Challenges in Smartphone-Based Crowdsensing for Railway Condition Monitoring

Insights into Variability and Track Quality Assessment

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***Abstract*—Modern smartphones, widely available and equipped with multiple sensors, offer the potential for railway infrastructure condition monitoring through mobile crowdsensing without disrupting operational railway services. This paper investigates key factors influencing the use of smartphone accelerometers for railway track quality assessment and highlights the associated challenges. Differences in accelerometer characteristics across three budget smartphones, including variations in sampling frequencies and dynamic sensitivity, are analyzed. A case study conducted on in-service passenger trains examines the effects of operational conditions, specifically vehicle speed and smartphone placement within the car body, on the frequency content and magnitude of recorded signals. Additionally, this study compares smartphone measurement results with a conventional track quality index derived from track geometry measured by specialized vehicles. Promising correlations are observed between the standard deviation of the smartphone vertical acceleration signals and the longitudinal level-based track quality index, demonstrating the potential of smartphones to assess track quality and detect local anomalies. However, variations caused by vehicle speed and smartphone placement pose challenges for standardizing track quality assessments. These findings highlight the potential of mobile crowdsensing for railway infrastructure monitoring while emphasizing the need for strategies to address variability in operational conditions and device characteristics.**

Keywords—Crowdsensing Measurements, Smartphone Accelerometers, Track Quality Assessment

I. Introduction

The European Union (EU) has implemented various policies and legislations to support interoperability and boost rail transportation usage, such as the Trans-European Transport Network (TEN-T) [1] and the legislative packages to establish the Single European Railway Area [2]. Additionally, under the European Green Deal [3], the EU aims to shift 75% of inland freight transportation from road to rail and inland waterways [4], recognizing the effectiveness of rail transportation in addressing climate change and environmental issues. Achieving this goal requires a strong focus on the reliability and availability of railway infrastructure to ensure safe and dependable train operations. This highlights the importance of infrastructure condition monitoring in the early detection of potential issues and enabling efficient maintenance planning, resulting in reducing the risk of service interruptions.

Focusing on railway tracks, the current track geometry condition monitoring practice relies on track geometry measurements conducted by specialized trains. These dedicated trains require scheduling around regular revenue services, impacting network availability and limiting the frequency of measurements. For example, in the Netherlands, track geometry measurements are conducted 1 – 4 times per year [5]. To meet the increasing demand for track usage, more frequent condition monitoring is essential to ensure an acceptable service level of the tracks. Increasing the frequency of these measurements affects network availability and would increase the costs of manufacturing, operating, and maintaining such measurement trains.

With the rise of smartphone technology, a new opportunity emerges for more frequent, network-wide, track condition monitoring. Modern smartphones are equipped with multiple sensors, such as accelerometers, gyroscopes, and GPS receivers, that can capture data on movement and vibrations. Since most passengers carry smartphones daily, this presents an opportunity to leverage an extensive network of smartphone users for crowdsensing and crowdsourcing initiatives. By gathering data from passengers traveling on in-service trains, this approach offers a supplementary source of information alongside track geometry data, enabling a more frequent and more comprehensive assessment of railway track conditions such as degradation and failure prediction.

Previous studies on mobile crowdsensing for railway condition monitoring on railway systems across the world have highlighted both opportunities and challenges associated with this emerging technology. Smartphone accelerometer signals measured from the car body have shown promising correlations with track geometry quality [6]. However, challenges include variations in the measured accelerometer signals due to differences in sensor characteristics [7], [8] and the repeatability of measurements caused by varying vehicle speeds [9], [10], [11]. Additionally, the effect of different positions within the car body on the acceleration signals has

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been left out of the scope [12] or not extensively studied [13]. The findings from several selected studies are summarized in Table I.

