

Proceedings of the Sixth International Conference on Railway Technology: Research, Development and Maintenance Edited by: J. Pombo Civil-Comp Conferences, Volume 7, Paper 2.9 Civil-Comp Press, Edinburgh, United Kingdom, 2024 ISSN: 2753-3239, doi: 10.4203/ccc.7.2.9 ©Civil-Comp Ltd, Edinburgh, UK, 2024

Track Management Method Based on In-Service Vehicle Vibration Measurements

H. Tsunashima and T. Nakano

College of Industrial Technology, Nihon University Narashino, Japan

Abstract

It is becoming increasingly difficult for regional railways in Japan to carry out adequate track management due to a lack of manpower and a deteriorating business environment. In response to these problems, a system has been developed to monitor track conditions by installing a sensing device on in-service trains and measuring car body vibration. However, the acceleration measured on the car body is affected by the condition of the track as well as the running speed, making it difficult to determine the threshold required for track management. This paper proposes a method for automatically calculating threshold values for determining outliers by setting a significance level using a chi-square distribution for the measured car body acceleration. The proposed method is applied to actual measured acceleration on a regional railway in Japan, and the results show that the proposed method is effective for practical use.

Keywords: railway, track, irregularity, condition monitoring, in-service vehicle, Chisquare distribution.

1 Introduction

It is important to maintain railway tracks to mitigate deterioration caused by deformation and damage. To achieve this, railway operators must monitor the condition of the track regularly and undertake maintenance work based on manual inspections by track maintenance staff and measurements by track inspection vehicles. However, these methods are expensive in terms of personnel and equipment costs, making it difficult for regional railways to conduct sufficient track management.

In response to these problems, a track management method was developed to monitor track conditions. The method involves measuring the car body vibrations with a sensing device on an in-service train, and using these vibrations to diagnose track defects. Although this method enables the assessment of track degradation by the magnitude of vibration acceleration, it requires a reference value for maintaining tracks and is considered only a supplementary method.

When considering car body vibrations for track management, it is necessary to set reference values for car body vibrations. However, because the condition of the track, including its deterioration level, varies between locations and train speed, it is not possible to set a uniform reference value.

This paper proposes a method for automatically calculating threshold values for determining outliers by setting a significance level using a chi-square distribution for the measured car body acceleration.

2 Track condition monitoring using in-service vehicle

2.1 Literature review on track condition monitoring using in-service vehicle

2.1.1 Track condition monitoring using an in-service vehicle

Track maintenance and management is based on measured track displacement data. However, track displacement measurements require expensive equipment, such as track inspection vehicles and measuring devices. Therefore, a more economical management method is required, particularly for the regional railways.

In addition to displacement measurement, other track management methods also exist, for example, train vibration inspection using in-service vehicle vibration measurement [1].

2.1.2 Axle-box mounted sensors

The relationship between axle-box accelerations and railway track defects or irregularities has been analysed [2–4]. By applying an onboard detection technique to commercial high-speed trains, the acceleration of the axle box of a high-speed train was evaluated [5]. Chudzikiewicz *et al.* demonstrated the possibility of estimating the track condition by using axle-boxes and car body motions described by acceleration signals [6].

2.1.3 Bogie mounted sensors

Some track faults were detected by measuring the acceleration of the bogies. Weston *et al.* demonstrated track irregularity monitoring by using bogie-mounted sensors [7]. Malekjafarian *et al.* investigated the use of drive-by-train measurements for railway track monitoring [8].

2.1.4 Car body mounted sensors

Tsunashima *et al.* developed a system to identify track faults using accelerometers and GNSS placed on the car body of in-service vehicles [9–13]. Bai *et al.* used low-cost accelerometers placed on or attached to the floors of operating trains to analyse track condition [14]. Track condition monitoring based on bogie and car body acceleration measurements was presented and verified [15]. Balouchi presented a cab-based track-monitoring system [16].

2.1.5 Signal processing

Several non-model-based and model-based techniques have been proposed to extract signals on faulty tracks from measured vehicle vibrations. Tsunashima proposed a non-model-based technique using time-frequency analysis [11].

A Kalman-filter-based method was proposed to estimate the track geometry of Shinkansen tracks from car body motions [17]. The proposed method was modified and applied to conventional railways [18]. Tsunashima proposed a classifier based on machine-learning techniques to automatically identify track faults from the measured car-body vibrations [10]. Another method that automatically classifies the type and degradation level of track faults has also been proposed. In this method, a convolutional neural network is used for imaging car body acceleration on a time-frequency plane by applying CWT [12].

