Investigating for Road Roughness using Smartphone Sensors

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Abstract— Smartphones are equipped with sensors such as accelerometers, gyroscope and GPS in one cost-effective device with an acceptable level of accuracy. Research has been carried out to determine the roughness of roads via smartphones. In order to justify the validity of using smartphones as tool to define the roughness of the road, it must be compared to other subjective methods such as user opinion. The aim of this paper is to calculate the roughness of the road via a smartphone using its embedded sensors. Additionally, this paper will investigate the correlation of road roughness with a user opinion to conclude ride quality. Moreover, the applicability of using smartphones to assess the road surface distresses is examined. Furthermore, to validate the smartphone sensor outputs objectively, the Road Surface Profiler is applied. Finally, a good roughness model is developed which demonstrates an acceptable level of correlation between the road roughness measured by smartphones and the ride quality rated by users.

Keywords— Road Roughness; Smartphone; User Opinion; Sensors; GPS; Accelerometer; Gyroscope.

I. INTRODUCTION

According to ASTM standard E867, the road roughness can be defined as “the deviation of a surface from a true planar surface with characteristic dimensions that affect the vehicle dynamics and ride quality” [1]. Road roughness is a criterion that is used to describe the road condition and the ride quality which is usually measured by an index such as the International Roughness Index (IRI).

Road roughness is a significant aspect for both travellers and city officials. Travellers are concerned about ride comfort and their vehicle's operating costs. Hence, city officials utilise the road roughness as an essential indicator to conduct an optimum road maintenance planning which significantly saves the life cycle, costs, and prolongs the service life of the roads.

Two major methods are used to collect the road roughness data: manual and automated (or semi-automated). Generally, manual data collection is labour-intensive, unsafe, time-consuming, and costly. On the other hand, automated data collection is precise, fast, safe, repeatable, and standardised. Automated data collection devices such as laser scanners and profilers are very expensive to purchase, operate, and maintain.

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It is rarely feasible for city officials in developing countries to conduct data collection using such devices to frequently monitor the entire road network condition. Alternative devices for road roughness data collection are smartphones.

Regarding the advancements achieved by researchers in the smartphone industry, several inexpensive sensors are embedded in smartphones such as 3-axis accelerometers, a gyroscope, and a GPS. These sensors are commonly deployed in different smartphone applications such as games and navigations; however, they can be applied in engineering fields of study such as transportation engineering.

II. LITERATURE REVIEW

Recently, cost-effective sensors have been applied in different fields of transportation such as traffic engineering and road management. Mohan et al. (2008) investigated road and traffic condition by different sensors such as accelerometer, microphone, GSM radio, and GPS in order to detect bumps, braking, and honking of the horn [2]. They investigated the traffic condition by considering the synchrony of honking with accelerometer data and braking with camera through the application of a threshold based method [2]. Some years later, Bhoraskar et al. (2012) employed a machine learning method instead of the threshold based method which ended up with detecting bumps and vehicle braking [3].

Furthermore, road distress detection is one of the applications of smartphones in road management. Researchers have proposed different algorithms for detecting different types of potholes [2, 4–7]. Eriksson et al. utilised smartphones to investigate road anomalies [4]. They introduced a system which was called "pothole patrol". Seven running taxis were hired and were equipped with smartphones to monitor the surface condition of roads to detect potholes through sharp vertical vibration of vehicles [4]. Mednis et al. (2011) defined "Z-THRESH" determining a threshold for the z-axis accelerometer data. The values outside the threshold were defined as various types of potholes. They also developed a new algorithm for detecting the anomalies called "G-ZERO" indicating a threshold in which all three axis accelerometer data have a value close to 0g (zero gravity) [5]. Aksamit and Szmechta (2011) evaluated the road quality by processing signals from accelerometers of smartphones mounted on four different locations in a car [8]. Seraj et al. (2014) employed Support Vector Machine (SVM) to distinguish and classify road anomalies. As a result, they devised a real-time multi-class road anomaly detector which was able to spot approximately 90 percent of severe anomalies [9]. Tai et al. (2010) applied smartphones with a 3-axis accelerometer when riding a motorcycle to detect road anomalies and evaluate the road quality with a high precision of 78.5% [10].