TABLE I. A SELECTION OF STUDIES ON MOBILE CROWDSENSING FOR RAILWAY CONDITION MONITORING

Ref.	Location Case Study	Key findings
[8]	England	Different smartphone models display different levels of noise and sensitivity in the vertical acceleration signals they record on a moving train.
[11]	Romania	Acceleration signals recorded by ultra-low-cost smartphones can detect variations caused by longwave irregularities, such as bridges and curves. The magnifying effect on the amplitude of the signals measured at higher vehicle speeds is discussed.
[10]	Australia	The relationship between vehicle speed and the acceleration magnitudes measured in the car body of a tram is highlighted. The relationship is presented through a regression model.
[6]	Portugal	Acceleration measurements from in-service passenger vehicles through mobile phones show promising correlations with the standard deviation longitudinal level of track geometry records.
[13]	Spain	The vertical acceleration signals of three tablets, located in different positions on the floor of a car body on a commuter line, show similar trends based on visual inspection.
[9]	France	The challenge of inconsistent measured accelerations of smartphones across different measurement runs due to slightly varying speed profiles is addressed.
[7]	N/A	Laboratory tests provide key insights into the heterogeneous characteristics of the transfer functions of different smartphones, including phenomena such as low-pass filters and resonance frequencies.

This paper, based on the findings from the first author's MSc thesis [14], investigates key challenging factors in monitoring railway track conditions through mobile crowdsensing, with a focus on vertical track conditions, as variations in vertical track geometry are highly relevant to overall track quality [15]. First, the characteristics of the measured accelerations across various smartphone devices are analyzed. Next, the influences of key operational conditions on the measured signals by smartphones are studied. Then, an assessment of track condition based on the measured signals is provided. Finally, conclusions and recommendations are drawn.

II. SMARTPHONE ACCELEROMETER HETEROGENEITY

Different smartphone models are equipped with accelerometers that vary widely in specifications, as mentioned in [7] and [8]. Variations, such as sensor type, sensitivity, and sampling rates, can significantly influence the characteristics of measured accelerations. Consequently, the quality and consistency of acceleration data may differ across devices, presenting a key challenge in mobile crowdsensing. Since the accelerometer specifications of smartphones are often not publicly accessible, empirical testing is required to identify these characteristics.

This study analyzes the characteristics of vertical acceleration measured inside the car body (wagon). To achieve this, three budget smartphone models were selected, each priced under 150 euros and launched in 2023: the Samsung Galaxy A14, the Nokia C32, and the Motorola G14. These devices were chosen because their lower-cost design likely includes cheaper sensors, making them ideal for evaluating the feasibility of mobile crowdsensing with affordable technology. If meaningful findings can be derived from these budget smartphones, the results would be promising and broadly applicable to a wide range of devices. The application PhyPhox [16], developed by RWTH Aachen University, was installed on each smartphone to record and export vertical acceleration signals.

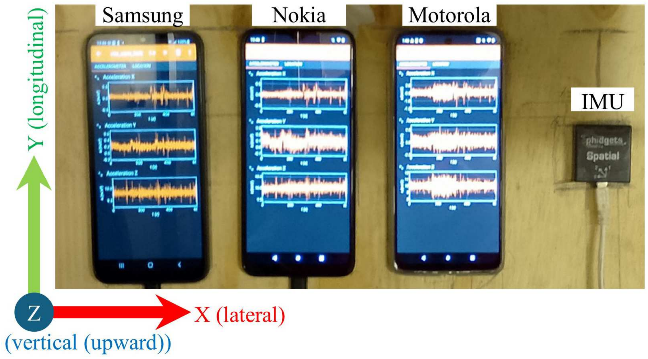

Fig. 1. Measurement setup: smartphones and IMU set-up on the wooden board.

The smartphones and the inertial measurement unit (IMU), the PhidgetSpatial Precision 3/3/3 High Resolution model 1044_0, which has an acceleration measurement range of ± 2g, were mounted on a wooden board using double-sided tape. This wooden board was placed on the floor directly above the bogie of the CTO, the measurement wagon of TU Delft. The test setup is shown in Figure 1. The test took place on the Dutch railway network at varying vehicle speeds during the test. All smartphones independently recorded acceleration signals using the PhyPhox application at their maximum sampling frequencies for 9 minutes: 381 Hz for the Motorola G14, 195 Hz for the Nokia C32, and 201 Hz for the Samsung Galaxy A14. Simultaneously, the IMU signal acquisition was conducted using a laptop running a LabView-based program via a USB interface at its maximum sampling rate of 250 Hz. To facilitate comparison across devices, the recorded signals were subsequently resampled to 180 Hz.

Figure 2 presents the signals in the time domain and the frequency domain, represented by Welch-periodograms, which were generated using 10-second Hanning windows with 50% overlap. The acceleration measured by the IMU is considered the baseline since the device is specifically designed for measurement purposes.

