Chapter

Track Condition Monitoring Based on In-Service Train Vibration Data Using Smartphones

Hitoshi Tsunashima, Ryu Honda and Akira Matsumoto

Abstract

Although track maintenance is important, many operators of regional railway with limited financial resources are unable to conduct sufficient track inspections. In response to this problem, a track condition diagnosis system using car-body vibration sensors has been developed. In this study, a track condition monitoring system using a smartphone for general use has been developed. A technique for identifying train location using global navigation satellite system (GNSS) speed is proposed. The results of field testing shows that track condition diagnosis is possible using a smartphone-based monitoring system.

Keywords: railway, track, condition monitoring, wavelet transform, Hilbert-Huang transform, smartphone

1. Introduction

Railway track management helps support and guide wheels and is very important in terms of comfort and safety. Track management is usually carried out by track maintenance workers and usually uses track geometry cars. However, these methods are labor-intensive and costly, and many operators cannot carry out sufficient track inspections of regional railways due to limited financial resources. To address this problem, a track diagnosis system using an exclusive onboard sensing device has been developed [1–5].

Currently, track maintenance and management on railways is based on measured data of track displacement. However, track displacement measurement requires expensive equipment such as track inspection vehicles and measuring devices. A more economical management method is required, especially for regional railways. Other methods of track management exist in addition to displacement measurement, e.g., train vibration inspection using vehicle vibration measurement, but none of them constitutes a fundamental inspection method such as track displacement inspection owing to the low reproducibility of measurement data.

Meanwhile, recent advances in the practical use of IoT devices such as smartphones incorporating accelerometers based on microelectro mechanical systems (MEMS) have been reported. These devices can be used as simple and inexpensive vehicle vibration measurement devices. Many studies on track monitoring systems using vehicle vibration measurement with such IoT devices were conducted.

In this study, a track condition monitoring system for use on a smartphone was developed to reduce the cost of such a system. Using two types of IoT devices for business use and a commercially available smartphone, we took measurements of an actual car, compared the performance of both IoT devices, and diagnosed the condition of the track.

2. Literature review on track condition monitoring based on in-serve train vibration

2.1 Track condition monitoring from an in-service vehicle

Track maintenance and management on the railway is based on measured data of track displacement. However, track displacement measurement requires expensive equipment such as track inspection vehicles and measuring devices. A more economical management method is required, especially for regional railways.

Other methods of track management exist in addition to displacement measurement, e.g., train vibration inspection using in-service vehicle vibration measurement [6, 7]. Many studies on track monitoring systems using in-service vehicle vibration measurement with on-board sensing devices were conducted both in Japan and abroad.

2.2 Axle-box-mounted sensors

Chen *et al.*, Karis *et al.*, and Tsai *et al.* analyzed the relation between axle-box accelerations and railway defects or irregularities [8–10].

Sun *et al.* proposed an on-board detection technique for longitudinal track irregularity that can be applied to commercial high-speed trains. The acceleration of the axle-box of the high-speed train was evaluated [11].

Chudzikiewicz *et al.* demonstrated the possibilities of estimating the track condition using axle-boxes and car-bodies motions described by acceleration signals. They presented the preliminary investigation on the test track and supervised runs on Polish Railway Lines of an Electric Multiple Unit (EMU-ED74), [12].

2.3 Bogie-mounted sensors

Some types of track faults were detected by measuring the acceleration of bogies. Weston *et al.* demonstrated track irregularity monitoring by using bogie-mounted sensors [13, 14].

Malekjafarian *et al.* investigated the use of drive-by train measurements for railway track monitoring on the Dublin-Belfast line with an in-service Irish Rail train. The measurements were taken with accelerometers and a global positioning system. They used the train bogie accelerations [15].

2.4 Car-body-mounted sensors

Tsunashima *et al.* developed a system to identify track faults by using accelerometers and GNSS placed on the car-body of in-service vehicles [1–5].

Bai *et al.* used low-cost accelerometers that were placed on or attached to the floors of operating trains for analyzing track quality [16].

A track condition monitoring based on the bogie and car-body acceleration measurements was presented and verified in Shang Hai metro Line 1 [17].

Balouchi presented a cab-based track monitoring system developed in the UK. They presented through comparison of vibration response from sites with known defects and outputs from Network Rail's New Measurement Train (NMT). Good agreement was reported for track faults in relation to vertical and lateral alignment and dip faults [18].

2.5 Signal processing

To extract a signal on faulty tracks from measured vehicle vibration, several techniques using nonmodel-based and model-based method were proposed.

Tsunashima *et al.* proposed a nonmodel-based technique using time-frequency analysis [4]. In this paper, detection performance using continuous wavelet transform (CWT) and Hilbert-Huang transform (HHT) were compared for identifying track faults from car-body vibration. They showed that track fault features can be identified in the time-frequency plane based on the analysis of simulation studies and field tests.

A Kalman filter-based method to estimate the track geometry of Shinkansen tracks from car-body motions was proposed [19]. The proposed Kalman filter-based estimation technique was modified and applied for conventional railways [20].

Tsunashima proposed a classifier based on machine learning techniques for identifying track faults automatically from measured car-body vibration [3]. It is shown that the degradation of track can be classified in the feature space consists of car-body vibration RMS.

A new method for automatically classifying the type and degradation level of track faults using a convolutional neural network (CNN) by imaging car-body acceleration on a time-frequency plane by continuous wavelet transform [5].

2.6 Smartphones-based system

Chellaswamy *et al.* proposed a method for monitoring the irregularities in railway tracks by updating the status of the tracks in the cloud. The IoT based Railway Track Monitoring System (IoT-RMS) is proposed for monitoring the health of the railway track [21].

Rodríguez *et al.* presents the use of mobile applications to assess the quality and comfort of a railway section track (narrow gauge) in northern Spain [22].