Moreover, road roughness has been studied using the embedded sensors within smartphones. The "SmartRoadSense" system introduced by Alessandroni et al. (2014) aimed to monitor road surfaces via smartphones. They developed a model in this study to calculate an index for the road roughness from captured data via the system [11]. Finally, they color-coded road sections on a map to prioritise the pavement rehabilitation [11]. Douangphachanh and Oneyama (2013, 2014) determined road conditions by utilising the VIMS component as a reference for calculating a road roughness index. They collected the data by the AndroSensor application installed on smartphones to determine road profiles and compute IRI [12, 13]. Islam et. al. (2014) numerically double-integrated acceleration data and processed them via a computer software, Proval [14, 15]. The study was conducted in three different sites for gathering road profile and acceleration data with both an inertial profiler and a smartphone mounted on a vehicle [15]. The outputs revealed that the smartphone devices were able to measure IRI with an acceptable accuracy compared with an inertial profiler [15]. Zeng et al. (2015) calculated the road roughness based on a normalised acceleration index. Data gathering was accomplished by employing two tablets mounted on a vehicle. The tablet sensors captured acceleration data in three dimensions, GPS coordinates, and vehicle speeds [16]. They declared that the proposed index could correctly detect deficient road segments at a high precision of 80 to 93 percent [16]. Hanson et al. (2014) attempted to correlate the road roughness captured by smartphones and a conventional profiler. They employed eleven different segments on one kilometre stretch of a secondary highway in New Brunswick, Canada and came up with the conclusion that there was a good correlation between output of the profiler and smartphone [17].

Panel rating has been applied to investigate the ride quality of pavement [18]. It is the best subjective method to collect the traveller's opinion about ride quality which can be effectively applied to validate the objective measurement of road roughness. The subjective validation of road roughness measured by smartphones has not been taken into much consideration. In other words, no one has investigated whether the smartphone roughness outputs would represent the real sense of users from the ride quality. This paper aims to fill this void and to investigate the correlation between the objective roughness measurements by smartphones and subjective rating by a panel.

III. Aims and Objectives

The main aim of this study is to examine the correlation between road roughness measured by smartphones mounted on a vehicle and user opinions obtained through a panel rating on the ride quality of the road. The scope of this study is calculating the road roughness in urban transportation networks on asphalt surface roads.

IV. Methodology

The research study was conducted through different processes including data collection, road indices measurements, and investigation of the validation and correlation of the indices. Fig. 1 schematically depicts the study approach.

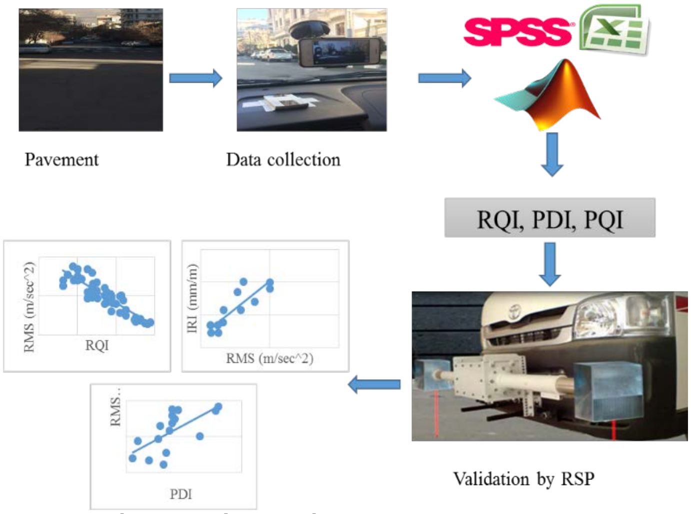

Fig. 1. Schematic study approach

This study can be divided into three modules. The first module is to design an experiment. For this purpose, a pilot study was carried out to capture some sample data to detect the drawbacks and issues that may arise in the experiment. In the second module, road conditions are measured using smartphones and panel rating. Finally, in the third module, the roughness obtained through smartphones is validated by a Road Surface Profiler (RSP) and the correlation between the roughness computed via the smartphones and the panel is investigated. Fig. 2 shows the study's research methodology.