When examining the acceleration signals in the time domain, all devices exhibit similar patterns. The peaks in these signals are well-aligned; however, the magnitudes differ due to the varying levels of sensitivity of the sensors. Analyzing the frequency domain of the signals in the measurement set-up enables the comparison of dynamic sensitivity across the different devices. When analyzing the acceleration signals in the frequency domain, the vertical acceleration measured by the Motorola G14 closely resembles the signal measured by the IMU, particularly in the frequency range below 15 Hz. In contrast, the signals measured by the Nokia C32 and the Samsung Galaxy A14 demonstrate lower magnitudes and exhibit flatter characteristics for frequencies around 8 Hz and higher, occurring at relatively low frequencies compared to the cut-off filters observed in [7]. Furthermore, the signal measured by the Nokia C32 shows device-specific resonance peaks within the range of 60 to 70 Hz, which are not observed in the signals measured by the other devices. Variations in sampling frequencies, low-pass filter behaviors, and resonance frequencies within the Nyquist rate limit the range of frequencies that can be accurately measured and analyzed.

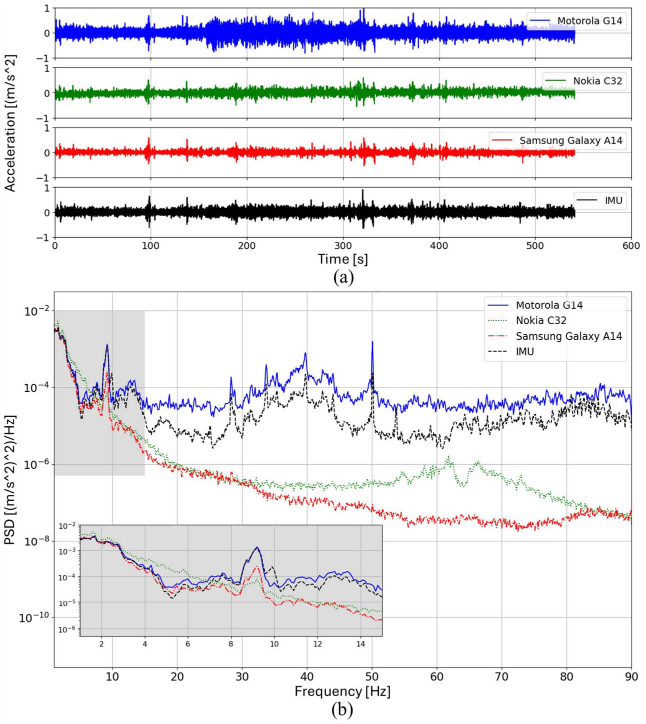

Fig. 2. Vertical acceleration measured by all devices: (a) signals in the time domain, (b) signals in the frequency domain.

III. Influence of Operational Conditions on Measured Acceleration Signals

In typical operations, variations in driving patterns may result in trains passing the same position within the railway network at different speeds. The effect of vehicle speed on the measured signals is discussed in [9], [10] and [11]. In addition, [10] introduces a regression model to explore the relationship between the magnitude of measured vibrations and tram speed. In addition, passengers and their smartphones can be located anywhere within the train wagon. In this section, the influence of vehicle speed and the smartphone position on the measured accelerations are investigated.

To evaluate the influence of operational conditions on measured accelerations, a case study was conducted on passenger trains operating on the railway track between Delft Campus station and Schiedam Centrum station. Five measurement runs, from Run A to Run E, were performed within the same day. Thus, the condition of the railway track can be considered similar across the five runs. Each run was conducted on a different in-service passenger train of the same model, the Sprinter New Generation, operated by the Dutch Railways. Instrumentation involved two board setups called Board 1 and Board 3, similar to those described in Section II, placed on the train floor in two distinct areas, as illustrated in Figure 3. Please note that the exact position of the boards may differ between measurement runs due to seat availability, as the measurements were conducted on operational trains without disturbing passengers. In addition, although placing smartphones on the floor does not reflect typical passenger behavior, this controlled setup allows a more consistent analysis of acceleration signals under defined conditions.

Board 1 and Board 3 contained each a different unit of the same smartphone model. The accelerometer specifications reported by PhyPhox were similar across the two units of the same model. Additionally, since all the devices were brand new, it can be assumed that there are no significant differences in the acceleration measurements among different units of the same model. However, for this analysis, only the results from the Motorola G14 are considered, as these demonstrated good replicability with the measured signals by the IMU, as discussed in Section II.