Cong *et al.* proposed an approach for using the smartphone as a sensing platform to obtain real-time data on vehicle acceleration, velocity, and location for monitoring the track condition during subway rail transit in China [23].

Paixão *et al.* presented an approach to use smartphones to perform constant acceleration measurements inside in-service trains to complement the assessment of the structural performance and geometrical degradation of the tracks. To demonstrate the applicability of smartphone's sensing capabilities for on-board railway track monitoring, they evaluated the accelerations inside the car-body of the Portuguese Alfa Pendular passenger train [24].

3. Constructing the track diagnosis system

3.1 Track irregularities and track faults

Major private railway companies and Japan Railways (JR) use track inspection vehicles to measure track displacement, and track management is based on such measurements. Track irregularities such as longitudinal level, alignment, gauge, cross level, and twist (depicted in **Figure 1**) should be controlled properly.

However, it is difficult for regional railway companies to introduce track inspection vehicles because of the cost. Moreover, manual inspection by track maintenance staff is inefficient and expensive.

3.2 Overview of track management with proposed system

Figure 2 depicts the track management method used in this study. A 3-axis accelerometer mounted on a smartphone was used to measure the vibration of the car-body, a 3-axis Gyro sensor was used to measure the angular acceleration, and a GNSS sensor was used to collect information about the position and traveling speed; all data are then transmitted to the server. By analyzing the transmitted data, the condition of the track can be diagnosed, and, based on the result, railway operators can prioritize track maintenance and work.

3.3 Measurement devices

A BL-02 IoT device for business use (hereafter referred to as Device B) and a commercial smartphone Galaxy S7-edge (hereafter referred to as Device G) were used for measurements. **Figure 3** shows a photograph of these devices, and **Table 1** details their specifications.

Both devices were equipped with a 3-axis accelerometer, a 3-axis Gyro sensor, a GNSS sensor that can determine the location and traveling speed, and 4G internet, which is required for data transmission and reception.

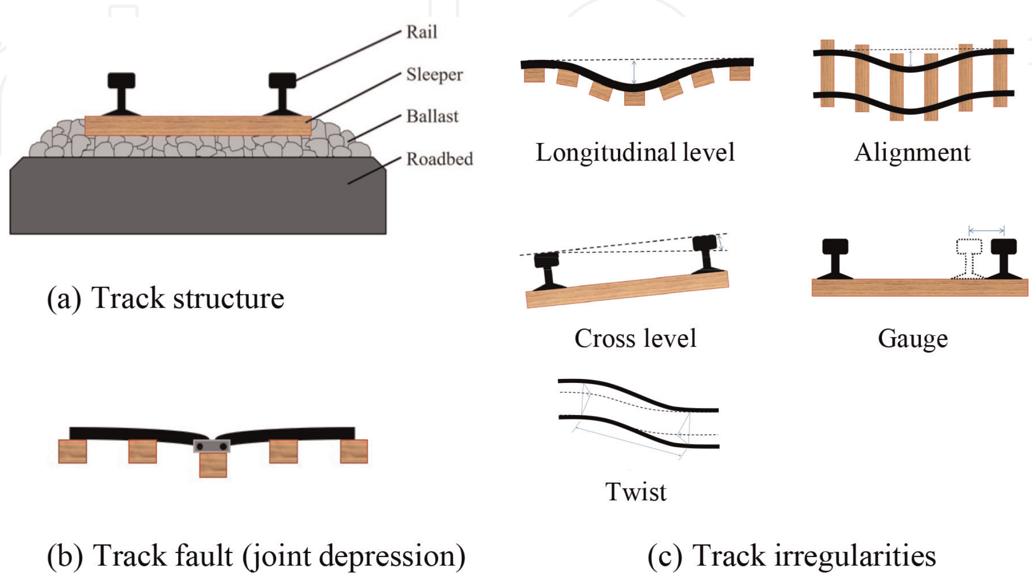

Figure 1.
Track structure and irregularities ([5]).

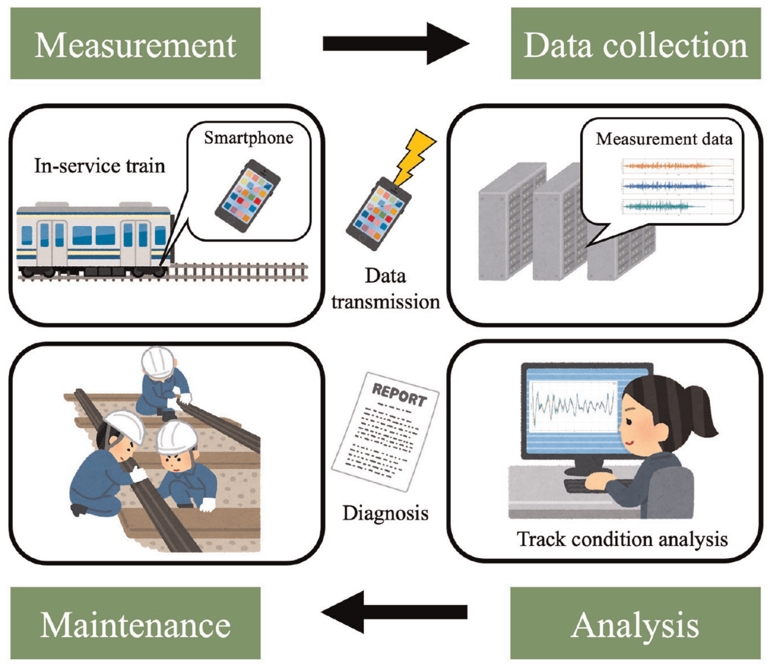

Figure 2.
Track condition management using car-body vibration.

