A review of smartphone-based methods for pavement roughness index estimation

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Abstract. Due to traffic loading and environmental conditions, pavement deteriorates over time, which leads to high roughness and surface distress, greatly compromising the ride quality and increasing safety risks and vehicle operating costs. Typically, pavement condition assessment is conducted using laser profilometers and response-type road roughness measuring methods (RTRRMs). Recently, attempts were made to leverage smartphones for roughness assessment and distress detection due to their increasing sensing capability and prevalent use among motorists. This research aims to analyse the body of knowledge in smartphone-based roughness assessment, report knowledge gaps, and cast light on future research directions. First, a systematic literature search found 88 academic publications in relevant fields. These works were critically reviewed with regard to sensor selection, pre-processing methods, and assessment algorithms. Special attention was given to practical factors that affect the accuracy and robustness of smartphone-based methods, including data collection speed, vehicle type, smartphone specifications and mounting configuration. Findings from this research are expected to provide a thorough understanding of the potentials and limitations of smartphone-based roughness assessment methods and inform future research and practices in this domain.

Keywords
Algorithm, pavement roughness, roughness index, smartphone, surface distress

1. Introduction

Under the combined effects of traffic loading and adverse environmental conditions, pavement deteriorates over time, regardless of how well they are designed and constructed. Deterioration of pavement not only affects ride comfort and imposes safety risks but also increases the cost for road users [1]. In Australia, the expenditure on the maintenance of road networks amounts to A$690 million per annum [2]. Typically, maintenance works are carried out based on an estimated deterioration model as well as field inspection data that reflects actual deterioration conditions. Hence, accurate and continual monitoring of the pavement condition is vitally important to maintain the expected pavement serviceability effectively and economically.

Pavement conditions are usually represented by roughness indices, such as the International Roughness Index (IRI) and Pavement Condition Index (PCI), which are calculated based on a driving vehicle's response to the road profile and visual inspection of pavement distresses, respectively [3]. Being one of the most popular roughness indices adopted globally, the IRI is typically measured by inertial laser profilometers, which accurately estimate road profiles with a high resolution. However, inertial profilers are expensive to own and operate, making data collections infrequent (typically once a year) and less affordable and accessible for small road authorities. Aside from pursuing high measurement precision, the focus should also be given to maximising the measurement sample size and coverage [4]. Thanks to the prolificity and increasing sensing capabilities of smartphones, measuring pavement roughness using smartphone sensors has become a viable approach and has drawn much attention from researchers and practitioners. Over the last decade, various approaches have been developed to achieve roughness index estimation (RIE) by processing sensor signals acquired from smartphones. This review has grouped the approaches applied in RIE into three categories, namely statistical-based, vehicle model-based, and machine learning methods.

Some previous works attempted to review research advancements in smartphone-based pavement condition assessment, but they mainly covered the response-based method, which has a broader scope than the smartphone-based method [5]. A thorough review of methodologies in RIE using smartphones is missing, and there is inadequate understanding of the impact of practical factors, including speed, vehicle type, and mounting configuration, on the accuracy and robustness of smartphone-based RIE. Therefore, this paper aims to critically review the body of knowledge in smartphone-based RIE with special attention paid to the impact of practical factors. The rest of the paper is organised as follows. Section 2 introduces the review methodology and the literature search results. Section 3 discusses three categories of smartphone-based methods in RIE and the impact of practical factors. Sections 4 and 5 shed light on future research directions and conclude the review.

2. Research methodology

A systematic review adopts a transparent and replicable process to exhaustively search for studies from where the boundary of knowledge and potential research gap can be identified [6]. To obtain a comprehensive understanding of the literature, this paper employed a three-step review approach (i.e., literature search, content review and discussion). Step 1 includes literature search and bibliometric data screening. In step 2, a critical review of smartphone-based methods in RIE was conducted. Step 3 focuses on discussing the knowledge gaps and future directions.

Using the searching string, as presented in Table 1, the initial search from Web of Science yielded 137 articles, and a manual inspection then checks if the paper is addressing smartphone-based RIE by scrutinising its titles and abstracts, and 49 articles were removed with subjects that are irrelevant to the target research topics. Finally, the literature search process resulted in 88 publications.

