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# Feasibility Assessment of a Smartphone-Based Application to Estimate Road Roughness

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## Abstract

Transportation agencies spend significant resources to collect pavement roughness data using profiler vans. A potential alternative to collect functionally equivalent data at a significantly lower cost and higher level of temporal resolution is to use existing accelerometers in smartphones as the "set" of sensors. In this research, a prototype smartphone application was developed to investigate the feasibility of such an approach. Acceleration data were collected using a prototype application running on Android tablets on two routes in Virginia. The analysis results show that the proposed smartphone application can generate consistent data sets from different data collecting runs. In addition, the average of the collected data sets is found to be highly correlated with the International Roughness Index data collected by the Virginia Department of Transportation using profiler vans. Also, a sample size analysis revealed that most pavement sections require fewer than 12 data collecting trips at a 50 Hz sampling rate while fewer than 16 trips are required for a rate of 10 Hz. Finally, a preliminary benefit assessment for Virginia showed that the proposed smartphone application approach allows for collection of comparable roughness data for more roadways, more frequently with significantly less cost.

Keywords: *pavement maintenance, roughness assessment, connected vehicle, feasibility, cost-effective, sample size*

## 1. Introduction

Pavement roughness is generally defined as an expression of the aggregation of irregularities in the pavement surface, per linear travel unit distance, that adversely affect the ride quality of a vehicle and thus road users. As a surrogate to this pavement roughness, measures of ride quality have been used by transportation agencies for the pavement system related tasks such as planning, maintenance, repair, and rehabilitation. The International Roughness Index (IRI) is one of the representative measurements (Sayers *et al.*, 1986). Like many transportation agencies, the Virginia Department of Transportation (VDOT) began employing automated pavement data collection using specialized sensors and equipment such as high-speed laser profilers and digital cameras in 2006 (VDOT, 2012). Since then, pavement roughness information, or the IRI, has been collected and updated every year for the interstate and primary highway systems in Virginia and every five years for the secondary systems. Due to the need for specialized equipment with sensors, collecting pavement roughness data is very costly. It was estimated that VDOT spends about $1.8 million per year in pavement condition data collection (Sauerwein and Smith, 2011).

With the advances in communication technologies, a connected vehicle environment – where vehicles can communicate with surrounding vehicles as well as with the infrastructure – is expected to provide new approaches for transportation professionals (MDOT, 2012). For example, the Basic Safety Message (BSM) that includes vehicle body accelerations, location, speed and other information will be sent from each connected vehicle every 0.1 second (USDOT, 2012). It allows an opportunity to develop alternative methodologies to assess pavement roughness conditions. The vehicle vibration response can be directly measured with the already existing sensors in vehicles or even mobile devices. In other words, the entire vehicle fleet – if equipped with appropriate communication devices – can be transformed into probes, measuring pavement conditions at more locations, at more frequent time intervals with minimum additional costs. In the near future, before the full implementation of the connected vehicle program, a potential alternative is to use existing accelerometers in smartphones as the "set" of sensors, and then developing sampling strategies to compile the assessment of pavement roughness. This smartphone-based approach (which would be an example of connected vehicles according to the current definitions presented by the federal connected vehicles program) can collect similar

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data including acceleration and location information through people's daily travel, does not need specifically equipped vehicles, and thus is possible to assess pavement roughness more timely with minimal data collection cost.

In current practices, a high-speed laser profiler used in pavement monitoring operates around 16,000 Hz (MnDOT, 2007), which is infeasible for a single smartphone trip to fulfill. One attractive solution is to combine data that are collected from multiple vehicles or multiple trips. The goal of this study is to demonstrate the feasibility of using smartphone sensors to estimate pavement roughness measures in "uncontrolled" real world driving conditions. In accomplishing this goal, several objectives will be addressed in this paper. The first objective is to investigate whether smartphone data sets collected from different trips show consistency especially given that, in the real world, vehicles run at different speeds and on a different path. The next objective is to address whether the aggregated data of these collected data sets is able to produce pavement roughness measures with an acceptable precision level. Finally, the last objective is to determine the number of data collection trips required to ensure the acceptable accuracy of the generated roughness measures, which is directly related to the data sampling rates.