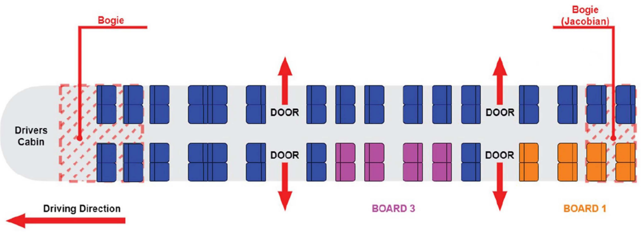

Fig. 3. Location of the measurement boards.

To acquire the train speed profile, an additional iPhone 13 Pro Max was placed on a table or a chair next to Board 1 during each measurement run. This setup was implemented because the phones are unable to receive GPS signals when placed on the vehicle floor. The iPhone recorded the latitude and longitude at a sampling rate of 1 Hz using the PhyPhox application. The exported latitude and longitude were then projected onto the track centerline to estimate the corresponding track kilometer positions at each timestamp. A univariate spline was applied to smooth the estimated track positions. Finally, the central difference method was employed to calculate the train speed based on the differences in kilometer position and time.

A. *Influence of Vehicle Speed on Frequency Content*

Analyzing signals in the frequency domain provides valuable insights, as dominant frequency components can reveal system behavior driven by specific excitation characteristics. In the context of train-track interaction, one such component identified in vertical acceleration signals measured onboard is excited by the wheels passing over consecutive sleepers [6].

The sleeper excitation frequency (f in Hz) is related to train speed (v in m/s) and the excitation wavelength, precisely the sleeper spacing (L in m), as shown in Equation (1).

$$f = v / L \tag{1}$$

Therefore, this subsection examines how the characteristics of the sleeper excitation frequency change with variations in vehicle speed.

Figure 4 presents a spectrogram of the vertical acceleration signals measured at Board 1, in which a 1-second Hann window, with no overlapping, is used in the spectral analysis. The sleeper excitation frequency, indicated by the red dashed line, is plotted as a function of the vehicle speed divided by the sleeper spacing (0.6 m on Dutch railway lines). The intense energy levels observed in the 50 – 70 Hz range closely correspond to the calculated sleeper excitation frequency. In addition, the changing pattern of the sleeper excitation frequency aligned well with the vehicle speed profile. These findings suggest that changes in vehicle speed significantly influence the frequency content.

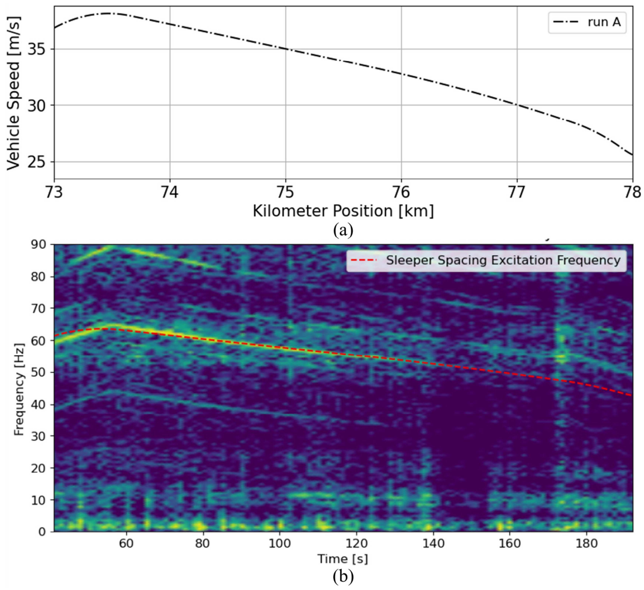

Fig. 4. (a) The vehicle speed profile of Run A; (b) the Spectrogram of the acceleration measured during Run A by the Motorola at Board 1, sleeper spacing frequencies indicated by the red dashed line [14].

B. *Influence of Vehicle Speed on Acceleration Magnitude*

Figure 5 illustrates the analyzed relationship between vehicle speed and absolute vertical acceleration. During measurement Run A, the vertical accelerations at Board 1 for 140 seconds, corresponding to a total of 5 kilometers, are selected as a case study. The signals were sorted by vehicle speed and divided into bins of 0.25 m/s, and then the mean and standard deviation of vertical accelerations within each bin were calculated.

