Frontiers of Information Technology & Electronic Engineering
www.jzus.zju.edu.cn; engineering.cae.cn; www.springerlink.com
ISSN 2095-9184 (print); ISSN 2095-9230 (online)
E-mail: jzus@zju.edu.cn

Subway rail transit monitoring by built-in sensor platform of smartphone*

Jian-li CONG[1,2], Ming-yuan GAO[3,4], Yuan WANG[‡5], Rong CHEN[1,2], Ping WANG[1,2]

[1]*School of Civil Engineering, Southwest Jiaotong University, Chengdu 610031, China*
[2]*Key Laboratory of High-speed Railway Engineering, Ministry of Education, Chengdu 610031, China*
[3]*College of Engineering and Technology, Southwest University, Chongqing 400716, China*
[4]*National & Local Joint Engineering Laboratory of Intelligent Transmission and Control Technology, Chongqing 400716, China*
[5]*School of System Design and Intelligent Manufacturing, Southern University of Science and Technology, Shenzhen 518055, China*
E-mail: jlcong2019@my.swjtu.edu.cn; gaomingyuan@swu.edu.cn; wangy39@sustech.edu.cn;
chenrong@home.swjtu.edu.cn; wping@home.swjtu.edu.cn

Received May 13, 2019; Revision accepted Jan. 3, 2020; Crosschecked June 19, 2020

Abstract: Smartphone, as a smart device with multiple built-in sensors, can be used for collecting information (e.g., vibration and location). In this paper, we propose an approach for using the smartphone as a sensing platform to obtain real-time data on vehicle acceleration, velocity, and location through the development of the corresponding application software and thereby achieve the green concept based monitoring of the track condition during subway rail transit. Field tests are conducted to verify the accuracy of smartphones in terms of the obtained data's standard deviation (SD), Sperling index (SI), and International Organization for Standardization (ISO)-2631 weighted acceleration index (WAI). A vehicle-positioning method, together with the coordinate alignment algorithm for a Global Positioning System (GPS) free tunnel environment, is proposed. Using the time-domain integration method, the relationship between the longitudinal acceleration of a vehicle and the subway location is established, and the distance between adjacent stations of the subway is calculated and compared with the actual values. The effectiveness of the method is verified, and it is confirmed that this approach can be used in the GPS-free subway tunnel environment. It is also found that using the proposed vehicle-positioning method, the integral error of displacement of a single subway section can be controlled to within 5%. This study can make full use of smartphones and offer a smart and eco-friendly approach for human life in the field of intelligent transportation systems.

Key words: Acceleration signals; Smart monitoring; Embedded sensors; Smartphones; Subway
https://doi.org/10.1631/FITEE.1900242 **CLC number:** U216.3

1 Introduction

1.1 Background

By the end of 2018, a total of 34 cities in mainland China had opened urban rail transit, with a total operating mileage of greater than 5766 km, of which the subway operation mileage was about 4354 km (Wang YF et al., 2018). As the operating mileage and service life of the track structure increase, the damage to the track structure continues to increase (Zhao et al., 2015). It is difficult to detect abnormal conditions in real time through traditional manual inspections and regular track inspections, posing a threat to operational safety. Therefore, it is necessary to use online monitoring to ensure the safety of trains and passengers (Chellaswamy et al., 2017; Gao et al., 2019).

In the railway system, vibration is caused by the interaction between wheel and rail (Gao et al., 2017,

‡ Corresponding author

* Project supported by the National Natural Science Foundation of China (Nos. 51425804 and U1734207) and the National Key R&D Program of China (No. 2016YFC0802203-4)

ORCID: Jian-li CONG, https://orcid.org/0000-0001-8909-7715; Yuan WANG, https://orcid.org/0000-0001-5952-1298

2018), and it not only influences the environment along the rail line but also leads to uncomfortable experience of passengers (Griffin, 2007). The measurement and evaluation of vehicle vibration are therefore of significant importance, and various studies in this context have already been conducted. Griffin (2007), Molodova et al. (2014), and Wang P et al. (2017) have reviewed the measurement, evaluation, and assessment of vehicle vibration considering the sensations and responses of people. Furthermore, the acceleration measured on a running vehicle is also related to the state of the railway track. The worse the track's state, the more severe the acceleration (Gao et al., 2020). Long-term records of acceleration, including vehicle acceleration, bogie acceleration, and axle box acceleration, can effectively predict the state of the railway track, such as track geometry irregularities (Tsunashima et al., 2014; Wang Y et al., 2018), corrugation (Jin et al., 2006), and rail damages (Kaynia et al., 2017).

At present, the state inspection method of subway lines in mainland China is mainly a combination of manual inspection and regular track inspection; however, power supply is a major issue limiting spot monitoring (Zhou and Zuo, 2018; Huang et al., 2019, 2020; Yang et al., 2019). Manual inspection is time-consuming, and the detection accuracy is highly dependent on the experience and skills of the staff, which means low efficiency and high error rate; although regular inspection is based on a fixed inspection schedule, it uses dedicated detection equipment with high cost, and the data are stored offline, which means poor data traceability. Both manual inspection and regular track inspection are not conducive to the sustainable development of the subway rail transit.

However, the measurement of accelerations of an operating vehicle is not always an easy job, especially in the urban rail transit system. Wei et al. (2013) measured the vehicle acceleration for monitoring the condition of railway tracks, but using such a measurement system is too costly and inconvenient. Other approaches are aimed only at the measurement of vehicle acceleration. In the high-speed railway system, the so-called train vibration analyzer (TVA) is used to measure and analyze vehicle vibration. However, the problem of high cost and poor adaptability limits the application of TVA in urban rail transit. In addition, the vibration evaluation process fails to take into account the special characteristics of urban rail transit, i.e., the fact that the vehicle is constantly accelerating and braking.

With the development of software and hardware technologies, smartphones have become popular in recent years. Smartphones are involved in all aspects of human social life and have greatly promoted the quality of human life. Smartphones with built-in accelerometers, gyroscopes, magnetometers, microphones, and other sensors offer an integrated sensing platform. Development of related application software and data-processing algorithms is the only contribution needed to implement the enabling, data recording, and analysis of each built-in sensor, which can thereafter be used for online monitoring of subway rail transit (to obtain real-time information, such as acceleration of the vehicle body, angular velocity of the vehicle body, and interior noise during train operation). The smartphone itself is mature, cost-effective, and easy to implement, providing a basis for the development of related applications. It is, therefore, a smart approach to use smartphones to accomplish online monitoring of subway rail transit. It can reduce the cost of subway operation, store the data online, improve the efficiency and intelligence of maintenance work, and also improve the stability and safety of subway operations. These factors constitute the main motivation of this paper. Fig. 1 illustrates the proposed solution for the online monitoring of subway tracks by vehicle-carried smartphones.