Following the introduction, a review of the previous research is provided. The methodology for the proposed application, the data collection effort, and the analysis results will then be presented. Also a preliminary benefit assessment for the proposed approach will follow. Finally, this paper concludes with a summary of findings and recommendations for future studies.

## 2. Literature Review

A considerable amount of work has been completed to improve the concept of using inexpensive vehicle or smartphone sensors to assess pavement roughness condition. In 2010, the Michigan Department of Transportation (MDOT) started to demonstrate and evaluate a system to monitor slippery roads and road surface roughness based on probe data (Robinson, 2012). A Droid phone platform, mounted on the windshield similar to a navigation device, was used to collect vehicle data and transmit it to a backend server. The platform mainly collected four kinds of data: vehicle Controller Area Network (CAN) messages; external road surface temperature and humidity (added external sensors); GPS position (from the Droid phone); and 3-axis accelerometer data (from the Droid phone). The system was installed in two vehicles, driven by MDOT employees over a two-year period (from 2010 to 2012). Over 13 G bytes of data were accumulated over 30,000 miles. In this project, variance of the vertical accelerometer signal was chosen as the metric to represent pavement roughness. The sample rate of the accelerometer is 100 Hz. After collection, the accelerometer readings were calibrated, using a curve fitting algorithm, to a 10-point scale known as the Pavement Surface Evaluation and Rating (PASER) system. The research team recommended refining the curve fitting algorithm with future data from MDOT's annual PASER rating study.

A research team from Auburn University investigated the application of using vehicle-base sensors to assess pavement condition (Dawkin, 2010). The main focus of the study was to utilize vehicular sensors to estimate the IRI. In addition, detection and mapping of potholes was addressed. Several vehicular sensors including accelerometers, gyroscopes, and suspension deflection meters were tested to estimate the IRI. Testing was conducted under controlled speed on a 1.7 mile (2,750 m) long test track at the National Center for Asphalt Technology (NCAT). The amount of overall vibrations across a given segment was determined by taking the Root Mean Square (RMS) of a signal measurement (i.e., vertical acceleration, gyroscopes, or suspension deflection). The detailed descriptions of RMS are provided in Section 3.2. Root Mean Squared Acceleration. The overall vibrations were then compared with the true IRI of the pavement segment. The resulting data indicated that the RMS of vertical accelerations represents the best case scenario to capture the true IRI. It displayed the same trend of the known IRI, with only a few expected differences in magnitude. The study also indicated that the estimation error increases with decreasing window size and thus recommended to use larger windows when possible to assure the most accurate IRI estimates. In conclusion, this study found that the most feasible application to estimate the IRI is to implement a root mean square algorithm on vertical acceleration measurements.

Flintsch *et al.* (2011) conducted a pilot study which used probe vehicles to measure road ride quality and roughness. Again, vertical acceleration data were used as an index of vehicle vibration. A smoothness profile was obtained using an inertial-based laser profiler, while the vertical accelerometer measurements were obtained using a vehicle instrumented with an accelerometer at the Virginia Smart Road facility in Blacksburg, Virginia. The accelerometer operated at a rate of 10 HZ. GPS positions were also recorded. A total of four runs were completed in the test track to collect acceleration data. The study confirmed that the acceleration runs are very repeatable. Analysis using the coherence function indicates that the acceleration measurements and smoothness profile are very similar.

Another study conducted by the Center for Transportation Studies at the University of Virginia has extended this work to investigate system-level designs. It extended the technical feasibility to a "system" that could support transportation agency pavement management (Sauerwein and Smith, 2011). In this project, three potential probe-based pavement roughness assessment systems were investigated in terms of technical feasibility and characteristics. These potential systems were: a) a system using ITS and connected vehicle technology, b) a system using an installed accelerometer and communications system instrument package, and c) a system using smartphone devices containing accelerometers. The third approach was identified as the most appropriate system in the near future. The study also addressed that such a data-gathering system will increase frequency of pavement roughness data collection, increase the number of lane-miles of monitored roadways, decrease lag time from collection to interpretation, and add to the information available to transportation professionals.