Table 1. Literature review searching string

Searching field	Keywords
Title	(*phone*) AND (road* OR pavement*)
+	AND
Article title, Abstracts, Keywords	assess* OR evaluat* OR acceleromet* OR roughness OR condition* OR IRI OR PCI OR PSI OR index* OR service*

3. Findings

A roughness index indicates the condition of the pavement and is of interest to road agencies and contractors for pavement condition evaluation and maintenance. The IRI was developed in the International Road Roughness Experiment (IRRE) as a standard scale of road roughness that allows the comparison of measurement surveyed by instruments of various kinds [7]. This section presents a summary of smartphone-based IRI estimation methods under three categories, including statistical method, vehicle model-based method, and machine learning method.

3.1. Statistical-based methods

Statistical methods aim to establish a relationship between the acceleration measurement and the reference IRI value. Root mean squared (RMS) is a statistical measure of a variable and is useful when the variable could be both positive and negative. It was discovered that the acceleration RMS method is the most studied statistic applied to correlate with the reference IRI. The correlation between acceleration-based statistics and the IRI is evidenced by a correlation coefficient greater than 0.8, as reported in [8]. Several studies attempted to establish a relationship between the smartphone's vertical acceleration and the IRI through regression analysis and suggested that the RMS of vertical acceleration could be referenced for pavement roughness assessment due to its high correlation with the IRI [9]. In addition to vertical acceleration, acceleration RMS from all three axials was considered to identify a relationship with the reference IRI [10]. In [11], the estimated IRI was computed using a linear conversion formula derived based on the peak and root mean square (RMS) of the acceleration data.

Apart from RMS, [12] described an empirical relationship between the standard deviation of the acceleration and the IRI. Moreover, a second-degree polynomial model was adopted in [13] to estimate IRI based on vertical acceleration and vehicle speed. The estimated IRI is then correlated with the reference IRI measured by a Class 1 profilometer with an R-squared value of 0.88. Expressed as the quotient of RMS of vertical acceleration divided by the vehicle's real-time speed, an IRI-proxy formula was proposed by [14], suggesting a correlation between the IRI and the speed-normalised RMS of z-axis acceleration. This correlation was subsequently validated in [10] using smartphone-collected data. Instead of focusing on the time-series acceleration data, a relationship between tri-axial acceleration's frequency magnitude and the roughness index was explored in [15]. They applied Fast Fourier Transform (FFT) on the smartphone-collected acceleration and found a linear relationship between the ground truth IRI and the sum of magnitudes of acceleration and gyroscope data.

3.2. Vehicle model-based methods

The nature of smartphone-based IRI computation is using a smartphone, more specifically the onboard sensors such as accelerometer and gyroscope, to measure the vehicle body's response to a road profile. Since the vehicle's mass and suspension characteristics affect how its body react to a road segment, it is essential to consider vehicle suspension characteristics when estimating the IRI. Vehicle model-based methods are classified into two main approaches, namely (1) Power spectral density (PSD) analysis and (2) Profile estimation.

Power spectral density (PSD) analysis. PSD measures the mean squared value of a random variable and indicates how such a value of a time-series signal distributes over a frequency spectrum. Pavement profiles can be represented in the form of PSD [16]. The pavement PSD can be linked to the frequency spectrum of the vehicle's acceleration response by considering the pavement roughness-vehicle mechanistic interaction. First proposed by [17], the PSD of pavement profile was estimated from measured vehicle response using a transform function that defines the relationship between the PSDs of the vehicle body or axel's acceleration and the road profile. The IRI can then be directly computed if the PSD of a road profile is known [18]. Furthermore, [19] attempted to explore the direct relationship between the IRI and roughness PSD through regression analysis, while [20] derived a stochastic model to relate the road roughness PSD and vertical acceleration of the QC vehicle model. Moreover, a linear relationship between the IRI and the squared root of pavement PSD was mathematically derived in [21]. This method regards the pavement profile as a continuous surface, defines the IRI simulation as a random sequence that obeys a zero-mean Gaussian distribution, and analyses the QC model as a linear time-invariant system. This theoretical system model was validated in a field experiment with the relative error of the estimated IRI being less than 15%. The same relationship was also adopted in [22], where the correlation between the estimated IRI and the reference IRI was 0.86.