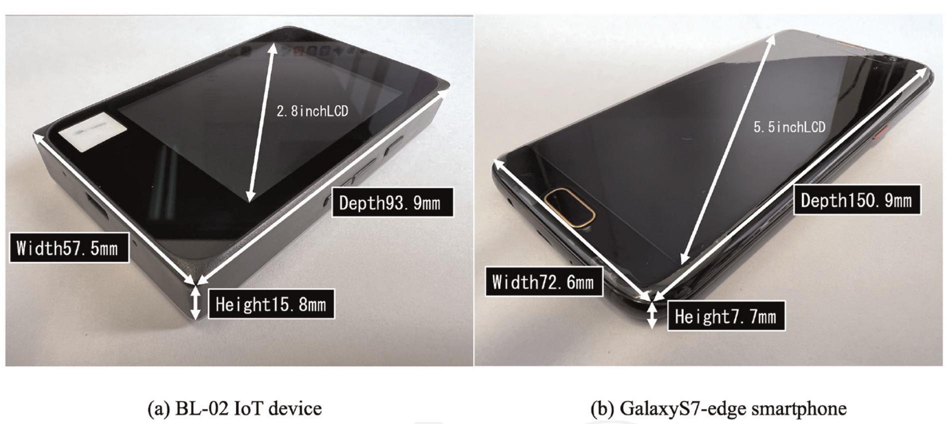

Figure 3.
Appearance of the BL-02 IoT device for business use and the GalaxyS7-edge smartphone for general use.

IoT Devices	Device B: BL-02	Device G: GalaxyS7-edge
CPU	Cortex-A7	Snapdragon820
OS	Android6.0	Andorid6.0
Display	2.8inch	5.5inch
Sensor	3-axis accelerometer, 3-axis Gyro sensor, GNSS sensor	3-axis accelerometer, 3-axis Gyro sensor, GNSS sensor
Sampling frequency	232 Hz	417 Hz
Size	94 × 58 × 16 mm	151 × 73 × 8.3 mm
Weight	102 grams	158 grams

Table 1.
Specifications of the device B and the device G.

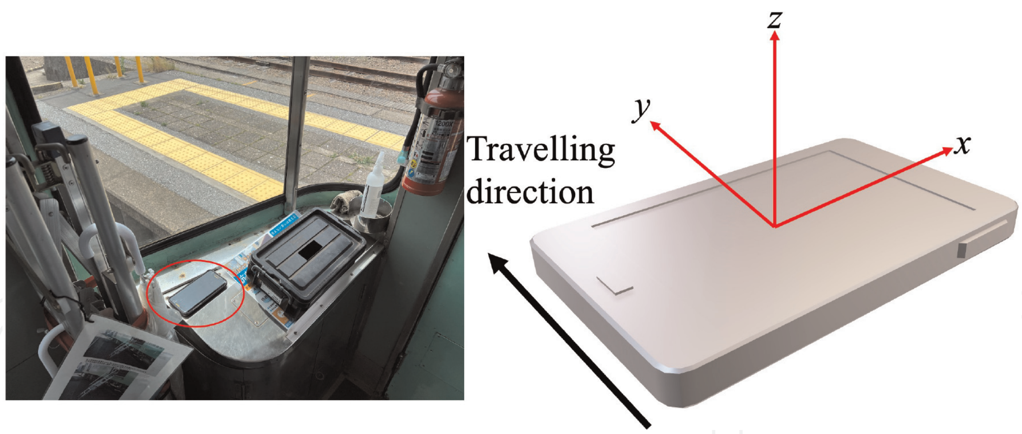

Figure 4.
Location of measurement devices.

At the time of measurement, data from Device B were measured at 232 Hz and data from Device G were measured at 417 Hz; both were down-sampled to 80 Hz at the time of acquisition from the server to reduce the amount of processing required for analysis.

Using these devices, we can measure and diagnose the vibration of the car-body. Considering convenience and GNSS reception environment, we installed the smartphone near the driver's cab, as shown in **Figure 4**.

3.4 Identifying the areas of interest from the vibration measurements

Smartphones are able to acquire latitude and longitude information; however, location detection errors increase when methods such as map matching are not employed. Therefore, we adopted a method to calculate the milage using the GNSS speed, which was, in turn, calculated using the Doppler effect of the GNSS carrier wave.

4. Verification of measurement data

4.1 Verification of vibration and angular velocity data

Figure 5 shows the measurements from Devices B and G installed on an actual car on Regional Railway A (line length: 30.5 km, Stations:17, Max. speed: 85 km/h) in December 2021. The data from both devices are almost identical in phase and amplitude.

Figure 6 shows the power spectral density (PSD) of the vertical acceleration of the vehicle. The frequency characteristics of both devices were consistent, and we can conclude that they yield sufficient accuracy as onboard sensing devices.

4.2 Identification of train location

4.2.1 Comparison of GNSS speeds

Identifying the location of a train is important for track management. In this system, the location of a train, D, is identified by integrating measured GNSS speed using a following equation.where $v_{GNSS}(t)$ is the measured GNSS speed.