Bridgelall (2013) derived a theoretical relationship between IRI and accelerometer data for a connected vehicle approach for pavement roughness estimation. The research introduced the Road Impact Factor (RIF) which is derived from vehicle integrated accelerometer data. A time-wavelength-intensity-transform (TWIT) algorithm was also developed to create a wavelength-unbiased measurement based on RIFs from different speed bands. The analysis demonstrates that RIF and IRI are directly proportional. Profile and acceleration data were collected from six runs with a constant speed (55.6 km/h) on a 150-meter pavement section in Minnesota to validate this relationship. The author concluded that the proposed application enables low-cost, network-wide and repeatable performance measures at any speeds. No discussion were provided on sample size and sampling rate for acceleration data collection.

In summary, the literature review reinforces that using vehicular or smartphone sensors for pavement roughness data collection is promising and a cost-effective approach. However, it should be noted that most of the studies so far were conducted in a controlled closed environment. In addition, no discussion of sampling strategies was provided. It is therefore necessary to take this concept to a real world situation to investigate its practical feasibility.

## 3. Methodology

This section introduces the methodology that has been used for this study, including data collection and the key algorithm to measure IRI.

### 3.1 Data Collection

An Android application was developed to collect the acceleration data. This application can be installed in most Android devices including smartphones, tablets, and so on. An Android device with this application running can record up to 50 acceleration readings per second (50Hz), and store the data in a database which can be exported later to a personal computer. Every acceleration reading has three values: one vertical acceleration and two horizontal accelerations. Only vertical acceleration was used to measure the pavement roughness condition. Note that the vertical acceleration also includes the impact from the force of gravity. Therefore, to measure the real acceleration, the contribution of the force of gravity must be removed from the original vertical acceleration reading. Other information that were recorded and stored included GPS location, time, and GPS accuracy.

The data collection effort used two Samsung Galaxy Note 10.1 tablets running on Android 4.0.4 (Ice Cream Sandwich). Like many smartphones, this model has standard GPS and internal sensors including accelerometer, gyroscope, digital compass and, light sensors. The two tablets were placed in the back of the car on the floor close to the two side doors so that both right-wheel-path and left-wheel-path data can be collected. To ensure the tablets not dislocate themselves when the vehicle is running, they were fit into two boxes sitting on the floor. The two tablets always faced up and were placed in the same location of the vehicle in all data collection runs to ensure that the acceleration sensors' vertical axis always points to the same direction and tangential to the driving direction (Google, 2017).

Data were collected under naturalistic driving conditions on Interstate 64 West and US 250 East between Richmond and Charlottesville in Virginia, as presented in Fig. 1. The I-64 West section is a four-lane divided freeway with a speed limit of 70 mph (112 km/h). The study section is 58 miles (93 km) long, between milepost 178 and milepost 120 in west bound direction. The US 250 East section, between mileposts 113.2 and 134.8, is a primary two-lane undivided route that is parallel to I-64 and has a speed limit of 55 mph (88 km/h). The vehicle driven is a small SUV, the 2012 model of Subaru Forester. The data