1.2 Related work

Currently, smartphones have a variety of high-quality sensors and powerful data-processing capabilities. Reading and recording sensor detection data in real time can be accomplished by installing dedicated application software, and the measured data can be used in various application scenarios, such as intelligent transportation, environmental monitoring, health care, and human activity recognition (Lane et al., 2010; Wang SQ et al., 2010; Ruiz-Zafra et al., 2015), as shown in Table 1.

Although the application of sensors in smartphones has been successful in many fields, research on online monitoring of the track condition in a subway rail transit system has not yet been conducted using smartphones. In this study, we intend to use a smartphone as a sensor platform to develop a suitable

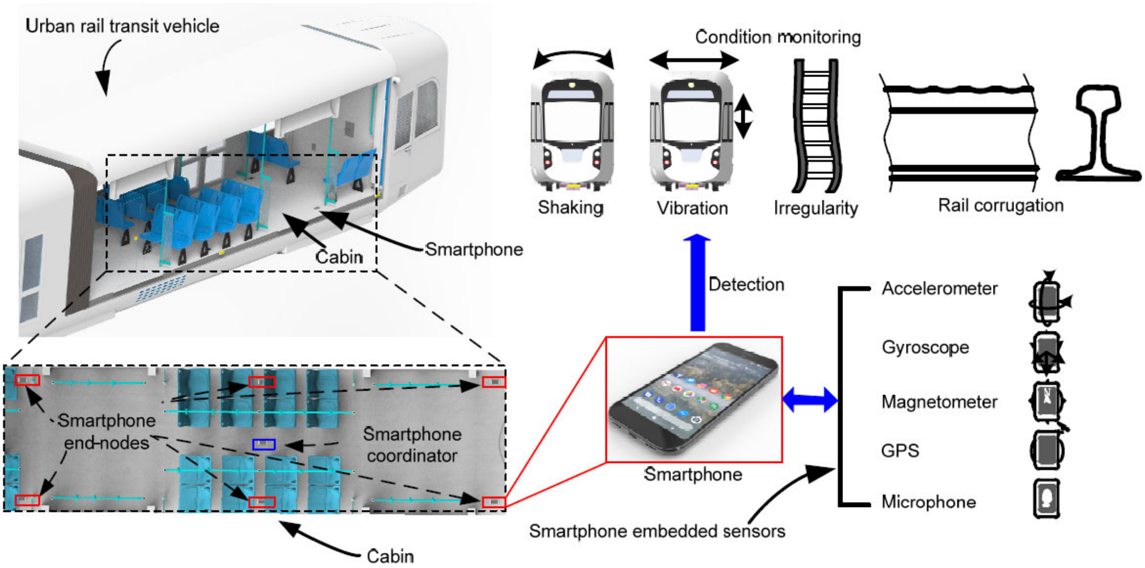

Fig. 1 Illustration of online monitoring of the condition of tracks during urban rail transit by vehicle-carried smartphones

Table 1 Application scenarios of smartphones

Scope	Sensors	Application	Functions	Publication
Intelligent transportation	Accelerometer, GPS, microphone, gyroscope, camera	Road condition (ruts, etc.), traffic condition (congestion, etc.), traffic safety (driver fatigue, etc.)	Diagnose road conditions based on changes in vertical, lateral, and longitudinal acceleration values	Mohan et al., 2008; Simonyi et al., 2014
Environmental monitoring	GPS, accelerometer	Overall carbon footprint	Gathered location time series data can be used as an index for the geospatial modes to infer personal environmental impact	Agapie et al., 2008
Health care	GPS, accelerometer, camera	Healthy eating, fall detector	Detect falls and send data to the server for further analysis to determine an emergency	Mosa et al., 2012
Human activity recognition	GPS, accelerometer	Transportation mode choice	Use a smartphone with a GPS receiver and an accelerometer sensor to determine an individual's travel patterns	Reddy et al., 2008

system for monitoring the condition of the railway track and solve the above-mentioned problems. Based on the above considerations, we introduce a promising and convenient way to measure acceleration using the accelerometer in a smartphone. A vehicle-positioning method, together with the coordinate alignment algorithm for a Global Positioning System (GPS) free tunnel environment, is proposed. Using the time-domain integration method, the relationship between the longitudinal acceleration signal of the vehicle and the vehicle's location is established.

1.3 Contribution and organization

The smartphone solution can effectively reduce costs and is convenient for use by railway operators. The online smartphone monitoring scheme of the state of the subway track does not need to be executed during the normal maintenance time and can monitor the track's service status in real time, which is beneficial in avoiding the safety hazard caused by emergencies. Fig. 2 is a smartphone application software interface developed for the Android system developed in this study. Using this software to call the built-in sensor of the smartphone, one can collect the vehicle running status information, such as the acceleration and angular velocity of the vehicle body.

The main contributions of this study are as follows:

1. The accuracy of the data measured by smartphones is evaluated and compared with the accuracy of high-precision sensors fixed nearby.

2. An automatic coordinate alignment algorithm

is proposed to estimate and correct the angular deviation between the smartphone coordinate system and the train's coordinate system.

3. An algorithm is proposed to fuse acceleration and angular velocity to provide the running speed and location information of a train.

This paper is organized as follows: Section 2 introduces the materials and methods for the field test, answering mainly whether the built-in acceleration sensors of smartphones can meet the requirements of rail transit vehicles in terms of acceleration amplitude accuracy and ride comfort index evaluation. Furthermore, the proposed method for vehicle location estimation by longitudinal acceleration integration used in the study is introduced. Section 3 shows the results of the accuracy of smartphone-embedded sensors. A coordinate alignment method by the maximum likelihood principle is adopted in the correction process to ensure the reliability of the angular deviation estimate. An application scenario is depicted, which describes the feasibility of vehicle positioning based on the acceleration of the vehicle body and the line curve information. Discussions are made and conclusions are drawn thereafter in Sections 4 and 5, respectively.

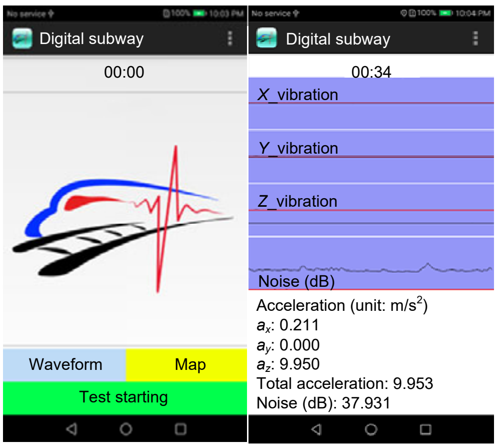

Fig. 2 Home page and monitoring interface of the APP developed for a smartphone with the Android operation system (OS)

2 Materials and methods

At present, there are many smartphone manufacturers and various models. To verify whether the sensor performance of smartphones can meet the demand for subway vehicles, we conduct a performance comparison test with high-precision accelerometers and smartphones. The configuration parameters of the high-precision sensors and smartphones are listed in Table 2; it can be seen that the smartphones do not require additional power or collection equipment (Gao et al., 2019). The built-in accelerometer of the smartphone plays an important role in the analysis of the motion state of the vehicle cabin, the speed of the train, and the acquisition of the location information. An Android APP was developed to call the sensor application program interface and display the acceleration signals (as shown in Fig. 2). The orientation of the smartphone and the direction of the movement state of the vehicle body are shown in Fig. 3.