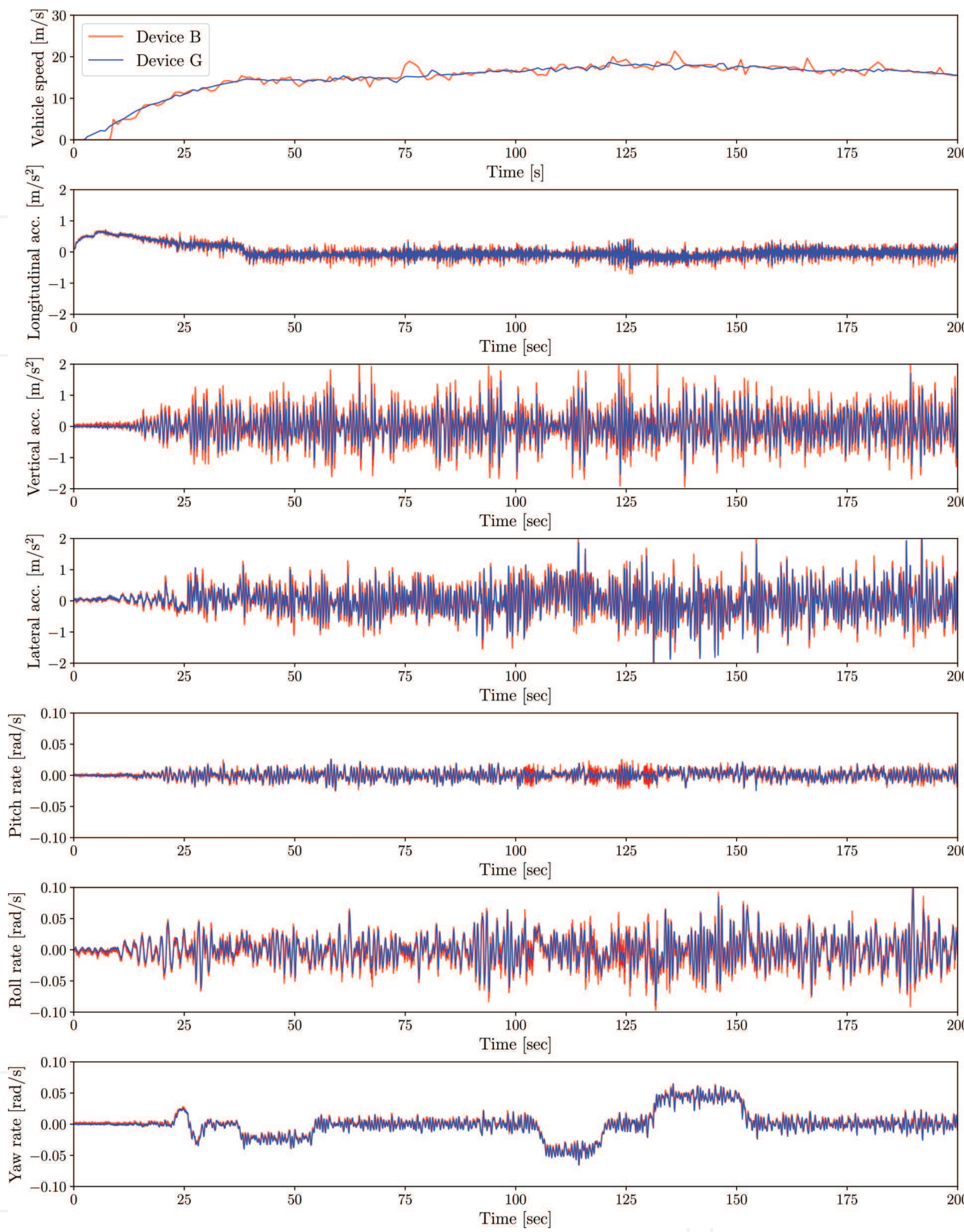

Figure 5.
Measured car-body vibration with Device B and Device G.

$$D = \int v_{GNSS}(t)dt, \quad (1)$$

The measured GNSS speed was shown in **Figure 7**. It should be noted that the measured GNSS speed was affected by multipath errors. Multipath is a major error source for GNSS receivers [25].

The location of a train can be estimated as shown in **Figure 8** using the measured raw GNSS speed. The location data are affected by the number of satellite navigation systems supported by the device. Device B supports few satellite positioning systems

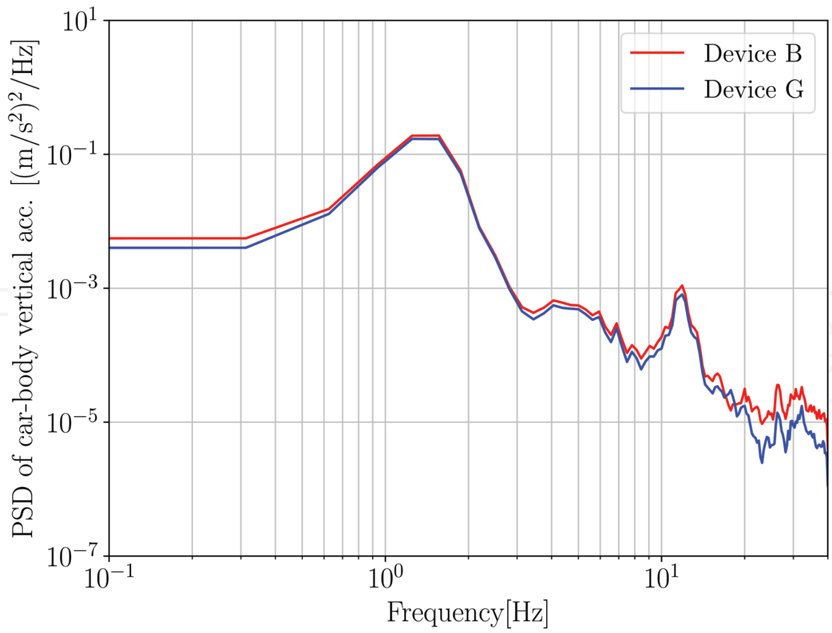

Figure 6.
Power spectral density (PSD) of measured car-body vertical acceleration by Device B and Device G.