2.1.6 Smartphones based system

Chellaswamy *et al.* proposed a method for monitoring railway track irregularities by updating the status of tracks in the cloud [19]. Rodríguez *et al.* proposed the use of mobile applications to assess the quality and comfort of railway tracks [20]. Cong *et al.* proposed using a smartphone as a sensing platform to obtain real-time data on vehicle acceleration, velocity, and location [21]. Paixão *et al.* proposed using smartphones to perform constant acceleration measurements inside in-service trains, which can complement the assessment of the structural performance and geometrical degradation of the tracks [22]. A track condition monitoring system for use on a smartphone was developed for regional railways in Japan [23].

2.2 Track condition monitoring system

Track inspection vehicles are used to measure track displacement. Track management, which is based on track displacement measurements performed by major railway companies, is crucial to control track irregularities such as longitudinal level, alignment, gauge, cross level, and twist (depicted in Figure 1).



Figure 1: Track structure and irregularities.

However, it is difficult for regional railway companies to introduce track inspection vehicles owing to their high costs. Moreover, manual inspections by track maintenance staff are inefficient and expensive.

Figure 2 shows the track condition monitoring system implemented on regional railway lines in Japan [9]. Accelerometers and rate gyros in the onboard sensing device measure the car body vibrations. A global navigation satellite system (GNSS) receiver detects the train speed and location. The collected data are continuously transmitted to the data server at the monitoring centre via a mobile phone network. The diagnostic software analyses the collected data, and the results are fed back to railway operators through online channels via tablet computers. The diagnostic results obtained are used to facilitate maintenance work for railway operators.

The car body vibrations are correlated significantly with the track irregularity. Therefore, the single-sided maximum amplitude of vibration in a 10-m-long section is calculated based on the measured car body vibration acceleration and then utilised in the evaluation. The single-sided maximum amplitude used as a feature value is the absolute value of half the amplitude of the highest vibration acceleration in this section.

We investigated the locations where the large car body vertical acceleration was measured on a regional railway line inside an in-service train equipped with a sensing



Figure 2: Track condition monitoring system.

device. The results are shown in Figure 3.

Figure 4 shows the change in acceleration at the points where large car body vertical acceleration was observed between the EF section (8.35 km to 8.50 km) from October 2016 to December 2023. The vertical axis represents the maximum value of the vertical acceleration, and the horizontal axis represents the date of measurement. To evaluate long-term changes in the track, one maximum value of the car body vertical acceleration in a 10-m-long section was extracted and plotted for each run of data. The figure shows that the vertical acceleration gradually increases with time, indicating that the track condition deteriorates. Owing to the general inspection of vehicles and software updates of onboard sensing devices, almost no data were obtained during some periods.

The sudden drop in vertical acceleration indicates the effect of track maintenance on 28 August 2021. The long-term trend of track condition deterioration can be determined by continuously measuring the car body vertical acceleration. For track maintenance using car body vertical acceleration, criteria are required to determine whether the measured acceleration is normal. However, setting the threshold for acceleration is very difficult because acceleration is significantly affected by running speed. We propose a method for determining when track maintenance should be performed, using the data shown in the figure 4.



Figure 3: Locations where high accelerations were observed (2016/09–2023/12).



Figure 4: Changes in maximum car body vertical acceleration between the EF section (8.35 km and 8.50 km).

3 Method of evaluating track condition

3.1 Chi-square distribution

We propose a method for evaluating track conditions using the chi-square test. The chi-square test is widely used for fault detection.

The chi-square variable is written in the general form as

$$\chi_k^2 = \sum_{i=1}^k \left(\frac{x_i - \mu_i}{\sigma_i}\right)^2,\tag{1}$$

where n is the number of observations, x_i is the observed variable, μ_i is the expected value, σ_i is the standard deviation, and k is the number of degrees of freedom.

The chi-square distribution has a single parameter, the degrees of freedom (k), which influences the shape and spread of the distribution, as shown in Figure 5.



Figure 5: Chi-square distribution.

3.2 Fault detection of track condition

To determine the outliers using the chi-square distribution, the following indices were defined to evaluate the track condition based on the observed vertical acceleration:

$$a(x_i) = \left(\frac{x_i - \mu}{\sigma}\right)^2,\tag{2}$$

where x_i is the measured acceleration, μ is the expected value of dataset, σ is the standard deviation of the dataset.

If the significance level are 0.05, 0.01, 0.005 when the degree of freedom is unity, the threshold of probability distribution are 3.84, 6.63, 7.88, respectively.

