance, to determine the grinding depth that is effective for defects of certain severity.

5 Conclusion and outlook

In this paper, we report a demonstrator campaign for rail defect detection in a freight-dominated line. The ABA measurements have been evaluated with field measurements in a total of 5 locations in Sweden. Using time-frequency analysis and an outlier detection approach, 100% detection of squats and other moderate and severe defects is achieved. In the locations selected without using the ABA results, a total of 7 squats were found over a length of over 2 km. In the other locations that were selected for analysis, 46 squats were found over a length of approximately 1.5 km in total. This shows the potential of the use of ABA data to identify priority locations in track for maintenance actions. Moreover, the detection of moderate and severe defects was almost obtained in real-time. The evolution from early squats to moderate/severe ones is a slow process with low dynamics, and moderate and severe defects tend to grow faster due to the higher impact forces involved. Therefore, a real-time detection solution is recommended for severe defects as it is crucial to prevent rail breaks.

In this demonstrator campaign, we assumed that no information on railway assets and defects was available. As a suggestion for implementation and further research and development, the ABA system can be embedded into existing railway track information systems to continuously monitor the ABA energy at defects and components such as welds, S&Cs, insulated joints, transition zones, bridges, etc. With data analytics, information from those different data types can be extracted and integrated to synergize with the physical understanding of the ABA signals. The integrated information can then enhance the effectiveness and interpretability of the continuous monitoring of assets, particularly to update the status of rail surface defects.

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References

1. Chen, J., Liu, Z., Wang, H., Nunez, A., Han, Z.: Automatic defect detection of fasteners on the catenary support device using deep convolutional neural network. IEEE Transactions on Instrumentation and Measurement **67**, 257–269 (2018)
2. Gibert, X., Patel, V., Chellappa, R.: Deep multitask learning for railway track inspection. IEEE Transactions on Intelligent Transportation Systems **18**, 153–164 (2017)
3. Li, Z., Molodova, M., Núñez, A., Dollevoet, R.: Improvements in axle box acceleration measurements for the detection of light squats in railway infrastructure. IEEE Transactions on Industrial Electronics **62**, 4385–4397 (2015)
4. Li, Z., Molodova, M., Zhao, X., Dollevoet, R.: Squat treatment by way of minimum action based on early detection to reduce life cycle costs. Proceedings of the 2010 ASME Joint Rail Conference Apr. 27-29, Urbana, Illinois, USA **1**, 305–311 (2010)
5. Liu, P., Liu, S., Yu, C., Gu, L., Zhou, Y., Zhao, C., Huang, Z.: Quantitative evaluation of the rotational stiffness of rail cracks based on the reflection of guided waves. Intelligent Transportation Infrastructure **1**, 1–12 (2022). Liac008
6. Molodova, M., Li, Z., Núñez, A., Dollevoet, R.: Automatic detection of squats in railway infrastructure. IEEE Transactions on Intelligent Transportation Systems **15**, 1980–1990 (2014)
7. Molodova, M., Oregui, M., Núñez, A., Li, Z., Dollevoet, R.: Health condition monitoring of insulated joints based on axle box acceleration measurements. Engineering Structures **123**, 225–235 (2016)
8. Phusakulkajorn, W., Hendriks, J.M., Moraal, J., Dollevoet, R.P.B.J., Li, Z., Nunez, A.: A multiple spiking neural network architecture based on fuzzy intervals for anomaly detection: a case study of rail defects. IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), Padua, Italy **2022**, 1–8 (2022)
9. Phusakulkajorn, W., Núñez, A., Wang, H., Jamshidi, A., Zoeteman, A., Ripke, B., Dollevoet, R., Schutter, B.D., Li, Z.: Artificial intelligence in railway infrastructure: Current research, challenges, and future opportunities. Intelligent Transportation Infrastructure **liad016**, 1–24 (2023)
10. Song, Z., Yamada, T., Shitara, H., Takemura, Y.: Detection of damage and crack in railhead by using eddy current testing. Electromagnetic Analysis and Applications **3**, 546–550 (2011)
11. Unsiwilai, S., Wang, L., Núñez, A., Li, Z.: Multiple-axle box acceleration measurements at railway transition zones. Measurement **213**, 1–21 (2023). 112688
12. Wei, Z., Núñez, A., Li, Z., Dollevoet, R.: Evaluating degradation at railway crossings using axle box acceleration measurements. Sensors **17**, 2236 (2017)
13. Zhu, H., Li, H., Al-Juboori, A., Wexler, D., Lu, C., McCusker, A., McLeod, J., Pannila, S., Barnes, J.: Understanding and treatment of squat defects in a railway network. Wear **442-443**, 1–9 (2020). 203139