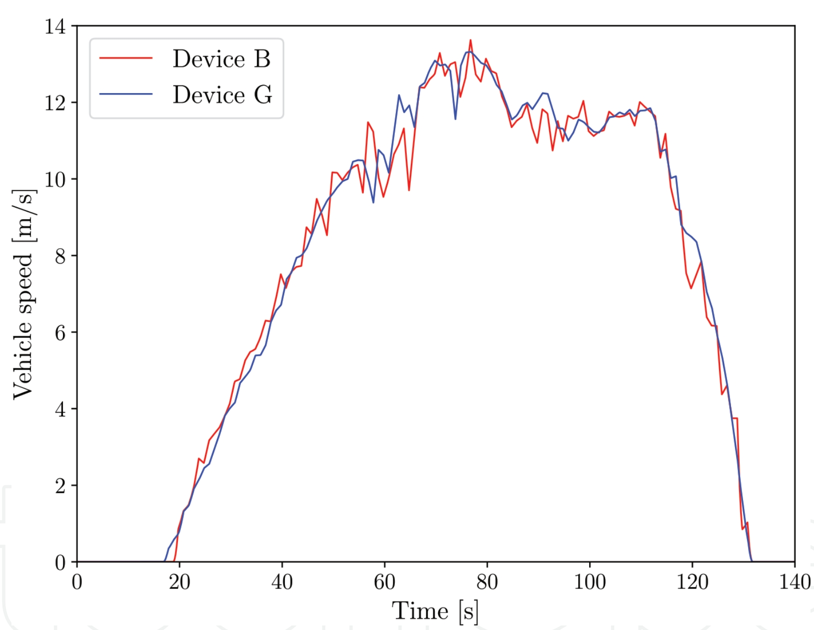

Figure 7.
Measured GNSS speed.

and is not compatible with A-GPS; therefore, the number of satellites it receives information from differs to that of Device G, and it is considered to be more susceptible to multipath errors.

We used a correction process that used a median filter for the GNSS speeds affected by multipath errors. By performing median filter processing with a window size of 800 data for approximately 5 seconds, and taking into account the magnitude of the effect of the multipath errors, we were able to improve the rapid decrease in speed due to multipath errors of the GNSS speeds measured by Device B, as shown in **Figure 9**.

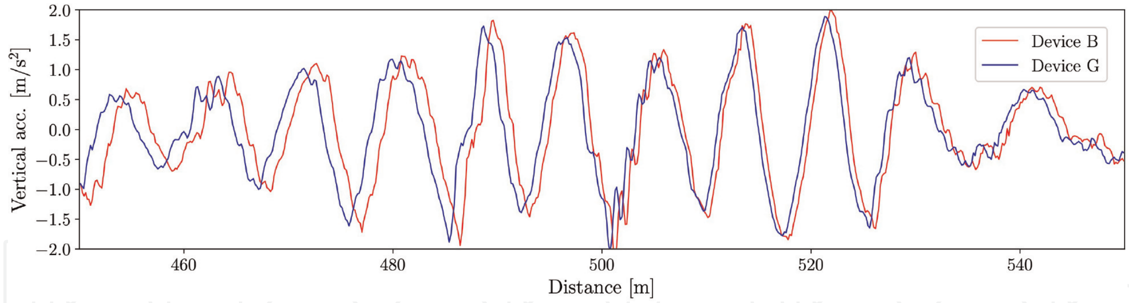

Figure 8.
Measured car-body vertical acceleration and vehicle location without GNSS speed filtering.

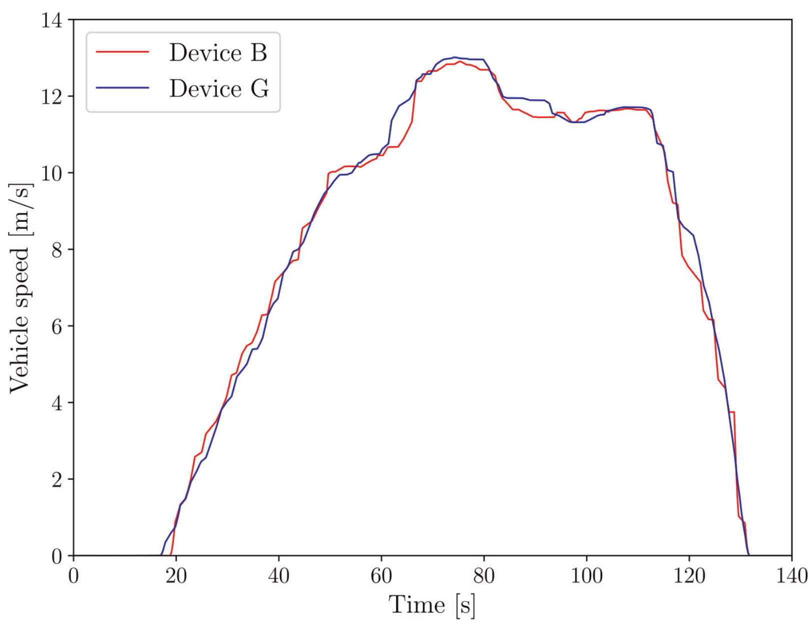

Figure 9.
Median filtered GNSS speed.

In addition, to evaluate the effect of the median filter processing on the accuracy of the location identification, we investigated the relationship between the vehicle location obtained by integrating the GNSS speeds and that obtained using the car-body vertical acceleration, as shown in **Figure 10**.

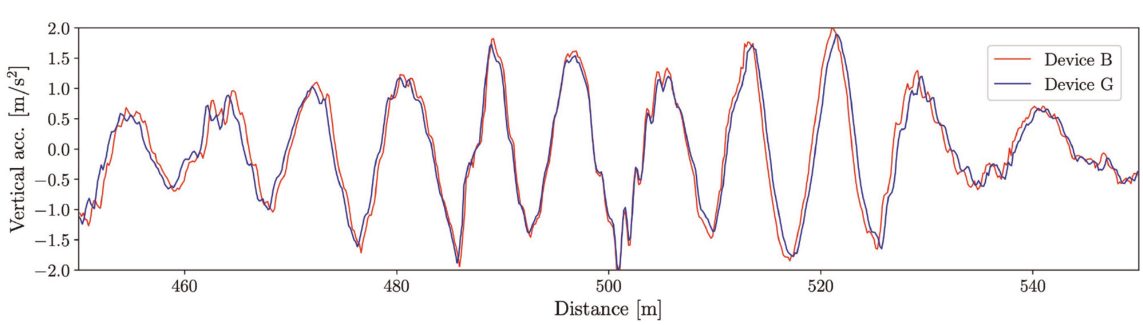

Figure 10.
Measured car-body vertical acceleration and vehicle location with GNSS speed filtering.