Profile estimation. Studies attempted to estimate the road profile from the vehicle's acceleration. Once the profile is estimated, the IRI could be calculated using the algorithm proposed by [8]. The IRI computation algorithm is included in (ASTM E1926-08 2015) and is incorporated in the software ProVal (Profile Viewing and analysis) [24]. One way to estimate the road profile is by double integrating the vehicle body's acceleration [25,26]. The estimation of road profile based on vehicle response can be interpreted as a suspension system identification problem [27]. Therefore, [28] firstly estimates the suspension system's resonant frequency and damping ratio by applying FFT to the acceleration. Next, instead of adopting the conventional QC model, a vehicle model that waives the suspension coefficient of unsprung mass was introduced to estimate the profile. Alternatively, road profile can be estimated by solving a QC model-based state-space matrix. This approach was applied in [29], where the vehicle's mass and suspension parameters were known, and the sprung mass acceleration was recorded. However, in most cases, vehicle parameters may be unknown and need to be estimated beforehand [30]. To do this, the testing vehicle was modelled as an HC model and was driven over a known hump with the vertical acceleration of the vehicle body recorded. Then, unknown vehicle parameters were determined using UKF (Unscented Kalman Filter) and GA (Genetic Algorithm). The IRI of an unknown road profile could be estimated from the actual vehicle body's response at different speeds. Meanwhile, [20] incorporated vehicle dynamics and random vibration theory in a two-layer inverse analysis to estimate road roughness and vehicle properties. Their study estimated the IRI with a relative error of 8% to the ground truth IRI.

3.3. Machine learning methods

Being a subset of artificial intelligence, machine learning algorithms build a model based on sample data to perform classification and prediction tasks. [31] suggested that ML algorithms capture 15.6% more variability in estimating IRI than conventional statistical methods. Various machine learning methods are being utilised to compute the IRI in recent studies. An artificial neural network (ANN) is a mathematical model composed of interconnected nodes that simulate how the human brain responds to signals and makes a decision. [32] first applied ANN for roughness classification and IRI estimation based on vehicle response. To account for speed and suspension variation in the vehicle model-based method, a deep learning approach with entity embedding was applied in [33] to train a model that uses smartphone accelerometer data and previous year's IRI values to predict the current IRI. Meanwhile, a convolutional neural network (CNN) was proposed to estimate the IRI from multiple vehicle responses measured by smartphones [34]. Notably, instead of arithmetically averaging the measurements obtained from all vehicles to obtain the IRI for a road section, [35] firstly estimates the suspension parameters of a vehicle when the vehicle traverses a road section with known IRI, then semi-supervised learning (SSL) model was adopted to estimate the IRI of other road sections that the vehicle drives on. Rather than estimating the suspension parameters of the vehicles, [36] extracted the statistical features (i.e., mean, range and variance) from smartphone acceleration and GPS signals. A prediction model was then trained from these features and the ground truth IRI.

3.4. Practical factors affecting RIE

Since smartphone-based RIE methods estimate the IRI indirectly based on smartphone acceleration data, the accuracy is greatly affected by factors including the driving speed, vehicle type and mounting configuration. This section will present previous works that investigated the impact of these factors on the performance of smartphone-based RIE.

3.4.1. Speed. The performance of response-based RIE systems is greatly affected by the speed of travel [37] since the magnitude of the vehicle body's vertical acceleration is dependent on the vehicle speed. Specifically, the coefficient of the IRI-acceleration regression model varies significantly as the speed changes [11]. Likewise, vehicle body acceleration was simulated at different speeds, and it was found that the acceleration increased by 93% when vehicle speed changed from 30 to 80 km/h [38]. The smartphone-based system was tested at the speed of 50 and 80 km/h, and it was discovered that the computed IRI values vary due to the increase in speed [39]. Incorporating the effect of speed in smartphone-based RIE is of paramount importance to achieving robust estimation results.