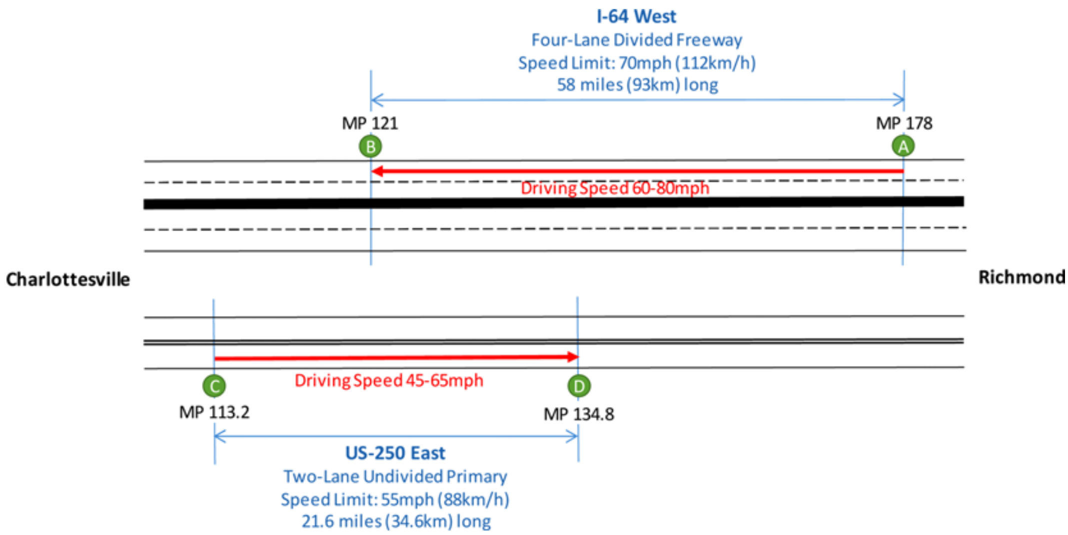


Fig. 1. Data Collection Routes; A-B: I-64 W (MP 178- 121) and C-D: US-250 E (MP 113.2- 134.8)

includes nine test runs on I-64 W within a three-week span from February 13 to March 4, 2013 and six test runs on US-250 E within a four-week span from June 26 to July 18, 2013. The vehicle was operated by the same driver under highway speeds, typically between 60 and 80 mph on I-64 and 45 to 65 mph on US-250. Usually the vehicle ran in the right lane. However, sometimes (between 10% and 30% of the time) it traveled on the left lane to pass slow vehicles on I-64. The pavement surface was dry and no passengers were in the vehicle during data collection.

The developed smartphone application collects GPS coordinates (X, Y, and Z) every tenth of a second. With this detailed GPS information, the location of each data point can be easily matched to the milepost location of a roadway through a map-matching process. Note here that, in this research, this map-matching process was not carried out in an automated fashion in real time. Rather, this map-matching was manually done off-line after all the data is collected, allowing the use of any map-matching algorithms suitable for this effort.

It was found that the estimated GPS accuracy was between 4 and 8 meters. It was authors' judgement that this GPS error range (between 4 and 8 meters) should be acceptable for estimating the roughness condition for a 0.1-mile (161-meter) section. However, this much accuracy may not be sufficient to provide a lane-specific location given the standard freeway lane width of 3.6 meters (AASHTO, 2011), or to identify the exact locations of pot-holes or damaged spots.

Currently, DOTs usually only collect the right most lane IRI for network roughness assessment and use it as a roughness indication for the whole pavement section (including left lane). Generally, VDOT's treatment decisions are made based on the data from the right-most lane for the entire section and not for individual lanes, although there are exceptions in rare cases. As a result, this research assumes that the two lanes of the studied segments have similar roughness level and did not collect lane-specific acceleration data.

In addition to the acceleration data, the latest IRI data of the study section were obtained from VDOT's pavement condition database. Note that the IRI data were calculated based on the profile of the studied routes measured in November 2012. So the time difference between VDOT's IRI data collection and this study's data collection is about three months on I-64 W and seven months on US-250. During this period, no rehabilitation or major treatment work was conducted on the pavement. As a result, it is assumed that the pavement roughness condition during data collection had a similar trend with that in November 2012. The VDOT-collected IRI data were used as the reference roughness condition.