2.1 Field test

To explore whether the performance of the built-in accelerometer of smartphones can meet the needs of practical applications, a field test was conducted, and the test setup is shown in Fig. 4. This test used two single-axis high-precision sensors and two smartphones of the same model. The two single-axis high-precision sensors tested the lateral and vertical vibration accelerations of the vehicle body. To avoid the impact of test point locations on the test data,

Table 2 Important parameters of the high-precision sensors and smartphones

Item for high-precision sensors	Description	Item for smartphones	Description
Type	891-II vibration meter	Operating system	Android 4.4
Data acquisition	IMC laptop	Chipset	Qualcomm MSM8274AB Snapdragon 800
Power	220 V/AC	CPU	Nvidia Tegra4
Maximum range	40 m/s^2	GPU	Adreno 330
Sensitivity	1×10^{-5} m/s^2	Maximum range	2*g*
Others	Connection bridge box, wire	RAM	2 GB

two high-precision sensors and smartphones were placed at the same test point (Fig. 4), where the sandbags simulated normal operating loads.

2.2 Location estimation by longitudinal acceleration integration

Vehicle speed is an important parameter in the field of rail transportation. In addition, it is necessary to locate the occurrence of suspected abnormal signals. Accurate location information can improve the ability of each detection system to locate defects and improve maintenance efficiency. However, existing train location methods such as GPS are not applicable inside the tunnel.

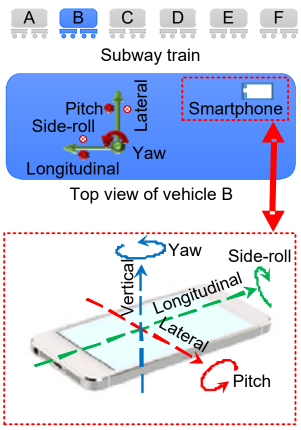

Fig. 3 Location and orientation of the smartphone inside the vehicle cabin

Fig. 4 Field test setup

In this study, we propose a comprehensive method for finding the location of a vehicle based on the smartphone accelerometer and gyroscope fusion method. The vehicle's longitudinal acceleration is detected by the accelerometer of the smartphone to achieve the initial positioning of the vehicle's location.

Random errors are caused by the sensor's signal-to-noise ratio. The error continues to accumulate and causes deviation from the actual location of the vehicle. The gyroscope is used to record the pitching, yawing, and rolling angular velocities of the vehicle during the running of the vehicle; the amplitude of the angular velocity of the moving body of the vehicle is significantly increased when the vehicle passes the line switch and the curve. The time and precise mileage information of the plane line and curve can be used to correct the initial location of the vehicle. The specific location correction flowchart is shown in Fig. 5. Time synchronization should be performed based on the time stamps of smartphones' acceleration and angular velocity. At the same time, the wavelet is used to remove random errors in the acquired data before vehicle location estimation (Cong et al., 2019).

The location calculation formulas can be written as follows:

$$\dot{x}(t)=\int_{t_1}^{t_2}\left[\ddot{x}(t)+\varepsilon(t)\right]\mathrm{d}t, \tag{1}$$

$$x(t)=\int_{t_1}^{t_2}\left[\dot{x}(t)+\int_{t_1}^{t_2}\varepsilon(t)\mathrm{d}t\right]\mathrm{d}t, \tag{2}$$

where $\ddot{x}(t)$, $\dot{x}(t)$, and $x(t)$ represent the longitudinal acceleration, velocity, and location at moment t respectively, t_1 and t_2 represent the start and stop

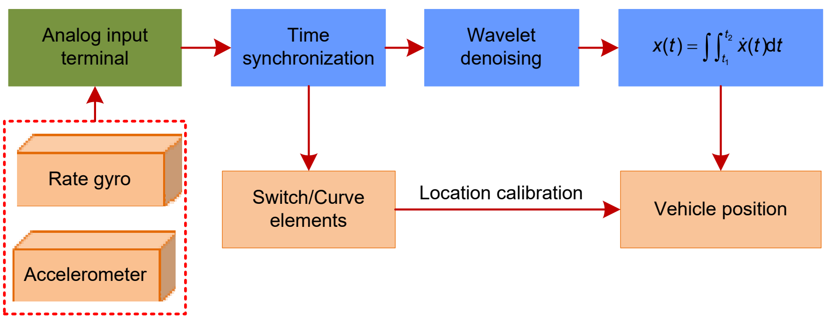

Fig. 5 Flowchart of vehicle location correction

time of the rolling stocks respectively, dt stands for the sampling interval of the sensors, and $\varepsilon(t)$ denotes the random errors induced by the built-in sensors of smartphones.

The vehicle acceleration signals are discrete-time series with an equal interval. To reduce numerical integration errors which may affect the positioning accuracy, we adopt the composite Simpson integration method, which is characterized by fast convergence and small integration errors. The sampled time series $[t_1, t_2]$ can be divided into n sections:

$$t_k = t_1 + kh,\ h = \frac{t_2 - t_1}{n},\ k = 0,\ 1,\ \cdots,\ n. \tag{3}$$

Using Simpson integration formulas in each section $[t_{k-1}, t_k]$, we obtain

$$\begin{aligned}\int_{t_1}^{t_2} \dot{x}(t)\mathrm{d}t &= \sum_{k=1}^{n} \int_{t_{k-1}}^{t_k} \dot{x}(t)\mathrm{d}t \\ &= \frac{h}{6}\sum_{k=1}^{n}\left[\dot{x}(t_{k-1}) + 4\dot{x}\left(\frac{t_{k-1}+t_k}{2}\right) + \dot{x}(t_k)\right] + R_n(f),\end{aligned} \tag{4}$$

$$x(t_2) = \frac{h}{6}\sum_{k=1}^{n}\left[\dot{x}(t_{k-1}) + 4\dot{x}\left(\frac{t_{k-1}+t_k}{2}\right) + \dot{x}(t_k)\right], \tag{5}$$

where $\dot{x}(t)$ is the predicted vehicle velocity, $x(t_2)$ is the vehicle location at time t_2, $\dot{x}(t_{k-1})$ and $\dot{x}(t_k)$ represent the vehicle velocities at time t_{k-1} and t_k respectively, $\dot{x}\left(\frac{t_{k-1}+t_k}{2}\right)$ is the vehicle velocity obtained by cubic spline interpolation, and $R_n(f)$ is the Simpson integration error.