Prevalent approaches of considering the impact of speed can be categorised into correction coefficient, varying regression parameters, and high pass filters. In terms of correction coefficient, one approach is to introduce a speed-dependent coefficient to the IRI-acceleration regression model [21]. Similarly, speed normalised acceleration RMS was adopted in [40] to build the IRI fitting model and the Ride Impact Factor (RIF) was multiplied by the squared root of the speed to account for speed variability [41]. Moreover, a correction function could be applied to the non-stationary acceleration signal collected from variable speeds [20]. However, it was noted that when there is high variability in driving speed, a stochastic HC dynamic model should be considered. Differing from introducing a calibration index, the coefficient of the regression models could be adjusted to be adaptive to speed. For instance, the regression coefficients of the IRI-PSD model in [42] were experimentally validated to be linearly correlated to speed variation. Similarly, a linear IRI-speed relationship was applied to calibrate the estimated IRI value based on acceleration data captured at speeds other than 50mph to the standard 50mph IRI value [43]. Meanwhile, speed is considered as a variable in a multivariate regression model in [44] and as a second-degree variable in a polynomial model in [13]. Furthermore, the effect of speed variation could be alleviated by effective signal filtering at the pre-processing stage. Specifically, multiple studies applied a high pass filter on the raw acceleration signals to compensate for the effect of speed change on IRI estimation [30].

3.4.2. Vehicle suspension. The smartphone-based measurement of road roughness is affected mainly by the discrepancies in the vehicle suspension types. Experimentally, smartphones surveyed the IRI adopting two different vehicles travelling at the same constant speed at the same test location [46]. The study indicated that the vertical acceleration collected from other vehicles was dampened to differing degrees due to varying vehicle suspensions. [39] adopted three vehicle types to survey the IRI and their measurements were not statistically similar. A calibration process was proposed to incorporate the vehicle suspension characteristics in computing the IRI using mobile devices [47]. The developed iDRIMS was tested on three different vehicle types (sedan, small van, and SUV), which showed consistent measurement results with a relative error of less than 10% compared to the profilers. In the calibration process of [43], a trial and error method was applied to account for different vehicle mass and suspension parameters to improve the accuracy of the estimated IRI. Besides, [48] proposed the application of smartphones in pavement profile estimating using the SMND (SDOF Model-Based Noisy Deconvolution) approach, which considers vehicle dynamic effects. Moreover, a CNN model, which was trained using multiple vehicle's dynamic responses collected by smartphones, was adopted to compute the IRI accommodating variations in vehicle types [34]. In terms of the simulation works, random mechanical properties were generated to simulate the variations of vehicle parameters in [49]. Moreover, [50] applied a Monte Carlo approach to simulate the response of three different vehicle types. With a large sample size (more than 50), their study concluded that there is no statistical significance in ride quality index estimation under different vehicles in mixed traffic cases.

3.4.3. Mounting configuration and location. Drivers tend to mount smartphones differently (e.g., windshield, dashboard, air vent), and the mounting rigidity affects the measurement of the vehicle body's acceleration. Previous research investigated the impact of different mounting configurations on RIE. [51] tested three mounting types and suggested that the windshield mount provides the closest result to a profiler while air vent mount presents an error of 85.8%. Compared with dashboard mounts, it was discovered that the measurements from a rigid mount on the windshield were more consistent [52]. Similarly, [53] tested four mounting types using Roadroid and Roadbump and found their measurements did not converge well in most road sections. A smartphone mount could be considered as a suspension model, which is added on top of the sprung mass of the QC model [54]. Using Monte-Carlo simulation, they validated the network-level road monitoring system using smartphones, suggesting a sample size of 300-400 is needed for the measurement results to converge. Similarly, while the variation of mounting type could cause discrepancies in RIE in a case-by-case scenario, the measurements should converge when there is network-level data with 50-60 samples [54]. Besides the rigidity of the mount, the position at which the phone is mounted also affects the acceleration measurement. In [20], the variability of predictions resulting from smartphone positions could be minimised in a crowdsourced setting. Nevertheless, instead of leveraging the smartphone's crowdsourcing feature, the HC model was applied to accommodate the impact of sensor location in the development of a smartphone-based RIE method. As [55] suggested, averaging sensor data collected at multiple locations of a vehicle during the same ride could produce more reliable roughness data.

4. Discussion on future research directions

Based on the literature review, the following research directions are proposed to improve the practicality and accuracy of smartphone-based RIE:

Different practical factors combinations. In the statistical-based methods, the regression coefficients are computed from data collected in a specific experimental setting. Once the setting is altered with different vehicle types or speeds, the regression coefficients should be adjusted to estimate the IRI with accuracy. Experiments are to be conducted to identify the correlation coefficient between the reference roughness index and the response-based statistics under various combinations of a vehicle body, speed, then verify the obtained relationships through field tests.