### 3.2 Root Mean Squared Acceleration

According to the Auburn study, Root Mean Squared (RMS) vertical acceleration, which is calculated with the equation below, represents the better case scenario for matching the IRI with acceleration measurements (Dawkin *et al*., 2010). Fig. 2

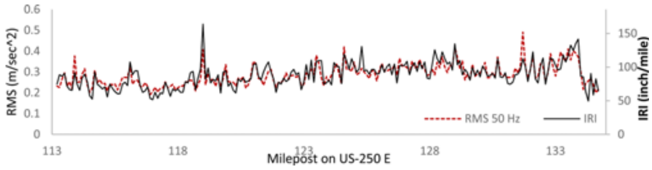


Fig. 2. IRI Compared to RMS Acceleration on US-250 E

illustrates the relationship between RMS acceleration and IRI on US 250 E as an example.

As a result, this study used RMS as the acceleration measurement to represent the IRI estimation.

$$a_{z,RMA} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(a_{z,i}-g)^2} \tag{1}$$

where $a_{z,i}$ = The i$^{th}$ vertical acceleration reading among the studied section

$a_{z,RMS}$ = The RMS vertical acceleration for the studied pavement section;

$N$ = The number of acceleration readings among the studied pavement section;

$g$ = The contribution of the force of gravity, 9.81 m/s$^2$.

In current practice, VDOT records IRI data for every 0.1-mile (0.16 km) pavement sections (VDOT, 2010). Therefore, the RMS acceleration was calculated with the data collected by this study for every 0.1-mile section. As a result, every data collection trip can generate 580 and 216 RMS accelerations on the I-64 and US-250 routes, respectively.

## 4. Analysis Results

This section presents the results from data analysis. The analysis first evaluated the repeatability of RMS accelerations collected from multiple trips, then investigated the correlation between the smartphone-based results with VDOT-collected IRI, and finally estimated the number of trips needed to estimate the pavement roughness.

### 4.1 Repeatability of RMS Accelerations Collected from Different Trips

Under naturalistic driving situations, the driving condition is not controlled and hence there could be more variations regarding vehicle speeds, travel lanes and other factors between different test runs. As a result, it is possible that data generated on one day is totally different from the data collected on another day, even for the same vehicle and driver. It is therefore important to investigate whether data collected from different test runs show consistent trends and magnitudes so that they can be combined and used together.

This section uses the I-64 data as an example to examine the repeatability of RMS acceleration results from different runs. For a first look, Fig. 3 plots the 580 0.1-mile RMS accelerations for each of the nine runs (between February 13 and March 4) on I-64 W, according to the milepost. All data were collected within a

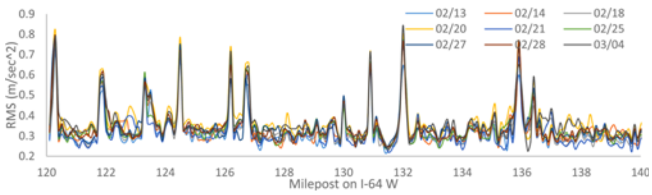


Fig. 3. RMS Accelerations for Nine Runs on I-64 W

month and the pavement condition during this period was assumed unchanged. It appears that the RMSs were generally consistent across these nine runs in terms of trends and magnitudes.

To further assess the repeatability of the RMS accelerations from different test runs, correlation coefficient was calculated using the Data Analysis Tool of Microsoft Excel, based on the RMS accelerations obtained. The correlation coefficient, as indicated by the equation below, was applied to measure the linear correlation between the RMS accelerations of each 0.1-mile segment from the two test runs. It has a value between -1 and 1; with -1 and 1 indicate the perfectly correlated situation (Frankfort-Nachmias and Leon-Guerrero, 2009).

$$r_{jk} = \frac{\sum_{i=1}^{n}(a_{RMS,j,i} - \overline{a_{RMS,J}})(a_{RMS,k,i} - \overline{a_{RMS,k}})}{\sqrt{\sum_{i=1}^{n}(a_{RMS,j,i} - \overline{a_{RMS,J}})^2}\sqrt{\sum_{i=1}^{n}(a_{RMS,k,i} - \overline{a_{RMS,k}})^2}} \tag{2}$$

where

$a_{RMS,j,i}$, $a_{RMS,k,i}$ =The RMS acceleration of the i[th] 0.1-mile pavement section in test runs j and k, respectively;