The figure shows fluctuating results, likely due to the varying conditions of a particular stretch of the 5-kilometer case study railway track. Nevertheless, the overall trend indicates that the magnitude of acceleration generally increases with higher vehicle speed. The result shows the variability and a nonlinear pattern of speed dependency, which may induce difficulties in using smartphone data under varying operational conditions along the track.

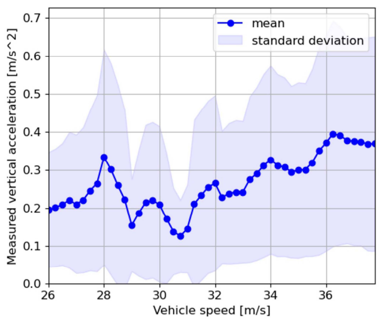

Fig. 5. Vehicle speed versus absolute vertical acceleration, measured at Board 1 during measurement Run A [14].

C. *Influence of Smartphone Position within the Car Body on Frequency Content*

Smartphones used for mobile crowdsensing can be located anywhere by passengers within the train car body, leading to variations in their position. Previous research has not in-depth examined how the position of smartphones within the car body affects the measured vertical acceleration signal. This study examined the frequency domain differences in smartphone acceleration signals measured near the bogie (Board 1) and at the center of the car body (Board 3).

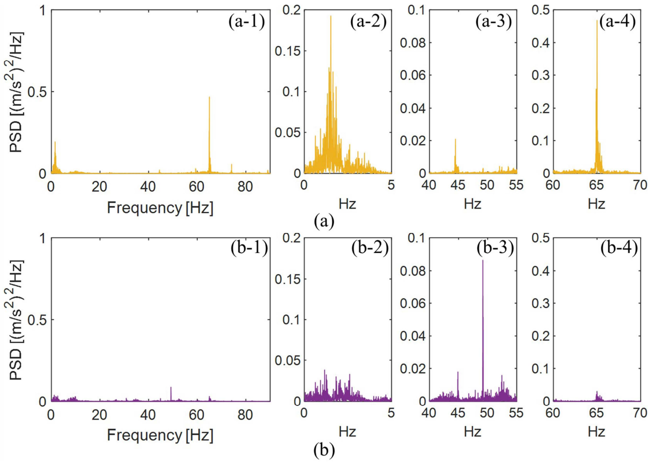

Fig. 6. Measured vertical accelerations during Run E from different locations within the car body in the frequency domain: (a) the signal from Board 1 (near the bogie), (a-2), (a-3), and (a-4) are zoom-in plots of (a-1) in different frequency bands; (b) the signal from Board 3 (near the center of the car body), (b-2), (b-3), and (b-4) are zoom-in plots of (b-1) in different frequency bands.

Signals measured over 135 seconds during Run E, corresponding to the 5 kilometers of the case study line, are selected for the analysis. Figure 6 shows signals from Board 1 and Board 3 in the frequency domains, visualized using periodograms generated with a rectangular window over the entire signal duration. The signals measured at two different locations show notable differences in frequency content and energy intensity. Considering Figure 6(a-2) and 6(b-2), the signal measured at Board 1 exhibits a dominant frequency at 1.5 Hz, whereas the signal measured at Board 3 does not show strong energy at this frequency. This can possibly be attributed to the pitch movement of the car body. In Figure 6(b-3), the signal from Board 3 exhibits three dominant frequencies at approximately 45, 50, and 53 Hz, whereas the signal from Board 1 (see Figure 6(a-3)) shows only a single dominant frequency at about 45 Hz. Additionally, within this frequency range, the signal from Board 3 demonstrates higher energy than that from Board 1. Further analysis is required to investigate the underlying reasons for this behavior. Lastly, in Figure 6(a-4) and 6(b-4), both signals exhibit a dominant frequency at approximately 65 Hz, corresponding to the sleeper spacing excitation frequency, which is calculated based on the maximum speed of Run E at 40 m/s. The signal from Board 3 is observed to be less pronounced than that from Board 1. This behavior can be attributed to the placement of the smartphones. The smartphone on Board 1, being closer to the suspension system, experiences stronger vibrations, whereas vibrations are less effectively transmitted to Board 3, which is located at the center of the car body. These findings indicate differences in the capability to assess railway track quality using smartphones placed at various locations within the train car body.