Pavement variety and temporal monitoring. Most studies have limited their research to a road section of a certain IRI range [56]. A study that evaluates the performance of smartphone-based systems on a wide spectrum of pavement types that have different IRI values is yet to be conducted. Moreover, it remains to be explored whether smartphone-based systems can identify temporal pavement deterioration. Periodic evaluation of a certain pavement over a long period using smartphone-based systems and verifying whether the evolution of pavement condition could be identified from smartphone-collected data is yet to be conducted.

Speed variation. Smartphone-based RIE methods that account for time-variant speed are still needed. The simulation works in previous research were conducted on discretised speed, and the response under continuously changing speed is yet to be explored. Moreover, most research studied the effect of speed variation by considering one vehicle model, and whether the developed relationship is applicable to other vehicle types is yet to be verified. In addition, our review revealed that the speed range that studies considered is 20km/h to 80km/h; this could be extended in future studies, especially for the low-speed band, to enable the surveying in metropolitan are.

Vehicle suspension variation. In lieu of calibrating the individual vehicle's parameters, a more straightforward approach is to empirically identify the response discrepancies amongst various classes of vehicles experimentally. An extensive field experiment that covers a wide spectrum of vehicle models with the intention of learning the vehicle's effect on smartphone-based road roughness evaluation is still needed in future research. With the comprehensive experimental data, deep learning models could be implemented to detect the intrinsic differences in the acceleration data resulting from the vehicle characteristics and to reveal the underlying parameters that empirically explain the effect of the vehicle's suspension characteristics on the vehicle body's response excited by the road profile.

5. Conclusion

Our review suggests that the acceleration-based statistics method is likely to remain prevalent as a supplementary pavement evaluation means because it requires relatively less computing effort and provides a reasonable estimate of the roughness index. It is also suggested that the vehicle model-based methods should be further validated under a more variety of practical setting combinations, which emulate the network-level application, prior to being adopted in road agencies' pavement management systems. With regards to ML approaches, it is anticipated that further field testing should be conducted to validate their effectiveness on various pavement conditions under more realistic driving settings. It is also envisaged ML algorithms be incorporated into statistical or vehicle model-based methods to improve the estimation performance.

References

[1] Islam S and Buttlar W 2012 Effect of pavement roughness on user costs *Transp Res Rec*. **2285** 47–55

[2] Commonwealth Grants Commission 2020 *Assessments of roads expenses*

[3] Piryonesi SM and El-Diraby 2021 TE Examining the relationship between two road performance indicators: Pavement condition index and international roughness index *Transp. Geotech*. **26** (September 2020) 100441

[4] Byrne M and Isola R 2016 All the data eggs in the one laser basket *Road and Tranp Res.* **30328**(July) 1–17

[5] Nguyen T Lechner B and Wong YD 2019 Response-based methods to measure road surface irregularity: a state-of-the-art review *Eur Transp Res* Rev **11**

[6] Tranfield D, Denyer D and Smart P 2003 Towards a Methodology for Developing Evidence-Informed Management Knowledge by Means of Systematic Review. *Br J Manag*.**14** 207–22

[7] Sayers MW, Gillespie TD and Paterson WDO 1986 Guidelines for Conducting and Calibrating Road Roughness Measurements *World Bank Technical Paper.* Number **46** 87

[8] Chou C-P, Siao G-J, Chen A-C and Lee C-C 2020 Algorithm for Estimating International Roughness Index by Response-Based Measuring Device *J Transp Eng Part B Pavements*. **146**(3) 04020031

[9] Zeng H, Park H, Smith BL and Parkany E 2018 Feasibility Assessment of a Smartphone-Based Application to Estimate Road Roughness. *KSCE J Civ Eng*. **22**(8) 3120–9

[10] Li X and Goldberg DW 2018 Toward a mobile crowdsensing system for road surface assessment *Comput Environ Urban Syst*. **69**(December 2017) 51–62

[11] Forslöf L and Jones H 2015 Roadroid: Continuous road condition monitoring with smart phone. *J Civ Eng Archit*. **9**(4) 485–96

[12] Chen K, Tan G, Lu M and Wu J 2016 CRSM: a practical crowdsourcing-based road surface monitoring system *Wirel Networks*. **22**(3) 765–79