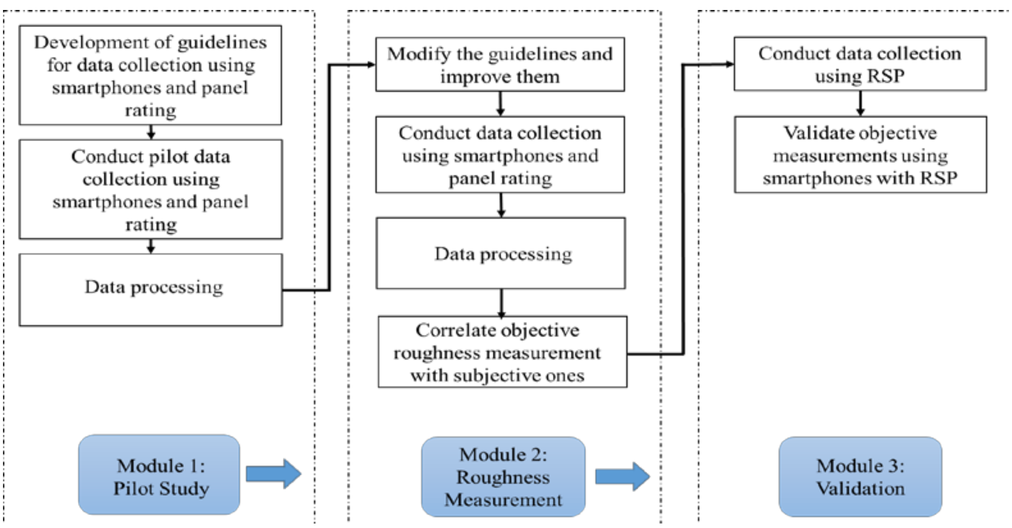

Fig.2. Research Methodology

A. Module 1: Pilot Study

The pilot data collection was conducted through panel ratings and smartphones. The experiment was initiated by designing guidelines for smartphone data collection and panel rating. The guideline for smartphone data collection was covered by the method of mounting the smartphones on the vehicle dashboard, running the smartphone application, and transferring the data to the station. The other guideline was developed for the panel. It described the method of road surface defect assessment i.e., it contained definitions of asphalt road distress types along with their various categories of severity and density. The guideline also categorised user opinions about the ride quality levels into five groups: very good, good, moderate, poor, and very poor. For instance, "good" expresses a condition that a driver feels comfortable and does not feel any jump when the car moves along the road, although the driver has a slight vibration sensation.

Participants were divided in different groups/vehicles. Each group included three members: a driver, a surveyor, and a rating assessor. The driver drove the car in a predetermined segment at the speed of 20 to 50 km/h. The surveyor sat in the front seat of the car and was responsible for both surveying the road condition and running a smartphone application. The smartphone was mounted on the car dashboard as shown in Fig. 3 to record GPS and the accelerometer data. The rating assessor, whom sat on the rear seat of the car, rated the ride quality. Moreover, a smartphone was mounted to the car windshield (Fig. 3) to capture a video of the segment to validate the rating of surveyors and assessor.

The data was captured from a segment divided into five sections (approximately one kilometre) located in an arterial street in the urban transportation network of Tehran, Iran by a team of more than 40 participants. The test was repeated three times in order to increase the validity of the experiment. Afterwards, the collected pilot data was successfully processed. After data processing, some minor shortcomings were detected such as (1) missing accelerometer data in some sections because of a surveyor's mistake to run the smartphones application (2) missing videos due to the shortage of smartphones memory. The shortcomings were both systematic errors due to the human mistakes. To prevent these errors occurring again in the main data collection, comprehensive explanation/training sessions were held for the participants.