IV. Track Quality Assessment

The current industry practice for assessing railway track quality relies on the Track Quality Index (TQI), an indicator derived from the track geometry parameters. One of the state-of-the-art methodologies for calculating TQI is specified in the EN 13848-6 standard [17], which involves the standard deviation of the longitudinal level (LL) over a distance of 200 meters. The specific wavelength range specified in EN 13848-6 and used for further analysis in this paper is the LL D1, which corresponds to the longitudinal level within the wavelength range of 3-25 meters. The EN standard specifies this wavelength range as relevant to track quality for railway tracks operating at conventional speeds. A higher standard deviation of the LL D1 indicates a poorer track quality.

As reported in [6], similar patterns between the standard deviation of the longitudinal level and vertical acceleration signals from smartphones were observed when similar window lengths were used for the computation of the standard deviation. Following this principle, this analysis investigates the characteristics of track quality derived from LL D1 and measured acceleration signals from smartphones recorded during Run B and Run E. The LL D1 dataset was retrieved from the ProRail monitoring database system, known as Branche Breed Monitoring Systeem (BBMS) [18], and was measured approximately 2 months before the smartphone acceleration measurements were conducted. The LL D1 values are measured separately over the left and right rail, and the mean values per left-right rail pair are used to compute the standard deviation of over 200 meters.

A 200-meter moving window was used to calculate the standard deviation for both LL D1 and the measured accelerations. However, before calculating the standard deviations for acceleration signals, the data was downsampled to 10 Hz. These preprocessing steps help in reducing the variance of the recorded signals caused by higher frequency components, as discussed in sections III-A and III-C.

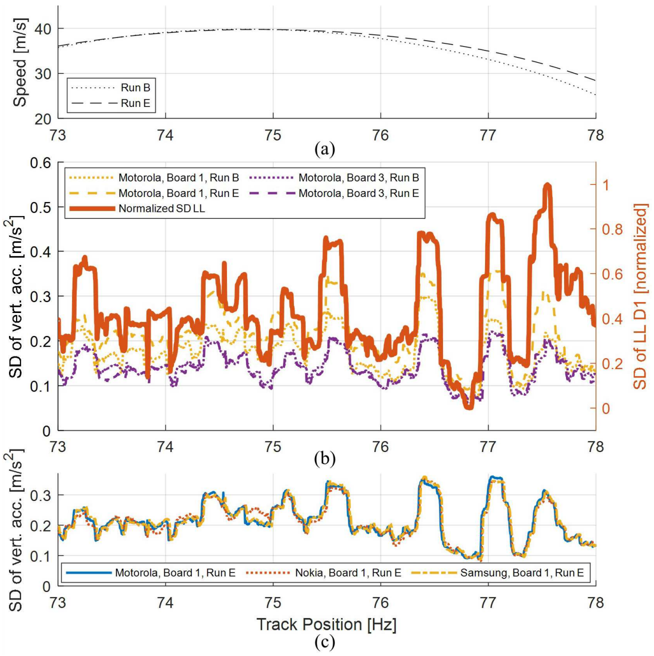

Fig. 7. (a) the vehicle speed profile of Run B and Run E; (b) standard deviations of the longitudinal level versus the vertical accelerations measured by the Motorola during Run B and Run E; (c) standard deviations of the vertical accelerations measured by all smartphones in Board 1 during Run E.

The same railway track segment as in Section II was selected as a case study. Figure 7(b) shows the calculated standard deviations of vertical accelerations from Board 1 and Board 3, as well as LL D1. The standard deviation of LL D1 is reported in a normalized form, with 1 being the relatively poorest track quality and 0 the relatively best. The results clearly demonstrate that the normalized standard deviation of LL D1 and the standard deviation of the measured accelerations exhibit similar patterns. This finding indicates the capability of mobile crowdsensing in track quality assessment. However, variations in the standard deviation are observed among the results. As discussed in Section III-B, higher speeds appear to amplify the standard deviation of vertical accelerations, even when the track quality is relatively good.

While similar patterns can be observed across the different signals, variations in vehicle speed significantly influence the results. For instance, according to the LL D1 results, the track condition at kilometer 77.5 is worse than at kilometer 77. However, the results from all measured accelerations indicate higher magnitudes at kilometer 77 compared to kilometer 77.5, which is attributed to the higher vehicle speed at kilometer 77. Furthermore, when comparing the results of Board 1 between Run B and Run E, the differences in the magnitude between kilometers 73 to 75, where the speeds of the two runs are similar, are smaller than the differences observed between kilometers 75 to 78, where variation in speeds are found.