This figure shows that the position error is greatly improved between 450 and 550 m, which is a section that is particularly affected by multipath errors.

5. Track condition diagnosis using time-frequency analysis

5.1 Effect of track faults on time-frequency plane

5.1.1 Continuous wavelet transform (CWT)

The wavelet transform is well-known technique for analyzing nonstationary signals [26, 27]. A CWT gives simultaneous detection of the frequency and time characteristics for a nonstationary signals using a wavelet ψ, which is a function of zero average:

$$\int_{-\infty}^{\infty} \psi(t)dt = 0. \tag{2}$$

The CWT is calculated using the mother wavelet $\psi(t)$ as

$$W_{\psi}(a,b) = \int_{-\infty}^{\infty} \frac{1}{\sqrt{a}} \psi^{*}\left(\frac{t-b}{a}\right) x(t)dt, \tag{3}$$

where a and b correspond to the dilatation and location parameters, respectively.

Eq. (3) translates a source signal $x(t)$ using the mother wavelet transformed by a time shift b in time, and by $1/a$ in frequency. ψ^{*} indicates the complex conjugate of ψ.

In this study, the *Morlet* wavelet, which has a good performance between localization of time and frequency, was used [5, 28].

The CWT is subject to the uncertainty principle on time-frequency domain. In case of fault detection using CWT, if we are focusing on frequency related on the fault, the time when the fault occurred will be vague. If we are focusing on the time when the fault occurred, the frequency will be spread widely on the time-frequency plane.

5.1.2 Hilbert-Huang transform (HHT)

The Hilbert-Huang transform (HHT) has been proposed for analyzing nonlinear and nonstationary data by Huang *et al.* [29]. This method is not subject to the uncertainty principle on time-frequency domain mentioned above. Thus, more localized fault detection is possible.

The HHT consists of two operations. The first operation is the empirical mode decomposition (EMD) and the second operation is Hilbert transform.

The EMD operation breaks time domain data into intrinsic oscillatory modes called intrinsic mode functions (IMFs). The second operation is the Hilbert transform. Instantaneous amplitude, instantaneous phase, and instantaneous frequency of the IMFs are obtained by the Hilbert transform.

An IMF must satisfy the following requirements: (1) the number of local extrema and the number of zero crossings must either equal or differ by at most one. (2) the mean value of the envelopes of local maxima and local minima is zero at any point.

For extracting IMFs from the original signal, the iterative sifting process is applied. Once the first IMF is calculated, it is subtracted from the original signal to obtain a residual value. The EMD operation is applied again to the residual. This process repeats until the residual no longer contains any oscillation modes.

The original signal, $s(t)$, can be expressed by EMD operation as:

$$s(t) = \sum_{i=1}^{m} x_i(t) + R(t), \tag{4}$$

where $x_i(t)$ is the ith IMF and $R(t)$ is a residual.

Followed by the EMD operation, the analytical signal $z_i(t)$ is constructed on each IMFs component by:

$$z_i(t) = x_i(t) + jy_i(t) = a_i(t)e^{j\theta_i(t)}, \tag{5}$$

where $y_i(t)$ is a Hilbert transform of $x_i(t)$ calculated by:

$$y_i(t) = \frac{1}{\pi}\mathrm{PV}\int_{-\infty}^{\infty} \frac{x_i(t)}{t-\tau}d\tau, \tag{6}$$

where PV shows Cauchy principal value.

Instantaneous amplitude, $a_i(t)$, and instantaneous frequency, $\omega_i(t)$, can be obtained from the analytical signal $z_i(t)$ as:

$$a_i(t) = \sqrt{x_i(t)^2 + y_i(t)^2}, \tag{7}$$

$$\omega_i(t) = \frac{d\theta_i(t)}{dt}, \tag{8}$$

where

$$\theta_i(t) = \tan^{-1}\left(\frac{y_i(t)}{x_i(t)}\right). \tag{9}$$

This data-driven method is highly adaptive. However, intrinsic mode functions (IMFs) obtained by EMD strongly depend on the data itself. Thus, a small change in the data will appear on different decomposition level.

5.2 Track condition diagnosis for regional railway lines

5.2.1 Regional railway A

Time-frequency analysis was performed on the measured data to identify and evaluate the detailed location and type of track fault. When a train runs on a track where a fault exists, characteristic vibration corresponding to the type of track fault occurs. Therefore, one could identify the type of track fault and location of its occurrence by analyzing the time-frequency plane of measured car-body vertical acceleration.