Fig. 3. Smartphones attached over the dashboard and on the car windshield

B. Module 2: Roughness Measurement

Having accomplished the pilot study and held the explanation/training sessions, the final data collection was carried out in September 2015 on the same segment and repeated five times by the trained participants. The raw data was applied to measure three meaningful indices which represent the road condition. These indices are described below.

1) Road Condition Indicies

Indices applied herein included Ride Quality Index (RQI), Root Mean Square (RMS), and Road Distress Index (RDI). The first index was RQI describing users' opinion about the road roughness while they were riding over roads. The RQI varies between 0 to 5 in which 0 represents the very poor condition, while 5 expresses the very good condition [19]. Table 1 shows the verbal description of different condition levels.

TABLE 1 Ride Quality Index

Verbal Rating	Numerical Rating
Very good	4.1 - 5.0
Good	3.1 - 4.0
Fair	2.1 - 3.0
Poor	1.1 - 2.0
Very poor	0.0 - 1.0

The second index was RMS deployed to assess vertical acceleration of vehicles. The vertical acceleration was measured via a smartphone application which used the accelerometer sensor embedded in the smartphones. The application recorded and stored acceleration data every 500ms. Equation (1) was employed to calculate RMS [16].

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(a_{zi} - g)^2} \quad (1)$$

RMS = Root Mean Square of acceleration data

N = total number of acceleration records for each section

a_{zi} = the i^{th} vertical acceleration record

g = gravity

The third index was RDI defined as the weighted summation of severity and density of six selected road distresses (shown in Table 2). The distresses and the associated weights were determined based on an expert knowledge. These road distresses have the most significant impact on the roughness and surface defects of asphalt pavement. To obtain a single quantitative index for the road distresses on each section, Equation (2) was utilised.

$$RDI = \sum_{i=1}^{n} W_i \ (s_i \times d_i \ ) \quad (2)$$

RDI = Road Distress Index

i = distress type

Wi = weighting factor for each distress (Table 2)

si = severity of distress (High = 3, Moderate = 2, Low=1)

di = density of distress (in meter or square meter)

TABLE 2 Selected distresses and weights

Distress type	W_i
Longitude crack	2
Transverse crack	2
Alligator crack	3
pothole	3
patching	1
corrugation	1.5

2) Data Processing

The data preparation was carried out by checking for a few criteria: completeness, consistency, outliers, systematic errors, precision, and repeatability. After a thorough review of the collected data, it was concluded that the data was complete and consistent. However, there were a few outliers in the data detected (Fig. 4(a)), using the boxplot method they were eliminated (Fig. 4(b)). Having a few outliers seems logical in terms of using a sensitive sensor such as an accelerometer or panel rating. For instance, as shown in Fig. 4(a) in the panel rating, there are few outliers related to sections 3 and 4. After a close investigation and discussion with the corresponding assessors, it appeared that they made some mistakes so that the associated data were removed. Fig. 4(b) shows the captured data after data preparation which does not have any outlier.