$\overline{a_{RMS,J}}$, $\overline{a_{RMS,k}}$ =The average RMS acceleration of all the 0.1-mile pavement sections in test runs *j* and *k*, respectively

n = Number of 0.1-mile sections; and

$r_{jk}$ = The correlation coefficient between RMS accelerations from test runs *j* and *k*

Table 1 summarizes the correlation. The test statistics indicates that there were good correlations ($r$ > 0.83) between any two runs, and runs 02/18 and 02/25 had the best correlation ($r$ = 0.917). In conclusion, it was found that data collected from different trips show consistent results. It is therefore expected that combining RMS results from multiple trips will generate highly repeatable pavement roughness estimations.

### 4.2 Comparison between Aggregated RMS and IRI

Previous studies have indicated a good correlation between IRI and simulated body-vehicle vibration response under constant speeds (Cantisani and Loprencipe, 2010; Múčka, 2013). However, none of them have investigated the correlation under naturalistic driving conditions, in which more variations are expected in terms of speeds, driving paths and other factors. The purpose of this analysis is to investigate whether the aggregated (or averaged) RMS acceleration is a good estimate of IRI. To illustrate the relationship between the RMS acceleration and the IRI, Figs. 4 and 5 plot the IRI and average RMS accelerations for all nine test runs on I-64 W and six test runs in July on US-250 E, according to the milepost.

An additional plot presents the moving average of RMS acceleration and IRI with a 1-mile (1.6 km) window to give readers a clearer impression. Depending solely on the original RMS estimates may cause some false positives as it contains fluctuations and thus may not align perfectly with IRI. It is therefore a reasonable approach to consider using a moving average as well. Given this, the prototype smartphone application developed in this paper is proposed as a pre-screening tool that can be used by transportation agencies to select a preliminary list of "likely" deficient pavement sections. Once these sections are identified, the agencies can decide whether to send their specialized equipment to conduct further measurements. It appears that the average RMS accelerations share a similar trend with the IRI data on both routes.

Table 2 summarizes the descriptive statistics of the IRI and averaged RMS acceleration data on the two routes, as well as the correlation coefficients between IRI and the RMS results. Note that both coefficients for the original 0.1-mile data and the averaged data using a 1-mile moving window were present in the table. The results indicate a good correlation between IRI data and RMS acceleration data. On both routes, the correlation coefficients between IRI and RMS acceleration data are larger than 0.70. After filtering by a moving average filter, they raise to 0.84 and 0.94 on I-64 W and US-250, respectively. Note that the RMS acceleration data were collected three months and seven months later than the IRI data. It is expected that the correlation coefficient value will be even larger if the RMS acceleration data and IRI are collected at the same time.

Table 1. Correlation Coefficients between RMS Results from Different Runs

| Date | 02/13 | 02/14 | 02/18 | 02/20 | 02/21 | 02/25 | 02/27 | 02/28 | 03/04 |
|---|---|---|---|---|---|---|---|---|---|
| 02/13 | 1.000 | | | | | | | | |
| 02/14 | 0.857 | 1.000 | | | | | | | |
| 02/18 | 0.876 | 0.885 | 1.000 | | | | | | |
| 02/20 | 0.836 | 0.894 | 0.889 | 1.000 | | | | | |
| 02/21 | 0.832 | 0.879 | 0.871 | 0.872 | 1.000 | | | | |
| 02/25 | 0.868 | 0.900 | 0.917 | 0.886 | 0.864 | 1.000 | | | |
| 02/27 | 0.836 | 0.887 | 0.899 | 0.894 | 0.860 | 0.892 | 1.000 | | |
| 02/28 | 0.868 | 0.893 | 0.916 | 0.884 | 0.853 | 0.916 | 0.903 | 1.000 | |
| 03/04 | 0.847 | 0.887 | 0.891 | 0.915 | 0.868 | 0.875 | 0.865 | 0.877 | 1.000 |