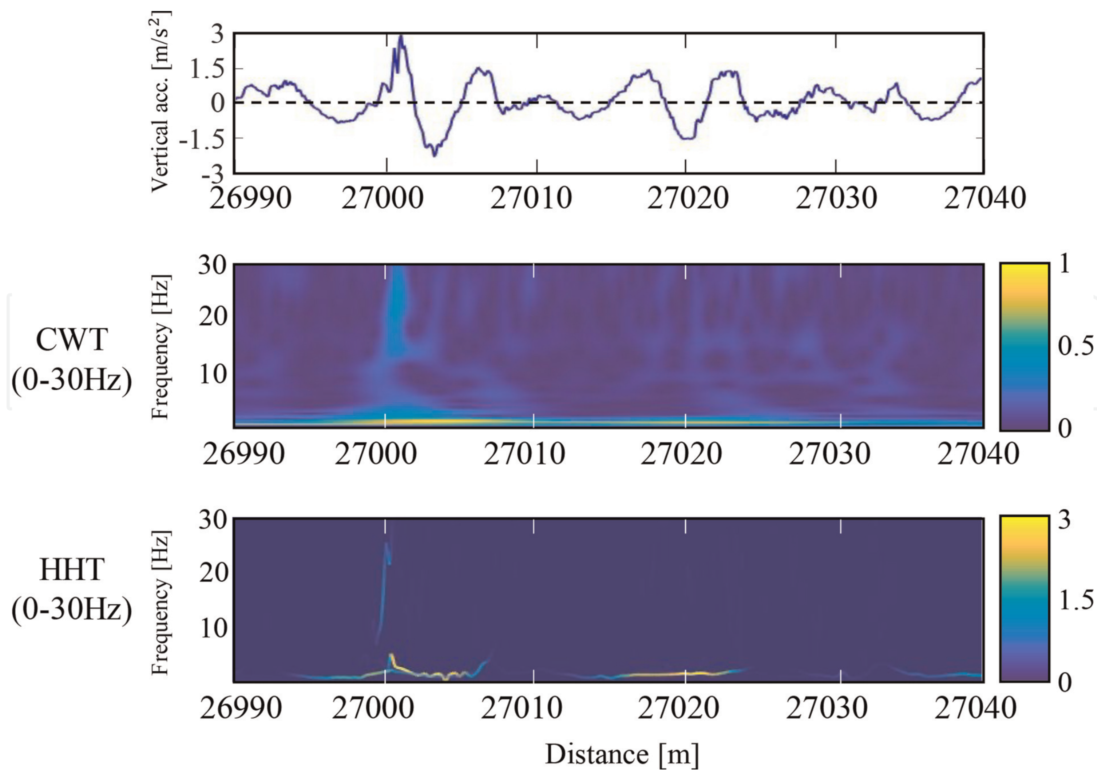

Figure 11.
Time-frequency analysis of date measured in December 23, 2021 in railway A.

Figure 11 shows the time-frequency analyses, CWT and HHT of data measured in December 23, 2021 in Railway A (line length: 30.5 km, Stations:17, Max. speed: 85 km/h). The data used for this analysis are data measured using Device G.

It can be seen from **Figure 11** that a high-frequency vibration appeared at 27000 m, which was caused by the joint depression [4]. Whereas a large vibration can be seen in low frequency in a 27,015–27,025 m section. This is caused by longitudinal-level track irregularities.

5.2.2 Regional railway B

Figures 12 and **13** show the time-frequency analyses, CWT and HHT of data measured in June and October 2022, respectively. In June 2022, vibrations due to longitudinal-level irregularity were detected at 1–2 Hz between 600 and 700 m but were no longer detected in October 2022 due to track irregularity correction. The data used for this analysis are data measured using Device G on Regional Railway B (line length: 6.4 km, Stations: 8, Max. speed: 40 km/h) in June 2022 and October 2022.

Figure 14 displays a photograph of the track section between 600 and 700 m in October 2022; the ballast was newly replenished, line maintenance work was carried out, and the longitudinal-level irregularity was eliminated. Thus, by performing time-frequency analysis using data measured by a smartphone, the type and location of track fault can be identified, and the effects of track irregularity correction can be confirmed.

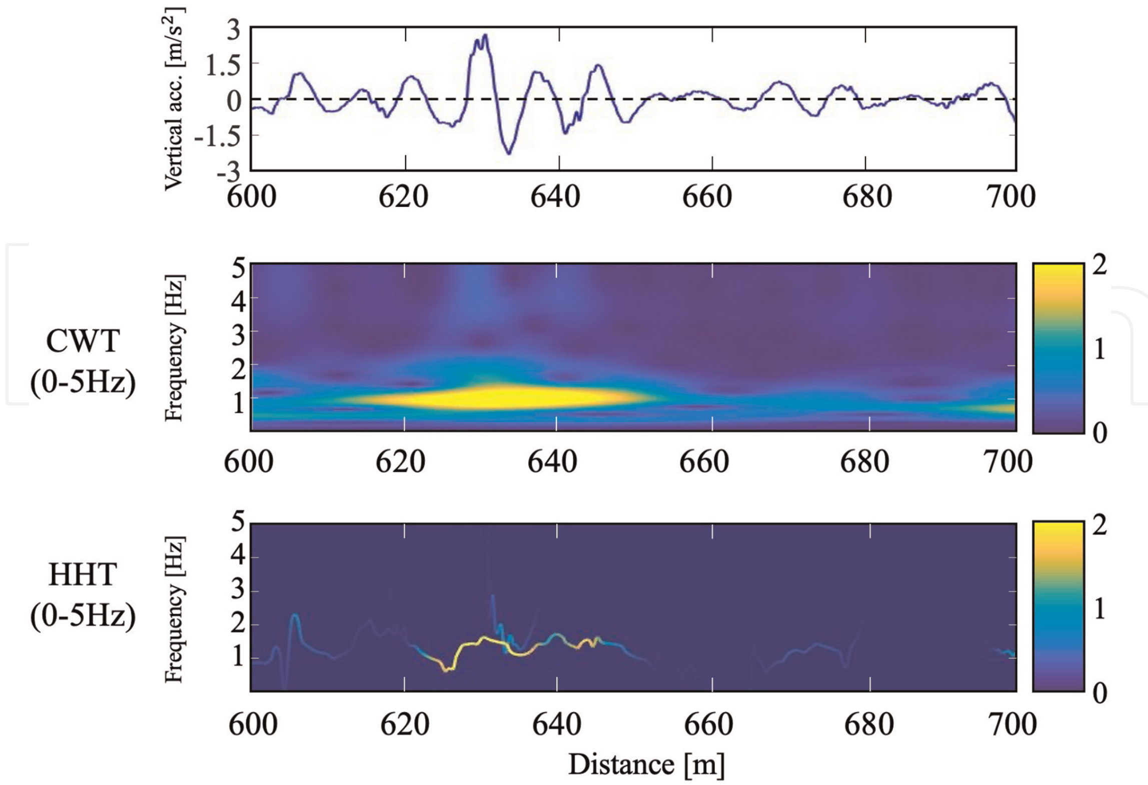

Figure 12.
Time-frequency analysis of date measured in June 2022 in railway B.