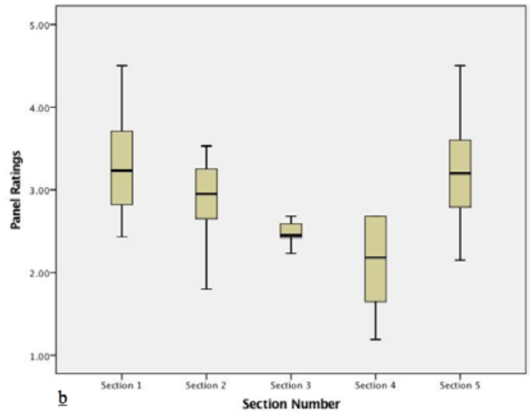

Fig.4(a). Panel rating by sections with outliers

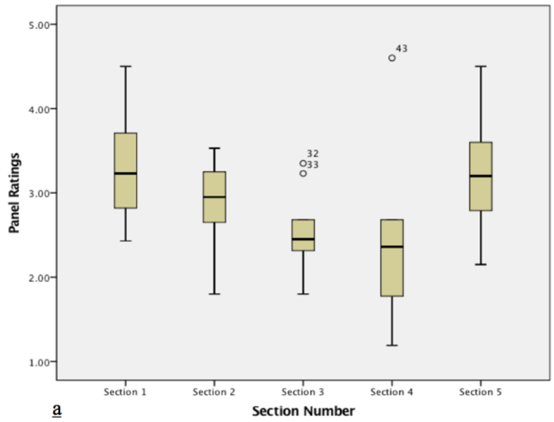

Fig. 4(b). Panel rating by sections after removing outliers

Furthermore, subjective rating is susceptible to suffer from systematic errors such as leniency and severity error and central tendency effect [20, 21]. Leniency and severity errors are defined as the deviation of each assessor's rating from the grand mean which is defined as the average of all assessor's rating (Table 3). "Delta R" in Table 3 shows the difference between grand mean and the average of assessor's ratings i.e., error. If an assessor rated a section too high or too low from the grand mean, leniency error and severity error would occur respectively. The last column, "Rank" priorities the assessors based on the highest difference from grand mean e.g., assessor 10 has the first rank due to his highest difference from the grand i.e., this assessor assessed the segment in the worst case comparing to the grand mean. As shown in Table 3, the magnitude of leniency and severity of the errors were negligible i.e., all errors are within two standard deviations of assessors.

TABLE 3 Deviation from the mean of ride quality rating.

	Ride Quality Rating			
Rater	Mean	SD	Delta R	Rank
1	3.71	0.135	0.41	5
2	3.23	0.094	-0.07	8
3	2.98	0.184	-0.32	6
4	2.43	0.061	-0.87	2
5	2.66	0.146	-0.64	4
6	2.43	0.504	-0.87	2

7	3.71	0.135	0.41	5
8	3.23	0.094	-0.07	8
9	3.43	0.17	0.13	7
10	4.5	0.418	1.2	1
11	3.95	0.218	0.65	3
Mean	3.3	0.652	0	---

Central Tendency Effect is defined as the tendency of an assessor to rate most cases on average rather than using high or low values. The range of assessors' rating was used as an indicator for this effect. This range should be high regarding the fact that the road segment was of different condition levels from very good to very poor. As shown in Table 4, the ranges of rating are adequately high. Therefore, no adjustments were required i.e., all ranges are within one standard deviation of ratings.

TABLE 4 Different range used by each assessor.

Assessor	1	2	3	4	5	6	7	8	9	10	11
Ride quality	2.25	1.38	1.75	0.81	1.75	2.63	2.25	1.38	2.5	2.5	2.5

To assess the precision of assessors, their rating on a single section should be almost identical. It means the standard deviation of rating should be low, while that of sections should be high. Sections should cover a wide range of road conditions i.e., a high variance, while the assessors should rate the same sections approximately as the same meaning of low variance. To investigate the variances, Analysis of Variance (ANOVA) test was conducted on sections and assessors at 5% level of confidence. Table 5 shows that the differences in standard deviation among assessors were not significant (sig>0.05), while the differences among standard deviation of section condition are significant (sig<0.05) as expected. Therefore, assessors would rate the sections at a sufficient precision.

TABLE 5 ANOVA test for ride quality ratings.

Source	**Ride quality ratings**				
	SS	df	MS	F	sig
Between sections	8.282	4	2.071	6.650	.000
Between assessors	7.473	10	0.747	1.975	0.063
Total	22.604	50	NA	NA	NA

In order to check the repeatability of the indices proposed from measurements by smartphones and the panel (RMS and RQI, respectively), their standard deviation (SD) and coefficient of variation (CV) were measured as presented in Table 6. The SDs are sufficiently low and CVs are almost all less than 8% except one which is 12.8% that is low enough (less than 20%). The figures express that on a single section, although five replications were conducted, the standard deviation and coefficient of variation of collected data on the section are low enough to present the repeatability of the experiment.