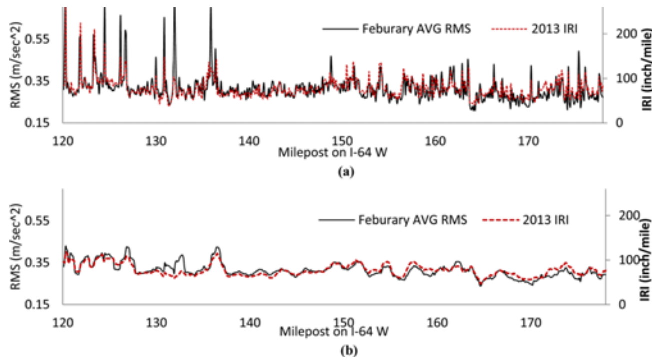


Fig. 4. IRI Compared to RMS Acceleration on I-64 W: (a) Original 0.1-mile Data, (b) Moving Average using a 1-mile Window

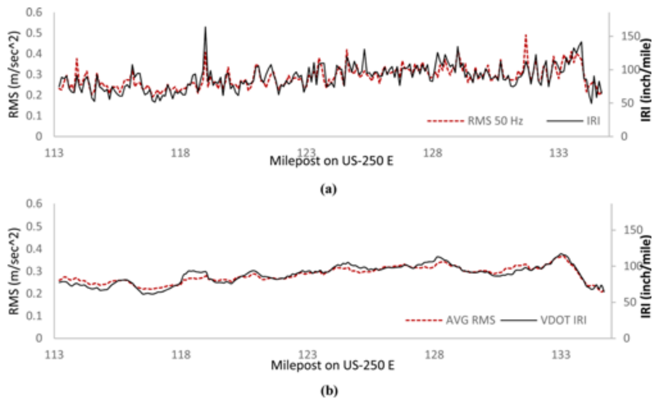


Fig. 5. IRI Compared to RMS Acceleration on US-250 E: (a) Original 0.1-mile Data, (b) Moving Average using a 1-mile Window

According to Table 2, the US-250 E data correlated with the VDOT-collected IRI better than the I-64 W data. One of the main reasons could be that there is only one travel lane on US-250 in one direction, while there are two lanes on I-64. As a result, unlike data collection on I-64, the IRI and RMS acceleration collection were always from the same lane on US-250. Another possible reason could be that the travel speed on US-250 was less than on I-64. Since the data collection rate did not change, more acceleration data were collected for each 0.1-mile section on US-250, which may result in a better indication of the real roughness level.

Also, the average RMS acceleration on US-250 E was lower than that on I-64 W, although US-250 E had higher average IRI. Previous research has indicated that speed is one of the factors that can impact the magnitude of RMS acceleration (Dawkin et al, 2010; Ahlin and Granlund, 2002). Since the posted speed limit on I-64 is higher than US-250 (70 mph vs. 55 mph), the pavement sections on I-64 can generate larger RMS results than sections of US-250 that have similar IRI values. The impact of speed on roughness estimation and the way of calibrating RMS acceleration with a speed factor will be investigated specifically in a follow up study.

The results indicate that the average of RMS acceleration can represent IRI with a high level of correlation under naturalistic driving situations, and it is therefore feasible to utilize RMS accelerations to assess pavement roughness.

### 4.3 Number of Required Trips for Data Collection

Given the results of last two sections, the next question is to determine how many data collecting trips are required to guarantee a certain level of accuracy. Currently not every transportation agency has the same criteria for the network-level pavement roughness measurement. The tolerance error rates range from 5% to 25% among different agencies (Flintsch and McGhee, 2009; Ong *et al*., 2010). For this study, the tolerance error rate was set to 10% and the acceptable confidence level was 95%.