3.3 Application examples

3.3.1 Example 1

We examined the proposed method for measured car body acceleration between the EF section (8.35 km to 8.50 km) from October 2016 to August 2023. In the training dataset shown in Figure 6, the acceleration gradually increases over time, indicating that the track conditions deteriorate. In particular, the acceleration dropped sharply after 28 August 2021, indicating the effect of maintenance work. As the acceleration was approximately 5 $[m/s^2]$, maintenance work was performed considering the possible risk of derailment. When conducting track management using the vehicle vertical acceleration, it is necessary to use a training dataset to detect track faults and clarify when maintenance work should be performed.



Figure 6: Measured acceleration between EF stations (8.35 km to 8.50 km) from October 2016 to August 2023.

Figure 7 shows the histogram of $a(x_i)$ and the chi-square distribution with one degree of freedom (solid red line) of the training data. The histogram shows that $a(x_i)$ is concentrated at small values, indicating a low probability of occurrence of large values. It can also be observed that the chi-square curve and histogram are in good agreement. Because the chi-square distribution is used to determine outliers, a threshold value of 3.84 is obtained when the significance level is set at 0.05.

Figure 8 shows the time variation of the index, $a(x_i)$, calculated from the measured car body vertical acceleration; outliers exceeding the threshold value of 3.84 were detected after 1 March 2020. Thereafter, the outliers increased rapidly, suggesting a rapid deterioration of the track condition. Although track maintenance should have been performed immediately, it was delayed until August 28, 2021. This resulted in a period of nearly one year during which a large car body vertical acceleration occurred, which was considered a safety problem.

Figure 9 shows the change in acceleration at the location where a large vehicle body

Figure 7: Distribution of $a(x_i)$ on training dataset.

Figure 8: Outlier detection on training dataset.

vertical acceleration was observed in the training dataset. On 1 March 2020, a vertical acceleration of 2.82 $[m/s^2]$ was measured. Therefore, a track management plan can be developed for this section of the track, with the threshold value for maintenance management set at 2.82 $[m/s^2]$.

Figure 9: Determination of threshold value for maintenance.

3.3.2 Example 2

Figure 10 shows the change in acceleration at locations where a large vehicle body vertical acceleration was observed between the NO section (26.3 km to 26.45 km) from October 2016 to December 2023. In the training dataset, the vertical acceleration increased over time, indicating deteriorating track condition. In particular, the vertical acceleration dropped sharply after track maintenance on 3 March 2019, indicating the effect of maintenance work. After track maintenance on 3 March 2019, the vertical acceleration increased again, indicating that the track condition deteriorated. Therefore, we used the training dataset to evaluate track conditions and determine when maintenance work should be performed.

Figure 11 shows the histogram of $a(x_i)$ and the chi-square distribution with one degree of freedom (solid red line) for the data after 3 March 2029. The means and standard deviations were obtained from the training dataset. The figure shows that the chi-squared curve and histogram are almost identical. As in Example 1, the significance level for outlier determination was set to 0.05. Therefore, a threshold value of 3.84, which was less than 5% of the probability distribution, was used to detect outliers.

Figure 12 shows the trends in $a(x_i)$ over time; an outlier above the threshold value was detected on 8 September 2021. Therefore, track maintenance should have been

Figure 10: Measured acceleration between NO stations (26.3 km to 26.45 km) from October 2016 to December 2023.

Figure 11: Distribution of $a(x_i)$ for the acceleration data after 3 March 2029.

carried out immediately; however, as of December 2023, no maintenance has been carried out. Therefore, track maintenance must be performed immediately.

Figure 13 shows the change in the measured car body vertical acceleration. An acceleration of $3.67 [m/s^2]$ was measured on 8 September 2021. This suggests that a threshold of 3.67 $[m/s^2]$ is appropriate for track management in this section of the track.

Figure 12: Outlier detection for the acceleration data after 3 March 2029.

4 Conclusions

A track management method based on the car body vertical acceleration was proposed for regional railways. By applying a chi-square distribution to the measured vertical acceleration and defining the significance level, the reference values required for track management can be automatically calculated. This helped determine when track maintenance should be performed, thereby contributing to the safety of regional railways. The proposed method should be implemented over a long duration to analyse its effectiveness in performing track maintenance.

Acknowledgements

This research was funded by JSPS KAKENHI Grant Number 20K04368.

Figure 13: Determination of threshold value for maintenance.