TABLE 6 Repeatability of roughness data

Section number	Average RQI	SD	CV	Average RMS (m/s^2)	SD (m/s^2)	CV
1	3.6	0.233	8.5%	0.60	0.051	6.5%
2	2.8	0.095	5.6%	0.91	0.051	3.5%
3	2.4	0.110	7.8%	0.94	0.073	4.6%
4	1.6	0.254	7.9%	1.15	0.091	12.8%
5	3.0	0.118	7.9%	0.84	0.067	4.0%

Fig. 5 shows RMS corresponding to each section for five replicates (runs). This figure illuminates that the replicates for each section are almost identical. To prove this fact, a two-way analysis of variance (ANOVA) was conducted showing that there was not a significant difference between different runs at 95% level of confidence. The ANOVA test supports the fact that there are no significant differences between replicates using smartphone expressing the data collection reparability.

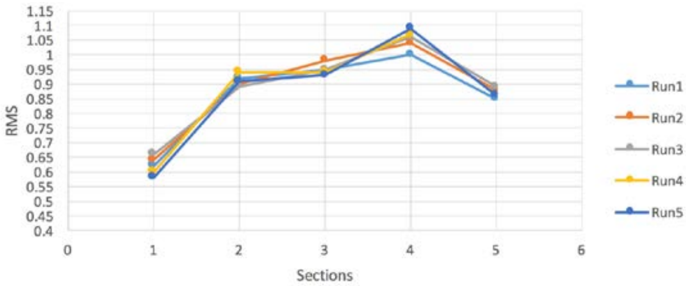

Fig. 5. RMS over five different runs for each section

C. *Module 3: Validation and Correlation*

Having calculated the road roughness using the indices mentioned above, the next step was to validate the roughness measured via smartphones (i.e., RMS) with the ground truth. The ground truth was attained through application of the Road Surface Profiler (RSP) which indicated the International Roughness Index (IRI) of the road. For this purpose, the roughness of road sections was simultaneously measured using RSP and smartphones with three to five replications. The measurements are shown in Fig. 6(a) and Fig. 6(b). The trend of the data illuminated in Fig. 6(a) makes engineering sense i.e., the more the RMS meaning vertical vibration, the more the IRI. It is observed that there is a good correlation between RMS and IRI with a good coefficient of determination of 0.757 and a high correlation coefficient of 0.870 (Fig. 6(b)). This figure illustrates the insignificant distance between RMS and RSP measurements.

Moreover, having calculated an equilibrium (3) between RMS and a conventional index such as IRI would help to measure the roughness through the application of RMS which can be computed using a smartphone that is inexpensive, easy to implement, and widely accessible to estimate IRI instead of employing RSP which is of a high cost (in terms of capital cost, operation, and maintenance). For instance, if the RMS for a road section measured via a smartphone is equal to 0.1, the IRI is approximated using (3) which is equal to 2.1 mm/m (4.19×0.1 + 1.73 = 2.1).

$$IRI = 4.19RMS + 1.73 \tag{3}$$

IRI = International Roughness Index
RMS = Root Mean Square of acceleration data

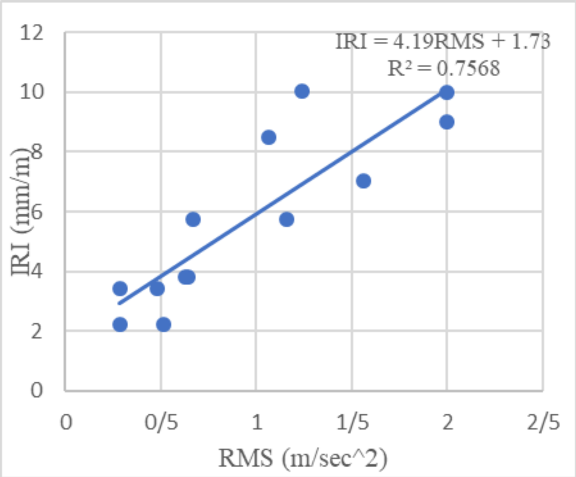

Fig. 6(a). Relationship between roughness (IRI) and vertical acceleration (RMS)