[13] Wessels I and Steyn WJM 2020 Continuous, response-based road roughness measurements utilising data harvested from telematics device sensors *Int J Pavement Eng*. **21**(4) 437–46

[14] Amador-Jiménez L and Matout N 2014 A low cost solution to assess road’s roughness surface condition for Pavement Management *TRB 2014 Annu Meet*. **2424** 16

[15] Douangphachanh V and Oneyama H 2014 A study on the use of smartphones under realistic settings to estimate road roughness condition *Eurasip J Wirel Commun Netw*. **2014**(1)1551–64

[16] Andrén P 2006 Power spectral density approximations of longitudinal road profiles *Int J Veh Des*. **40**(1–3) 2–14

[17] González A, O’Brien EJ, Li YY and Cashell K 2008 The use of vehicle acceleration measurements to estimate road roughness *Veh Syst Dyn*. **46**(6) 483–99

[18] Sun L 2002 Simulation of pavement roughness and IRI based on power spectral density *Math Comput Simul*. **61**(2) 77–88

[19] Chen K, Lu M, Fan X, Wei M and Wu J 2011 Road condition monitoring using onboard three-axis accelerometer and GPS sensor *Proc 2011 6th Int ICST Conf Commun Netw China*, **2011** (August) 1032–7

[20] Botshekan M, Asaadi E, Roxon J, Ulm FJ, Tootkaboni M and Louhghalam A 2021 A Smartphone-enabled road condition monitoring: From accelerations to road roughness and excess energy dissipation *Proc R Soc A Math Phys Eng Sci*. **477**(2246)

[21] Du Y, Liu C, Wu D and Jiang S 2014 Measurement of international roughness index by using Z -axis accelerometers and GPS. *Math Probl Eng*. 2014

[22] Janani L, Sunitha V and Mathew S 2020 Influence of surface distresses on smartphone-based pavement roughness evaluation *Int J Pavement Eng*. **0**(0):1–14

[23] ASTM E1926-08 2015 Standard Practice for Computing International Roughness Index of Roads from Longitudinal Profile Measurements. *ASTM Stand (Reapproved 2021)*

[24] The Transtec Group 2015 ProVAL User's Guide
[25] Mirtabar Z, Golroo A, Mahmoudzadeh A and Barazandeh F 2020 Development of a crowdsourcing-based system for computing the international roughness index. *Int J Pavement Eng.***0**(0) 1–10
[26] Islam S, Buttlar WG, Aldunate RG and Vavrik WR 2014 Measurement of pavement roughness using android-based smartphone application. *Transp Res Rec*. **2457** 30–8
[27] Qin Y, Langari R and Gu L 2014 The use of vehicle dynamic response to estimate road profile input in time domain *ASME 2014 Dyn Syst Control Conf.***2** 1–8
[28] Koichi Y 2016 Preliminary report for IRI changes after KUMAMOTO earthquake Japan, by using Smartphone roughness measurement *2nd IRF Asia Regional Congress & Exhibition*
[29] Islam S 2015 Development of a Smartphone Application To Measure Pavement
[30] Zhao B and Nagayama T 2017 IRI Estimation by the Frequency Domain Analysis of Vehicle Dynamic Responses *Procedia Eng.* **188** 9–16
[31] Bashar MZ and Torres-Machi C 2021 Performance of Machine Learning Algorithms in Predicting the Pavement International Roughness Index *Transp Res Rec J Transp Res Board*. **2675** 226-237
[32] Ngwangwa HM, Heyns PS, Labuschagne FJJ and Kululanga GK 2010 Reconstruction of road defects and road roughness classification using vehicle responses with artificial neural networks simulation *J Terramechanics*. **47**(2) 97–111
[33] Aboah A and Adu-Gyamfi Y 2020 Smartphone-Based Pavement Roughness Estimation Using Deep Learning with Entity Embedding *Adv Data Sci Adapt Anal.* **12**(03n04) 2050007
[34] Jeong JH, Jo H and Ditzler G 2020 Convolutional neural networks for pavement roughness assessment using calibration-free vehicle dynamics *Comput Civ Infrastruct Eng*. **35**(11) 1209–29
[35] Liu C, Wu D, Li Y and Du Y 2021 Large-scale pavement roughness measurements with vehicle crowdsourced data using semi-supervised learning *Transp Res Part C Emerg Technol*. **125** 103048
[36] Laubis K, Simko V and Schuller A 2016 Road condition measurement and assessment: A crowd based sensing approach *Int Conf Inf Syst ICIS*.1–10
[37] Galagoda DY and Lanka S 2019 Smartphone Applications for Pavement Roughness Computation of Sri Lankan Roadways *Eastern Asia Society for Transportation Studies*. **13** 2581–97
[38] Wang G, Burrow M and Ghataora G 2020 Study of the Factors Affecting Road Roughness Measurement Using Smartphones *J Infrastruct Syst.* **26**(3) 04020020
[39] Cameron CA 2014 Innovative means of collecting international roughness index using smartphone technology *Univ New Brunswick*
[40] Meng L, Yang S, Yang H and Xiao F 2017 The Crowdsourcing-Based Estimation and Display of Rural Highway Condition from Smartphone Sensors under Natural Driving *Int. Conf. Transp.* 5015–26
[41] Bridgelall R, Hough J and Tolliver D 2019 Characterising pavement roughness at non-uniform speeds using connected vehicles. *Int J Pavement Eng*. **20**(8) 958–64
[42] Liu C, Wu D, Li Y, Jiang S and Du Y 2020 Mathematical insights into the relationship between pavement roughness and vehicle vibration. *Int J Pavement Eng*. **0**(0) 1–13
[43] Stribling J 2016 Use of Smartphones To Measure Pavement Roughness Across Multiple Vehicle Types At Different Speeds *University of Illinois at Urbana-Champaign*
[44] Douangphachanh V and Oneyama H 2014 Formulation of a simple model to estimate road surface roughness condition from Android smartphone sensors. *2014 IEEE 9th Int Conf Intell Sensors*. 21–4
[45] Zhao B, Nagayama T, Toyoda M, Makihata N, Takahashi M and Ieiri M 2017 Vehicle model calibration in the frequency domain and its application to large-scale IRI estimation *J Disaster Res*. **12**(3) 446–55
[46] Islam S, Buttlar WG, Aldunate RG and Vavrik WR 2014 Use of cellphone application to measure