2.3 Ride comfort index

Vehicle ride comfort is formed by various factors, such as temperature, humidity, noise, passenger's physiological and psychological state, and vibration of the vehicle body, among which vehicle vibration is the main factor. The frequency range that affects human comfort is between 0.5 Hz and 80 Hz, and the influence of vibration on the human body varies with the vibration frequency. Therefore, it is necessary to let the frequency be weighted. The International Organization for Standardization (ISO)-2631 specification is used to evaluate the human body's vibration and it can be widely used in various environments (International Organization for Standardization, 1997). The basic evaluation formula is as follows:

$$\mathrm{WAI} = \left(\frac{1}{T}\int_0^T a^2(t)\mathrm{d}t\right)^{1/2}, \tag{6}$$

and the equivalent equation in the frequency domain is as follows:

$$\mathrm{WAI} = \left(\frac{1}{f_\mathrm{u} - f_\mathrm{l}}\int_{f_\mathrm{l}}^{f_\mathrm{u}} w^2(f)a^2(f)\mathrm{d}f\right)^{1/2}. \tag{7}$$

In Eqs. (6) and (7), WAI (m/s^2) is the weighted acceleration index of the time history, T (s) is the measurement time length, $w(f)$ is the 1/3 octave weighted coefficient, $a(f)$ (m/s^2) is the acceleration spectrum amplitude, and f_u and f_l are the upper and lower 1/3 octaves respectively. The specific calculation process is shown in Fig. 6. The comfortable response of the human body to the vibration environment of the vehicle is shown in Table 3.

In addition, to meet the requirements of vehicle ride comfort and protect passengers from the impact of large-scale vibration, China, France, Japan, Germany, and several other countries stipulate that the instantaneous vertical acceleration of the vehicle body caused by partial track irregularity should not exceed the half-peak value (0.12g–0.15g), and that the lateral acceleration also should not exceed its half-peak value (0.10g–0.12g).

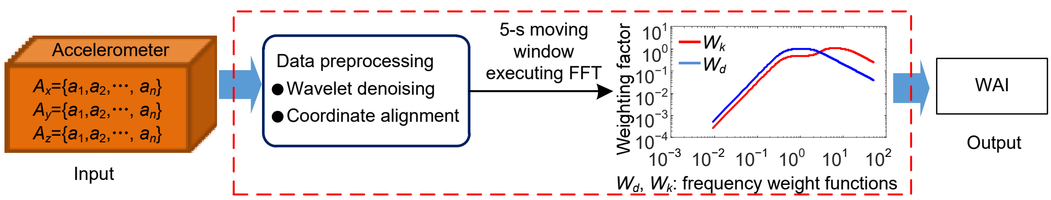

Fig. 6 Process of calculating the weighted acceleration index (WAI)

Table 3 Reactions to various magnitudes of vibration values in public transport

WAI (m/s^2)	Ride comfort
≤0.315	Very comfortable
0.315–0.63	Comfortable
0.5–1.0	Medium
0.8–1.6	Uncomfortable
1.25–2.5	Very uncomfortable
≥2	Extremely uncomfortable

WAI: weighted acceleration index

3 Results

3.1 Smartphone coordinate alignment

To verify the effect of the proposed approach, we conducted on-site tests on Chengdu Subway Line 2, with a total of 12 stations and 11 intervals. According to the China Standard GB5599-85, "Railway Vehicle Dynamics Performance Evaluation and Test Identification Procedures," the smartphone was placed on the floor surface of the vehicle that is laterally offset from the side of the core plate by 1 m. The direction of the smartphone coordinate system (x', y', z') and the direction of the coordinate system of the vehicle body (x, y, z) are not completely aligned; there exists an angle θ between the longitudinal axis and the traveling direction of the vehicle (Fig. 7).

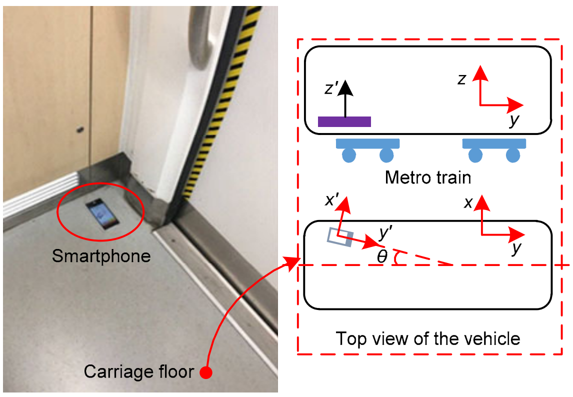

Fig. 7 Placement points of the smartphone during the field test

The detected three-axis accelerations of the smartphone are shown in Fig. 8. The average values of the longitudinal acceleration and lateral acceleration are 0.10 m/s^2 and −0.13 m/s^2, respectively, indicating that there is an angle θ between the smartphone coordinate system and the coordinate

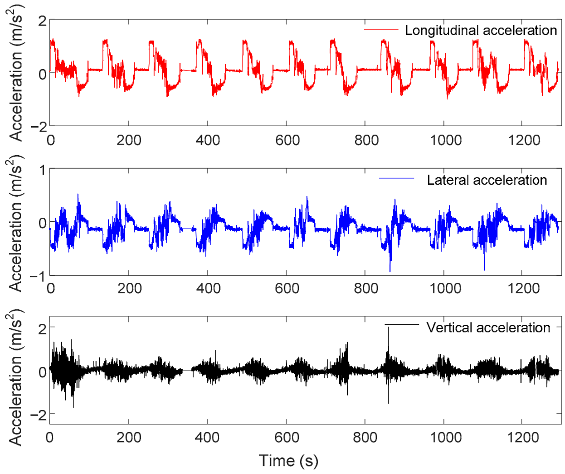

Fig. 8 Smartphone records

system of the vehicle body. Thus, the detection data of the smartphone cannot truly reflect the vibration response of the vehicle body and cannot be directly applied to evaluate the ride comfort and estimate the vehicle location; therefore, coordinate alignment (coordinate correction) of the smartphone coordinate system should be performed.

To improve the operation of the smartphone for detection, no special method is needed to ensure that the coordinate system of the smartphone is parallel to the coordinate system of the vehicle body. Only the coordinate axes of the two coordinate systems are set approximately parallel during the measurement. Using the orthogonality of the longitudinal and lateral accelerations of the vehicle body, the plane deviation of the smartphone and the coordinate system of the vehicle body can be corrected. The maximum likelihood principle was adopted in the correction process to ensure the reliability of the angular deviation estimate. It was found that the angle between the smartphone and the horizontal coordinate axis of the coordinate system of the vehicle body is 16.4° (Fig. 9). After coordinate correction of the smartphone, its longitudinal, lateral, and vertical accelerations can truly reflect the vibration situations of the vehicle. The actual vibration accelerations of the body are shown in Fig. 10.

3.2 Accuracy of smartphone-embedded sensors

Accelerations of a certain interval measured by the high-precision sensors and the smartphones are shown in Fig. 11.