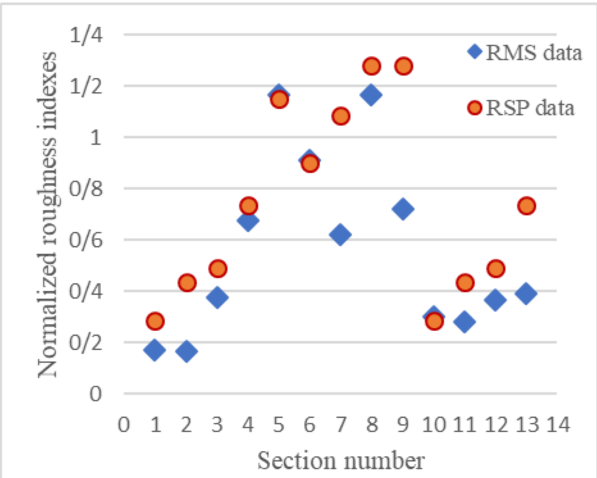

Fig. 6(b). Correlation between IRI and RMS

1) Correlation Between RMS and RDI

The correlation investigation was conducted between RMS and RDI. It was to examine whether or not RMS has significant coloration with RDI. In other words, it is to investigate that if the road roughness (RMS) is correlated with the road surface distress (RDI). The captured data were plotted i.e., RMS versus RDI (Fig. 7(a)). The linear regression illustrates that RDI could not be an adequate predictor for the RMS (R2=0.5). This result makes engineering sense regarding the fact that the measured distresses are not totally related to the road roughness leading to the vertical acceleration of the vehicle. Therefore, there may be a road section with several distresses (such as transverse and longitudinal cracking and patching) but be relatively smooth. On the contrary, a road section may be rough without several road surface distresses. Furthermore, the road roughness is measured under wheel paths not the whole area in a lane. There could be a road section with surface defects on areas between the wheel paths (not under the wheel path). In this case, RMS would be low, while RDI could be high. Therefore, it makes logical and engineering sense that RMS and RDI are not highly correlated.

2) Correlation Between RMS and RQI

Finally, the correlation between RMS and RQI was studied. This is to investigate whether the roughness measured by smartphones can represent the real sense of convenience from the user point of view called the ride quality (expressed by RQI). The acquired data (RMS versus RQI) were plotted in Fig. 7(b). As shown in this figure, RMS is highly related to RQI with a high coefficient of determination of 0.805. The trend of data and associated linear equation seems logical i.e., the more the RMS, the less the RQI.

This is an important achievement of this study which validates the objective roughness measurements via smartphones with subjective ride quality obtained by the panel rating. In other words, the roughness index (RMS) calculated by smartphones has significant compatibility with the user opinion about the ride quality. Therefore, RMS can be applied as an indicator which is showing the real sense of comfort or discomfort for road users.