pavement roughness *Proc 2nd Transp Dev Inst Congr*. 553–63

[47] Xue K, Nagayama T and Zhao B 2020 Road profile estimation and half-car model identification through the automated processing of smartphone data *Mech Syst Signal Process*. **142** 106722

[48] Moghadam A and Sarlo R 2021 Application of smartphones in pavement profile estimation using SDOF model-based noisy deconvolution *Adv Civ Eng*

[49] Zhang Z, Sun C, Bridgelall R and Sun M 2018 Application of a Machine Learning Method to Evaluate Road Roughness from Connected Vehicles. *J Transp Eng Part B Pavements*. **144**(4) 04018043

[50] Medina JR and Salim R 2020 Underwood BS, Kaloush K. Experimental Study for Crowdsourced Ride Quality Index Estimation Using Smartphones *J Transp Eng Part B Pavements*. **146**(4) 04020070

[51] Hanson T, Cameron C and Hildebrand E 2014 Evaluation of low-cost consumer-level mobile phone technology for measuring international roughness index (IRI) values *Can J Civ Eng*. **41**(9) 819–27

[52] Ordaz M and Doyle J 2021 Quantifying extreme event-induced pavement roughness via smartphone apps *Geo-Extreme*. 222–31

[53] Hossain M, Tutumluer E and Nikita G 2019 Evaluation of Android-Based Cell Phone Applications to Measure International Roughness Index of Rural Roads *Int. Conf. Transp. Dev.* **4** 309–18

[54] Medina JR, Noorvand H, Shane B and Kaloush K 2020 Statistical Validation of Crowdsourced Pavement Ride Quality Measurements from Smartphones. *J Comput Civ Eng*. **34**(3) 04020009

[55] Opara KR, Brzezinski K, Bukowicki M and Kaczmarek-Majer K 2021 Road Roughness Smartphone-Measured Estimation Through Acceleration *IEEE trans Intell Transp Syst*. 2–13

[56] Daraghmi YA, Wu TH and Tsi-Ui 2020 Crowdsourcing-Based Road Surface Evaluation and Indexing *IEEE Trans Intell Transp Syst*. 1–12