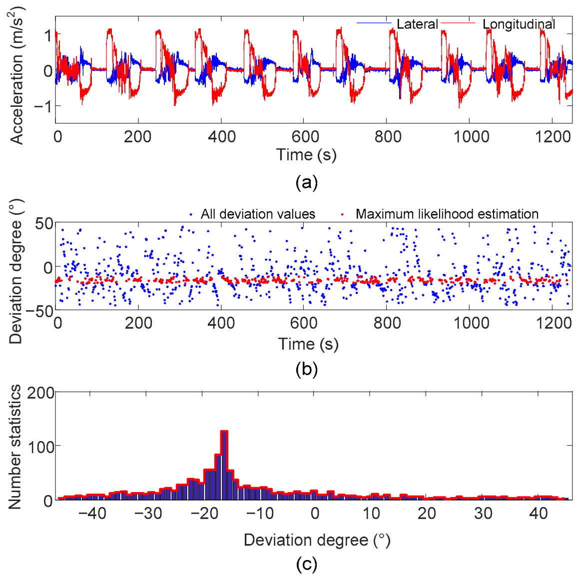

Fig. 9 Smartphone lateral and longitudinal accelerations after coordinate alignment (a), all deviation degree (b), and statistical distribution histogram of the deviation angle (c)

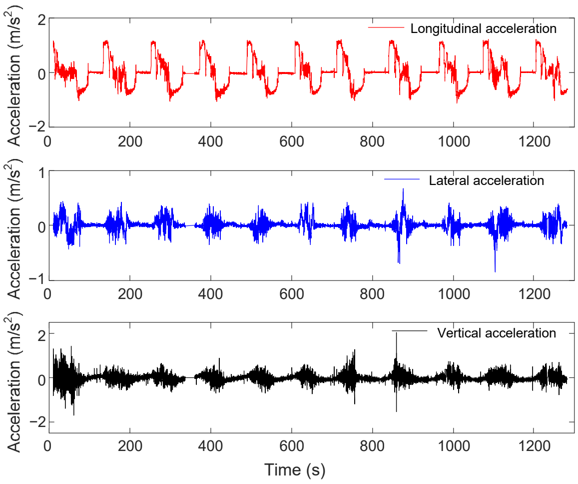

Fig. 10 Actual vibration accelerations of the vehicle body after coordinate alignment

To verify whether the accuracy and stability of smartphone sensors can meet the requirements, comparisons between smartphone sensors and high-precision accelerometers were carried out considering three aspects: standard deviation (SD) of detection data, vehicle running stability Sperling index (SI), and ISO-2631 weighted acceleration index (WAI) (Paddan and Griffin, 2002; Kim et al., 2003). Indicators SD and SI are calculated as follows:

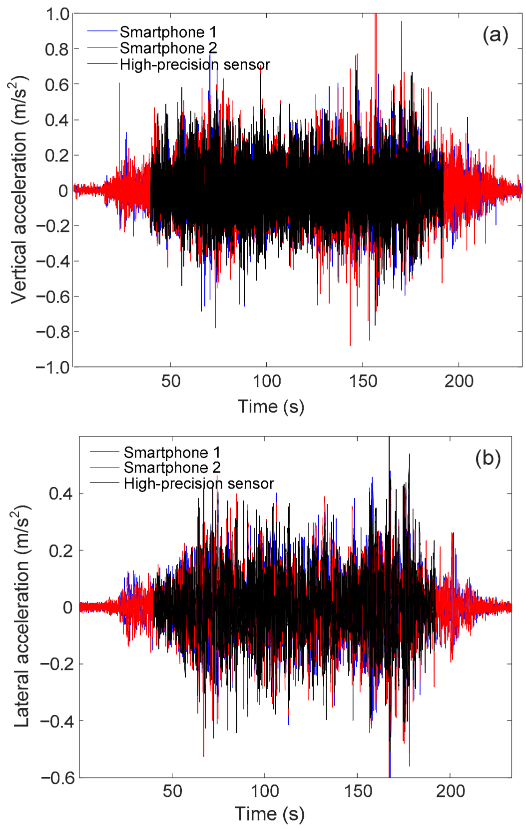

Fig. 11 Comparison of vertical (a) and lateral (b) accelerations obtained from smartphones and high-precision sensors

$$\mathrm{SD}=\sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(a_i-\bar{a}\right)^2}, \tag{8}$$

where N is the number of data sample points in the 5-s moving window, a_i (m/s^2) is the i^{th} element in the 5-s moving window, and $\bar{a}$ (m/s^2) is the mean value of all elements in the 5-s moving window.

$$\mathrm{SI}=0.896\sqrt[10]{\frac{a^3}{f}F(f)}. \tag{9}$$

The frequency correction factor of the vertical acceleration is as follows:

$$F(f)=\begin{cases}0.325f^2, & f\in[0.5,\ 5.9]\ \text{Hz},\\ 400/f^2, & f\in(5.9,\ 20]\ \text{Hz},\\ 1, & f>20\ \text{Hz}.\end{cases} \tag{10}$$

The frequency correction factor of the lateral acceleration is as follows:

$$F(f)=\begin{cases}0.8f^2, & f\in[0.5,\ 5.4]\ \text{Hz},\\ 650/f^2, & f\in(5.4,\ 26]\ \text{Hz},\\ 1, & f>26\ \text{Hz}.\end{cases}\quad(11)$$

In Eqs. (9)–(11), f is the vibration frequency, $F(f)$ is the frequency correction coefficient, and a (cm/s^2) is the acceleration amplitude corresponding to the frequency.

The running process of the subway vehicle can be roughly divided into three stages: acceleration, uniform speed movement, and deceleration. By setting the 5-s moving window, the trends of the three indicators in relation to the running speed of the vehicle can be observed (Fig. 12). The SD, SI, and WAI of the vertical acceleration detected by smartphone 1 and the high-precision sensor are similar, whereas those detected by smartphone 2 and the high-precision sensor show a slight deviation of only about 150 s. From Figs. 12b, 12d, and 12f, the SD, SI, and WAI of the lateral acceleration obtained from smartphones 1 and 2 and the high-precision sensor are similar. It can be seen that smartphones can be used to detect the vibration response of the vehicle body and evaluate the ride comfort of the vehicle.