References

- P. Weston, C. Roberts, G. Yeo, E. Stewar, "Perspectives on railway track geometry condition monitoring from in-service railway vehicles", Vehicle System Dynamics, 53(7), 1063-1091, 2015.
- [2] X. Chen, X. Chai, X. Cao, "The time-frequency analysis of the train axle box acceleration signals using empirical mode decomposition", Computer Modelling and New Technologies, 18(7), 356-360, 2014.
- [3] T. Karis, M. Berg. S. Stichel, M. Li, D. Thomas, and B. Dirks, "Correlation of track irregularities and vehicle responses based on measured data", Vehicle System Dynamics, 56:6, 967-981, 2018.
- [4] H. C. Tsai, C. Y. Wang, N. E. Huang, T. W. Kuo and W. H. Chieng, "Railway track inspection based on the vibration response to a scheduled train and the Hilbert-Huang transform", Proc IMechE Part F: J Rail and Rapid Transit 2014;0(0), 1-15. 2014.
- [5] X. Sun, Y. Fei, J. Shi, K. Zaitian and Z. Yunlai, "On-Board Detection of Longitudinal Track Irregularity", IEEE Access, Volume 9, 14025-1437, 2021.
- [6] A. Chudzikiewicz, R. Bogacz, M. Kostrzewski and R. Konowrocki, "Condition monitoring of railway track systems by using acceleration signals on wheelset axle-boxes", Transport, Volume 33(2), 555-566, 2019.
- [7] P. Weston, C. Ling, C. Goodman, C., Roberts, P. Li and R. Goodall, "Monitoring vertical track irregularity from in-service railway vehicles", Proc IMechE Part F: J Rail Rapid Transit, 221, 75-88, 2007.
- [8] A. Malekjafarian, E. Obrien, P. Quirke and C. Bowe, "Railway Track Monitoring Using Train Measurements: An Experimental Case Study", Appl. Sci., 9, 4859, 2019.

- [9] H. Tsunashima, H. Mori, M. Ogino and A. Asano, "Development of Track Condition Monitoring System Using Onboard Sensing Device", In: Zboinski, K. (ed.). Railway Research; IntechOpen; 2015.
- [10] H. Tsunashima, "Condition Monitoring of Railway Tracks from Car-Body Vibration Using a Machine Learning Technique", Appl. Sci. 9(13) 2734; 2019.
- [11] H. Tsunashima and R. Hirose, "Condition monitoring of railway track from carbody vibration using time–frequency analysis", Vehicle System Dynamics, 60:4, 1170-1187, 2020.
- [12] H. Tsunashima and M. Takikawa, "Monitoring the Condition of Railway Tracks Using a Convolutional Neural Network", In: Bulnes, R. (ed.). Recent Advances in Wavelet Transforms and Their Applications, IntechOpen, 2022.
- [13] H. Tsunashima, H. Ono, T. Takata, S. Ogata, "Development and Operation of Track Condition Monitoring System Using In-Service Train", Applied Sciences, 13(6):3835, 2023.
- [14] L. Bai, R. Liu and Q. Li, "Data-Driven Bias Correction and Defect Diagnosis Model for In-Service Vehicle Acceleration Measurements", Sensors, 20, 872, 2020.
- [15] X. Wei, F. Liu, L. Jia, "Urban rail track condition monitoring based on in-service vehicle acceleration measurements", Measurement, Volume 80, February, 217-228, 2016.
- [16] F. Balouchi, A. Bevan and R. Formston, "Development of railway track condition monitoring from multi-train in-service vehicles", Vehicle System Dynamics, 59(9), 1397-1417, 2021.
- [17] H. Tsunashima, Y. Naganuma and T. Kobayashi, "Track geometry estimation from car-body vibration", Vehicle System Dynamics, 52(sup1), 207-219, 2014.
- [18] M. Odashima, S. Azami, Y. Naganuma, H. Mori and H. Tsunashima, "Track geometry estimation of a conventional railway from car-body acceleration measurement", Mechanical Engineering Journal, 4(1), JSME, Paper No.16-00498, 2017.
- [19] C. Chellaswamy, T. S. Geetha, A. Vanathi and K. Venkatachalam, "An IoT based rail track condition monitoring and derailment prevention system", International Journal of RF Technologies 11, IOS Press, 81-107, 2020.
- [20] A. Rodríguez, S. Sanudo, M. Miranda, A. Gomez and J. Benavente, "Smartphones and tablets applications in railways, ride comfort and track quality", Transition zones analysis, Measurement 182, 2021.
- [21] J. Cong, M. Gao, M., Miranda, Y. Wang, R. Chen and P. Wang, "Subway rail transit monitoring by built-in sensor platform of smartphone", Frontiers of Information Technology & Electronic Engineering, 21(8), 2020.
- [22] A. Paixão, E. Fortunato and R. Calçada, "Smartphone's Sensing Capabilities for On-Board Railway Track Monitoring: Structural Performance and Geometrical Degradation Assessment". Advances in Civil Engineering, 2019.
- [23] H. Tsunashima, R. Honda, and A. Matsumoto, "Condition Monitoring Based on In-Service Train Vibration Data Using Smartphones", IntechOpen, Jan. 24, 2024.