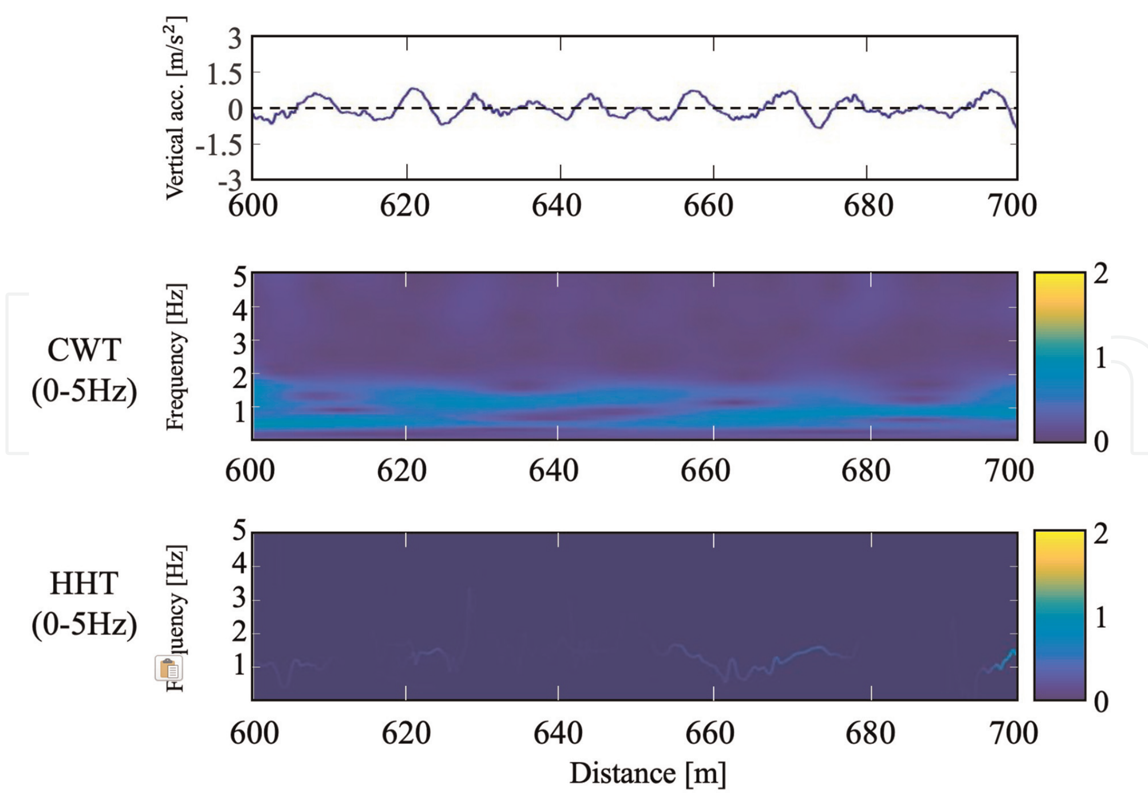

Figure 13.
Time-frequency analysis of date measured in October 2022 in railway B.

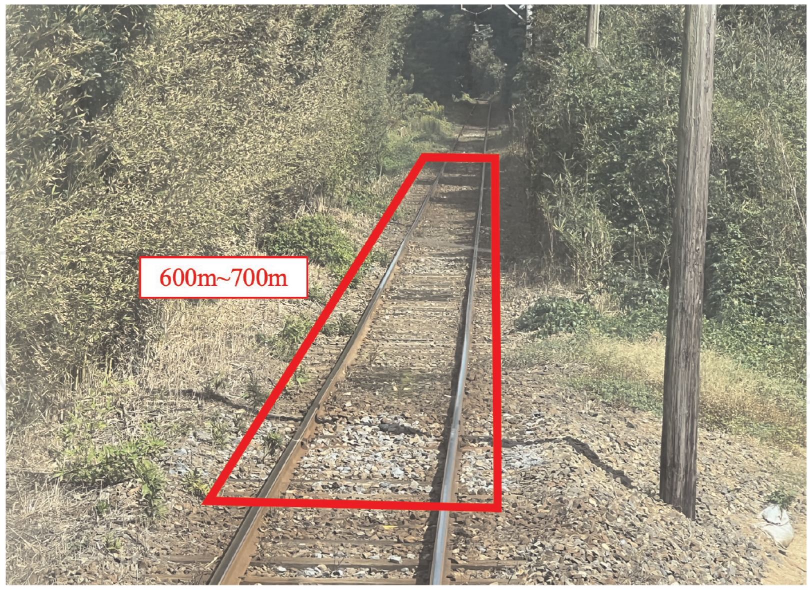

Figure 14.
Section where track maintenance work done.

6. Conclusion

In this study, we measured the car-body vibration of an in-service train using a smartphone and verified whether the track condition could be diagnosed. We were able to monitor and diagnose the track condition using both the IoT device for business use and the commercially available smartphone.

The accuracy of the GNSS speed, which is necessary to identify the location of the train, was reduced by the number of satellites received by the smartphone, that is, by the number of compatible satellite positioning systems. Therefore, when selecting a smartphone, the number of supported satellite positioning systems must be considered. In addition, we determined that the performance of devices susceptible to multipath errors can be improved by performing median filtering on the GNSS speed.

Time-frequency analysis of measured car-body acceleration obtained by a smartphone shows that proper diagnosis of track condition is possible using smartphone-based track condition monitoring system.

In the future, we plan to acquire data on a continuous basis and conduct track condition diagnosis.

Acknowledgements

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Conflict of interest

The authors declare no conflict of interest.

Abbreviations

CWT	continuous wavelet transform
HHT	Hilbert–Huang transform
GNSS	global navigation satellite system
MEMS	microelectro mechanical systems
IoT	internet of things
RMS	root mean square
EMD	empirical mode decomposition

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