3.3 Vehicle location estimation

To verify the accuracy of the above vehicle-positioning method, a field test is conducted to obtain the real-time running speed and position of the subway vehicles from station A to station B of Chengdu

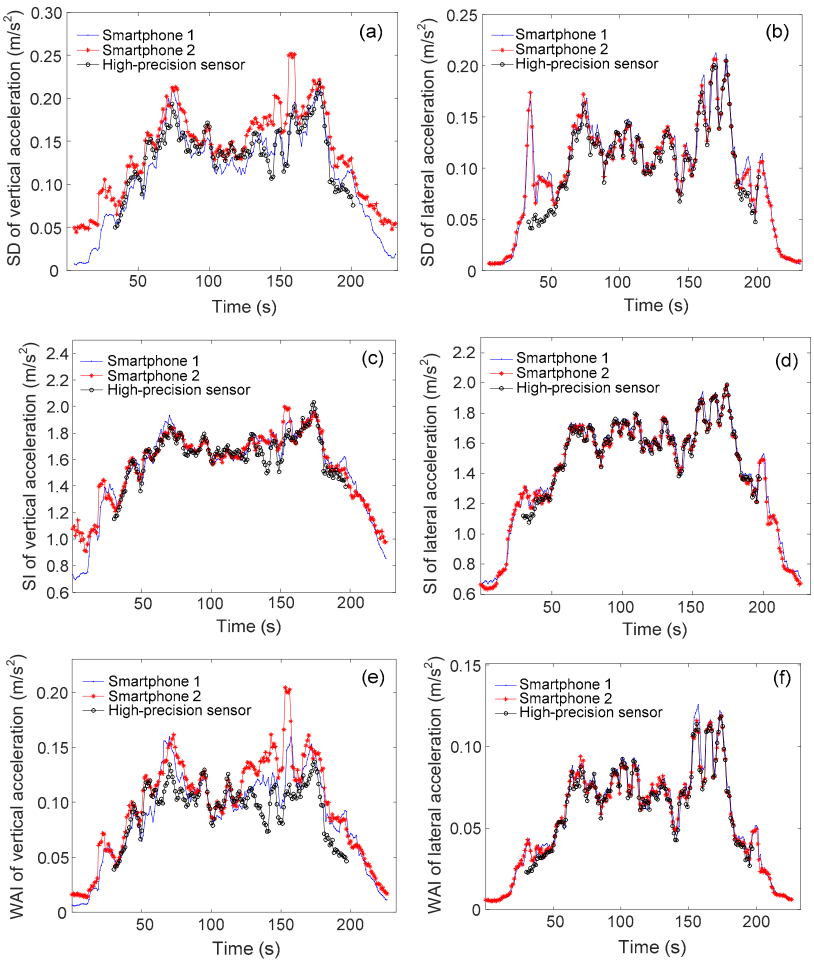

Fig. 12 Comparison of evaluation indexes with 5-s moving window: SD (a), SI (c), and WAI (e) of the vertical acceleration, and SD (b), SI (d), and WAI (f) of the lateral acceleration

Subway Line 2 (Fig. 13). The curve information of the route from station A to station B is shown in Fig. 14.

After smartphone coordinate alignment, the three-axis acceleration of the smartphone from station A to station B is shown in Fig. 15. The longitudinal acceleration of the vehicle body is integrated once to obtain the running speed of the vehicle body, which is compared with the actual running speed of the vehicle body (Fig. 16). It can be seen that during the uniform motion of the vehicle, the tiny change of the vehicle acceleration cannot be detected by the smartphone's acceleration sensor. Then, the second integral is used to estimate the vehicle location information. The total mileage from station A to station B is obtained as 1235 m, whereas the actual mileage between the two stations is 1411 m, and the maximum error is 176 m, 12% relative to the total mileage. It can be seen from Fig. 16 that during the running of the vehicle, the yaw angular velocity of the vehicle increases when passing the line curve, and the key features of the line curve can be identified. The curve information can be used to correct the location of the vehicle. As shown in Fig. 17, the corrected error between the estimated position and the actual location of the vehicle is only 68 m, and the error is 5% relative to the total mileage, which can meet the regular maintenance requirement.

The smartphone can achieve high-frequency detection of the acceleration of the vehicle body, provide the subway engineering department with

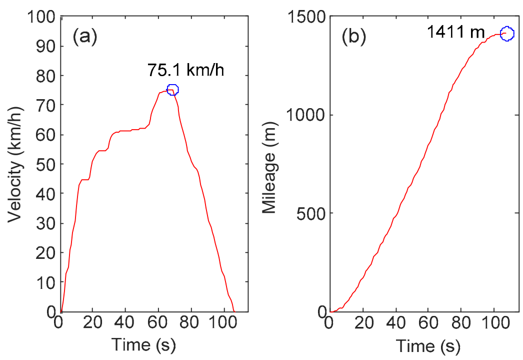

Fig. 13 Actual vehicle velocity (a) and mileage (b)