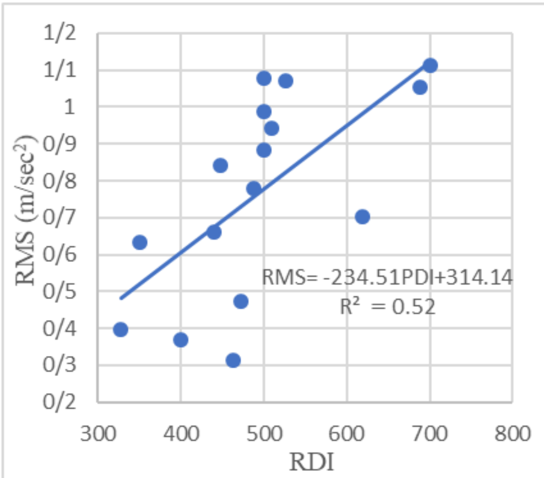

Fig. 7(a). Relationship between roughness – pavement condition

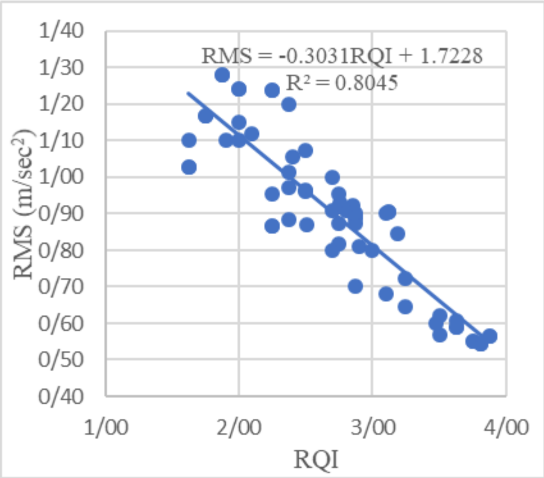

Fig. 7(b). Relationship between roughness – user's opinions

To sum up, it is concluded that smartphones can be deployed to estimate the road roughness at an adequate level of precision and accuracy. The smartphone measurements are not only highly correlated with IRI, but also, they represent significant correlation with the ride quality expressed by travellers. The latter correlation has not been investigated to date; however, the travellers' opinion about the ride quality plays the main role in evaluating the roughness of a road. Subsequently, the outcomes obtained from smartphone accelerometer sensor can rigorously present the real road roughness with regards to the travellers' sense of comfort.

V. Conclusion

The core of the road management systems is road data collection. Sophisticated vehicles facilitated by an array of sensors have been widely utilised to automatically capture the road roughness data. These vehicles are too expensive to purchase, operate, and maintain. A sustainable approach is to apply smartphones with embedded sensors such as an accelerometer and GPS which is cost-effective to collect the data with an acceptable level of accuracy and precision to estimate the road roughness. However, the road roughness measured by smartphones have not been validated by researchers through travellers' comfort sense about ride quality. This paper aimed at investigating whether or not smartphones merely can represent the real sense of ride comfort of travellers. The founding of this study are summarised as follows:

(1) Travellers' opinions about road roughness had an excellent correlation (R2=0.8) with smartphone-based roughness measures. It emphasises that smartphones can express the road roughness which is compatible with travellers' sense of comfort. So, smartphones can merely express the road roughness.

(2) Smartphone-based roughness measures did not have a strong correlation (R2=0.5) with road distresses due to the fact that all distresses do not have an impact on the road roughness.

(3) Smartphone-based roughness measures expressed a good correlation (R2 =0.76) with the International Roughness Index (IRI) measured by the Road Surface Profiler conveying the validity of smartphones outputs. Thus, through the application of an inexpensive smartphone, IRI can be approximated which is conventionally measured using the Road Surface Profiler that is of a high cost.

VI. Further Work

Throughout this study, the road roughness was investigated using smartphone sensors. These sensors have been employed within a vehicle and different assessors have been utilised. Due to the limited time for this study, a variety of assessors, vehicles and smartphones have been used to be able to investigate different roads simultaneously. However, the difference of opinions amongst the assessors have been considered but the differences between the drivers and the equipment such as smartphone and vehicle has not been analysed due to time. A strong recommendation to further enhance this study would be to analyse the effects of using different vehicles, smartphones, and drivers upon the determination of road roughness. On the other hand, these variables can be kept constant by using the same driver, assessor, vehicle, and smartphone to eliminate the effects of these variables. Furthermore, a smartphone can be placed at the rear of the vehicle so that an average can be taken to enhance the precision of the results. Moreover, the vibrations of the car suspensions can be used for this investigation as another variable to further support the results.

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