Moreover, within the same run, inconsistencies are observed in the variation of standard deviation magnitudes between signals measured near the bogie (Board 1) and those measured at the center of the car body (Board 3). When comparing results from the same board across different runs between kilometers 73 to 75, where vehicle speeds are similar, the level of differences of Board 1 is significantly higher than Board 3. This observation aligns with the discussion in Section III-C.

Additionally, the variation in seat positions between different measurement runs, as discussed in Section I, may also contribute to these differences in results. Considering signals from Board 1, variations between Run B and Run E can further be attributed to slight variations in the instrumentation location. In Run B, Board 1 was 2 rows of seats closer to the center of the car body than in Run E. Section III-C demonstrated differences in the frequency range of 0 – 5 Hz between signals measured by a smartphone near the bogies and one located near the center of the car body. Thus, the slight difference in positioning between runs can result in the different frequency content and magnitude of the measured acceleration signals.

To analyze the results from different smartphone models, Figure 7(c) shows the standard deviation of the vertical acceleration signals recorded by all smartphones at Board 1 during Run E. Overall, results from all smartphones exhibit a consistent pattern. Although the acceleration characteristics measured by different smartphones are not identical, as discussed in Section II, the standard deviation patterns remain largely similar across devices. That is attributed to the downsampling of acceleration signals to 10 Hz, where acceleration characteristics exhibit significantly less variation within this frequency below 15 Hz, as shown in Figure 2(b).

These findings indicate that operational variables, including vehicle speed and the placement of devices within the car body, significantly influence the consistency of the assessment, highlighting the need for strategies to reduce the effects of these factors.

V. Conclusion and Recommendations

This paper highlights some key challenges in using mobile crowdsensing for railway track condition monitoring and quality assessment. Smartphone accelerometer characteristics, such as sampling frequencies, low-pass filter behavior, and the presence of eigenfrequencies, vary significantly between devices, affecting the accuracy and quality of acceleration measurement. Vehicle speeds influence both the frequency content and the magnitude of the vertical acceleration signals, while accelerations measured near the bogie differ in frequency content and energy compared to those measured near the center of the car body. These operational factors affect the consistency of railway track quality assessment. Nevertheless, the findings from the assessment using mobile crowdsensing highlight its potential to deliver reliable results, suggesting it could complement existing methods by offering frequent and cost-effective insights into track conditions.

For future research, increasing the scale of case studies is recommended. Current studies, including this study, have tested the concept of mobile crowdsensing for railway condition monitoring on a small scale, providing insufficient data to fully assess the operational variance observed. Expanding the scale could involve instrumenting multiple railway vehicles traveling the same route with numerous smartphones over an extended period. A larger dataset would enable more robust analyses, such as statistical or machine learning models, to evaluate the magnifying effect of vehicle speed, similar to those conducted [10]. It would also facilitate more detailed investigations into frequency content changes at different positions within the car body and analyses of how vehicle suspension system conditions affect recorded acceleration signals.

Additionally, signals measured from smartphones can be analyzed to derive key performance indicators (KPIs). While this study focuses on vertical track quality, incorporating lateral and longitudinal accelerations could offer additional insights into track irregularities and vehicle dynamic responses, providing a more comprehensive assessment of track conditions. Although these KPIs may exhibit lower levels of accuracy compared to standard measurement methods in practice, they provide significant advantages of more frequent assessments of track conditions. Future research could explore the dual role of smartphones: providing high-frequency, network-wide monitoring for a broader view of infrastructure health and complementing detailed but less frequent measurements from specialized vehicles. This dual approach could enhance maintenance decision-making, particularly for early anomaly detection and degradation trends.

Future research could also address challenges associated with mobile crowdsensing under more realistic conditions. For instance, studying the typical usage of a smartphone by a passenger on a train could provide valuable insights. This includes scenarios where the smartphone records data in a random orientation, such as when placed in a bag or pocket. Investigating how changes in device orientation during a journey affect the measurements could further enhance understanding of the challenges in using crowdsensing technology for railway infrastructure monitoring. Additionally, future case studies could include scenarios where passengers actively use or interact with their smartphones. This would enable researchers to differentiate accelerations caused by human-induced disturbances from those related to the railway infrastructure.

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