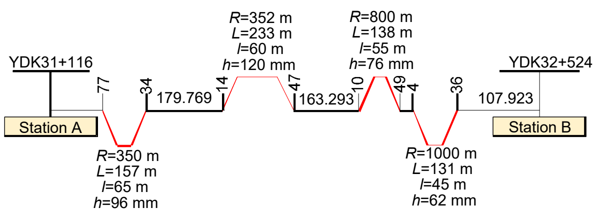

Fig. 14 Station A to station B: subway line curve information

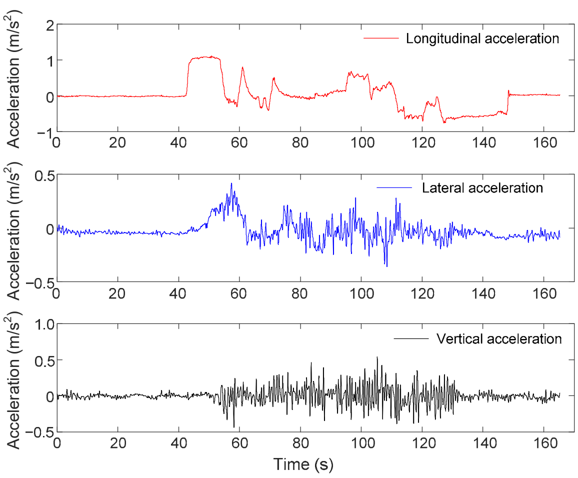

Fig. 15 Vehicle vibration acceleration

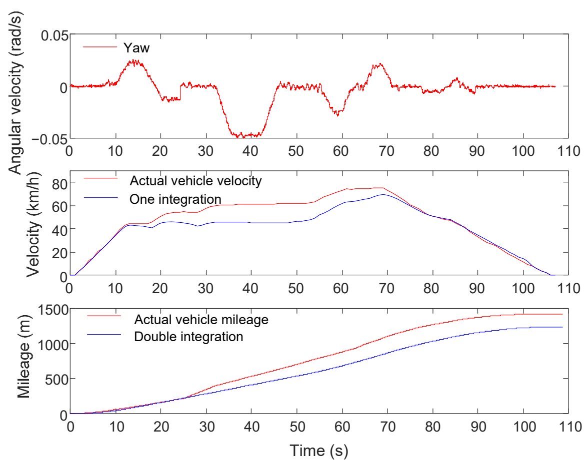

Fig. 16 Vehicle yaw angular velocity, speed, and location

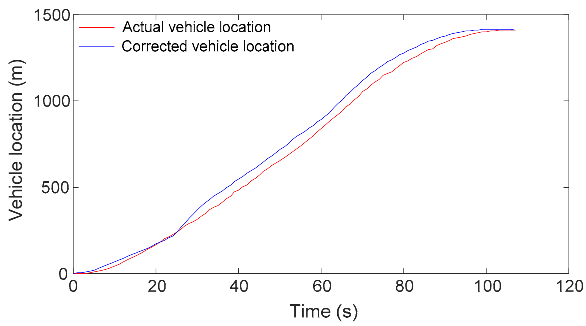

Fig. 17 Vehicle location after curve information correction

detailed vehicle vibration history information (running speed and position of the vehicle, as well as lateral and vertical accelerations of the vehicle body), develop a reasonable maintenance and repair plan for the engineering staff, and provide data support for scientific management of the subway line status. To obtain the specific position information of the vehicle when the instantaneous vibration response of the vehicle exceeds the specification limit, the smartphone detection data can be converted into the spatial domain (Fig. 18), if the half-peak value of the vertical vibration acceleration of the vehicle body detected by the smartphone exceeds the limit (for vertical acceleration, the value is 0.15*g*; for lateral acceleration, the value is 0.12*g*). It can provide the vehicle staff with the running speed and position information of the vehicle at the overlimit amplitude and ensure timely check at the corresponding position or nearby.

According to the WAI, the ride comfort of the section is evaluated. As shown in Fig. 19, the blue curve indicates the ride comfort of the vehicle from station A to station B in relation to the running speed of the vehicle (red curve), and the *x* axis represents the vehicle running position. If the vehicle ride comfort indicator, WAI, exceeds the specification limit, the vehicle's running speed and the corresponding location can be checked to further analyze the reasons.

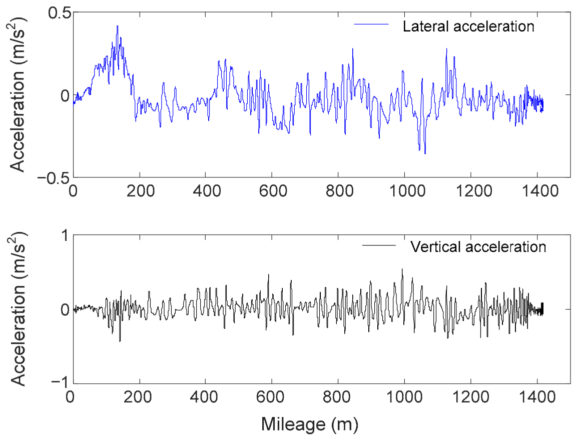

Fig. 18 Lateral and vertical accelerations of the vehicle in the spatial domain

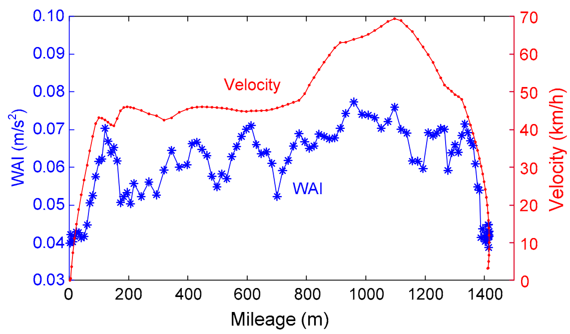

Fig. 19 Vehicle ride comfort WAI and velocity in relation to mileage (References to color refer to the online version of this figure)

4 Discussion

In the above, we have shown that smartphones have significant potential and effectiveness in monitoring the condition of the vehicle in urban rail transit. In this section, we discuss the weaknesses in this work.

First, we slightly sacrifice the accuracy by putting smartphones on the floor of the vehicle directly for convenience. Further work should be carried out to analyze the influence of different installation methods of smartphones. It is necessary to calibrate the data measured by a smartphone, which is put on a train rather than fixed on the train. Second, there are various brands of smartphones, and there may be differences in the built-in sensor types. Before large-scale promotion and application, field tests and indoor frequency sweep tests are needed to calibrate the accuracy of different smartphone sensors. Finally, in this study we use the track curve information to correct the estimated running mileage of the vehicle. The error of the location estimation value can be controlled to within 5%. However, the estimated running speed of the vehicle has a large deviation from the actual one. In future research, smartphones can be placed in the same position of each vehicle in the train group, and a data fusion approach can be developed for the speed estimation of a subway train based on the local time delay and waveform similarity between the accelerations measured by different smartphones.

5 Conclusions

In this paper, we have presented a method for smart monitoring of track status using a smartphone as the sensing platform in a subway tunnel without

GPS signal environment. This study has enabled the full use of smartphones and offered a smart and eco-friendly approach for human life in the field of intelligent transportation systems. Conclusions are drawn as follows:

1. The built-in accelerometer of smartphones plays an important role in obtaining the acceleration information of the vehicle body. To explore whether the performance of the built-in accelerometer of smartphones can meet the application requirements, a field test was conducted to make a comparison with high-precision accelerometers. Comparisons between smartphone sensors and high-precision accelerometers were conducted from three aspects: SD of detection data, vehicle running stability Sperling index (SI), and ISO-2631 weighted acceleration index (WAI). The results indicated that smartphone can fulfill the requirement for measurement of vibration response of the vehicle body and evaluate the ride comfort of the subway vehicle.

2. To improve the operation convenience of smartphone detection, no special installation method is needed during the smartphone detection process. To ensure this point, the maximum likelihood principle was adopted in the correction process to ensure the reliability of the angular deviation estimate. The proposed coordinate alignment method is capable of achieving convenient detection operation by smartphones.

3. The time-domain integration method has been used to estimate the location of the subway vehicle. The field test results showed that the integrated distance deviation between stations can be controlled to within 5% after line curve information correction. The actual distance between subway stations was, in general, less than 1500 m; therefore, the method described in this paper can meet the ±100 m positioning error requirement for on-site maintenance work. The proposed approach can estimate the location of the subway vehicle without the GPS signal environment and is advantageous in quickly locating abnormal track defects, thereby ensuring timely diagnosis and maintenance. The detection device is a smartphone and is thus cost-effective and environment-friendly.

Contributors

Jian-li CONG, Rong CHEN, and Ping WANG designed the research. Jian-li CONG processed the data and drafted the manuscript. Ming-yuan GAO and Yuan WANG helped organize the manuscript. Jian-li CONG, Yuan WANG, Rong CHEN, and Ping WANG revised and finalized the paper.

Compliance with ethics guidelines

Jian-li CONG, Ming-yuan GAO, Yuan WANG, Rong CHEN, and Ping WANG declare that they have no conflict of interest.

References

Agapie E, Chen J, Houston D, et al., 2008. Seeing our signals: combining location traces and web-based models for personal discovery. Proc 9th Workshop on Mobile Computing Systems and Applications, p.6-10. https://doi.org/10.1145/1411759.1411762

Chellaswamy C, Balaji L, Vanathi A, et al., 2017. IoT based rail track health monitoring and information system. Int Conf on Microelectronic Devices, Circuits and Systems, p.1-6. https://doi.org/10.1109/ICMDCS.2017.8211548

Cong JL, Wang Y, Yang CP, et al., 2019. Data preprocessing method of vehicle vibration acceleration by smartphone. *J Data Acquis Proc*, 34(2):349-357 (in Chinese). https://doi.org/10.16337/j.1004-9037.2019.02.018

Gao MY, Wang P, Cao Y, et al., 2017. Design and verification of a rail-borne energy harvester for powering wireless sensor networks in the railway industry. *IEEE Trans Intell Transp Syst*, 18(6):1596-1609. https://doi.org/10.1109/TITS.2016.2611647

Gao MY, Wang P, Wang YF, et al., 2018. Self-powered ZigBee wireless sensor nodes for railway condition monitoring. *IEEE Trans Intell Transp Syst*, 19(3):900-909. https://doi.org/10.1109/TITS.2017.2709346

Gao MY, Su CG, Cong JL, et al., 2019. Harvesting thermoelectric energy from railway track. *Energy*, 180:315-329. https://doi.org/10.1016/j.energy.2019.05.087

Gao MY, Cong JL, Xiao JL, et al., 2020. Dynamic modeling and experimental investigation of self-powered sensor nodes for freight rail transport. *Appl Energy*, 257:113969. https://doi.org/10.1016/j.apenergy.2019.113969

Griffin MJ, 2007. Discomfort from feeling vehicle vibration. *Veh Syst Dynam*, 45(7-8):679-698. https://doi.org/10.1080/00423110701422426

Huang DM, Zhou SX, Yang ZC, 2019. Resonance mechanism of nonlinear vibrational multistable energy harvesters under narrow-band stochastic parametric excitations. *Complexity*, 2019:1050143. https://doi.org/10.1155/2019/1050143

Huang DM, Zhou SX, Han Q, et al., 2020. Response analysis of the nonlinear vibration energy harvester with an uncertain parameter. *Proc Inst Mech Eng K*, 234(2): 393-407. https://doi.org/10.1177/1464419319893211

International Organization for Standardization, 1997. Mechanical vibration and shock: evaluation of human exposure to whole-body vibration. Part 1, general requirements. ISO 2631-1:1997. International Organization for Standardization.

Jin XS, Wen ZF, Wang KY, et al., 2006. Three-dimensional train–track model for study of rail corrugation. *J Sound Vibr*, 293(3-5):830-855. https://doi.org/10.1016/j.jsv.2005.12.013

Kaynia AM, Park J, Norén-Cosgriff K, 2017. Effect of track defects on vibration from high speed train. *Proc Eng*, 199:2681-2686. https://doi.org/10.1016/j.proeng.2017.09.551

Kim YG, Kwon HB, Kim SW, et al., 2003. Correlation of ride comfort evaluation methods for railway vehicles. *Proc Inst Mech Eng F*, 217(2):73-88. https://doi.org/10.1243/095440903765762823

Lane ND, Miluzzo E, Lu H, et al., 2010. A survey of mobile phone sensing. *IEEE Commun Mag*, 48(9):140-150. https://doi.org/10.1109/MCOM.2010.5560598

Mohan P, Padmanabhan VN, Ramjee R, 2008. Nericell: rich monitoring of road and traffic conditions using mobile smartphones. Proc 6th ACM Conf on Embedded Network Sensor Systems, p.323-336. https://doi.org/10.1145/1460412.1460444

Molodova M, Li ZL, Núñez A, et al., 2014. Automatic detection of squats in railway infrastructure. *IEEE Trans Intell Transp Syst*, 15(5):1980-1990. https://doi.org/10.1109/TITS.2014.2307955

Mosa ASM, Yoo I, Sheets L, 2012. A systematic review of healthcare applications for smartphones. *BMC Med Inform Dec Mak*, 12(1):67. https://doi.org/10.1186/1472-6947-12-67

Paddan GS, Griffin MJ, 2002. Evaluation of whole-body vibration in vehicles. *J Sound Vibr*, 253(1):195-213. https://doi.org/10.1006/jsvi.2001.4256

Reddy S, Burke J, Estrin D, et al., 2008. Determining transportation mode on mobile phones. 12th IEEE Int Symp on Wearable Computers, p.25-28. https://doi.org/10.1109/ISWC.2008.4911579

Ruiz-Zafra A, Orantes-González E, Noguera M, et al., 2015. A comparative study on the suitability of smartphones and IMU for mobile, unsupervised energy expenditure calculi. *Sensors*, 15(8):18270-18286. https://doi.org/10.3390/s150818270

Simonyi E, Fazekas Z, Gáspár P, 2014. Smartphone application for assessing various aspects of urban public transport. *Transp Res Proc*, 3:185-194. https://doi.org/10.1016/j.trpro.2014.10.104

Tsunashima H, Naganuma Y, Kobayashi T, 2014. Track geometry estimation from car-body vibration. *Veh Syst Dynam*, 52(S1):207-219. https://doi.org/10.1080/00423114.2014.889836

Wang P, Wang Y, Wang L, et al., 2017. Measurement of car-body vibration in urban rail transit using smartphones. Proc Transportation Research Board 96th Annual Meeting, p.15.

Wang SQ, Chen CF, Ma J, 2010. Accelerometer based transportation mode recognition on mobile phones. Asia-Pacific Conf on Wearable Computing Systems, p.44-46. https://doi.org/10.1109/APWCS.2010.18

Wang Y, Wang P, Wang X, et al., 2018. Position synchronization for track geometry inspection data via big-data fusion and incremental learning. *Transp Res Part C Emerg Technol*, 93:544-565. https://doi.org/10.1016/j.trc.2018.06.018

Wang YF, Yang Z, Pang J, 2018. Statistical analysis of urban rail transit lines in 2017 China—express delivery of annual report on urban rail transit V. *Urban Mass Trans*, 21(1):1-6 (in Chinese). https://doi.org/10.16037/j.1007-869x.2018.01.001

Wei XK, Jia LM, Liu H, 2013. A comparative study on fault detection methods of rail vehicle suspension systems based on acceleration measurements. *Veh Syst Dynam*, 51(5):700-720. https://doi.org/10.1080/00423114.2013.767464

Yang K, Wang JL, Yurchenko D, 2019. A double-beam piezo-magneto-elastic wind energy harvester for improving the galloping-based energy harvesting. *Appl Phys Lett*, 115(19):193901. https://doi.org/10.1063/1.5126476

Zhao YJ, Deng X, Liu SQ, et al., 2015. Interior noise prediction of high-speed train based on hybrid FE-SEA method. Proc 11th Int Workshop on Railway Noise, p.699-705. https://doi.org/10.1007/978-3-662-44832-8_83

Zhou SX, Zuo L, 2018. Nonlinear dynamic analysis of asymmetric tristable energy harvesters for enhanced energy harvesting. *Commun Nonl Sci Numer Simul*, 61:271-284. https://doi.org/10.1016/j.cnsns.2018.02.017