To simplify the question, this study focuses on assessing pavement roughness on two types of facilities: four-lane divided interstate freeways with a speed limit of 70 mph (112 km/h) and two-lane undivided primary roads with a speed limit of 55 mph (88 km/h). It is assumed that the data collection will be conducted on dry pavement surface with average highway speeds using a single vehicle or vehicles with similar dynamic characteristics. Two sampling rates were investigated including 50 Hz and 10 Hz. Sampling theory suggests using the equations below to determine the minimum sample size needed to achieve a robust estimation given the tolerance error rate and an acceptable confidence level (Cochran, 2007).

$$N = \left(\frac{ZS_s}{eX_s}\right)^2, X_s = \frac{\Sigma a_{RMS_j}}{n}, \text{ and } S_s = \sqrt{\sum (a_{RMS_j} - X_s)^2/(n-1)} \quad (3)$$

where

$a_{RMSj}$ = The RMS acceleration of the studied 0.1-mile pavement section from the $j^{th}$ test run; and
e = Tolerance error rate, for example, 10%;
$n$ = The number of sample test runs.
$N$ = Number of data collecting trips needed;
$S_s$ = Sample standard deviation;
$X_s$ = Sample mean;
$Z$ = $Z$-score of the desired confidence level, it equals to 1.96 at 95% confidence level;

The statistical principle behind the equation above is the Central Limit Theorem (CLT). The CLT is based on a sample size that is large enough, usually considered as greater than 30

Table 2. IRI and RMS Data Summary

| Route | # of Sections | 2013 IRI (in/mile) | | | | RMS Acceleration (m/sec$^2$) | | | | Correlation Coefficient with IRI | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Mean | STD | Min | Max | Mean | STD | Min | Max | 0.1-Mile RMS | 1-Mile RMS with Moving Window |
| I-64 W | 580 | 77.34 | 21.7 | 37 | 260 | 0.317 | 0.066 | 0.211 | 0.762 | 0.71 | 0.84 |
| US-250 E | 216 | 88.95 | 18.7 | 50 | 164 | 0.286 | 0.050 | 0.192 | 0.491 | 0.83 | 0.94 |

(Mason *et al.*, 1989). However, the number of trips needed is likely to be much smaller than 30. When determining the minimum sample size for travel time estimation, Richardson *et al.* (2011) applied a slightly different equation by replacing the *Z*-score with Student's *t*-statistic, as shown in the equation below. This equation is applicable when the minimum sample size is believed to be less than 30.

$$N = \left(\frac{tS_s}{eX_s}\right)^2 \tag{4}$$

where $t$ = Student's *t*-statistic of the desired confidence level.

Student's *t*-statistic is determined by the confidence level and degree of freedom, which is simply the number of required samples minus one ($N$-1). As a result, the equation should be solved iteratively when a Student's *t*-statistic is used, given the relative degree of variation [i.e., the ratio of sample standard deviation to sample mean ($S_S/X_S$)], tolerance error rate (i.e., 10%), and desired confidence level (i.e., 95%).

The process is described for one example. If the ratio of standard deviation to mean RMS acceleration from five runs is 0.05 for a 0.1-mile segment, we can compute the minimum trips required by iterating different values of $N'$ into the equation above and comparing the equation result to $N'$. When $N' = 3$, the *t*-statistic is 4.3 and the computed value of estimated minimum number of trips ($N$) is 4.6. Since the value of $N$ is greater than the value of $N'$, the next larger value of $N'$ will be iterated and repeat the calculation. When $N' = 4$, the *t*-statistic is 3.18 and $N$ is 2.53. Once $N$ is smaller than $N'$, the iteration process should be ended and therefore the minimum number of required trips is 4, which is the value of current $N'$.

Specific for this study, the data from the nine data collection runs on I-64 W and six runs on US-250 E were used as samples to estimate the number of trips needed for every 0.1-mile pavement section. The original data set was collected at a 50 Hz rate using the smartphone application. In addition, to create another data set for a 10 Hz sampling rate which is same as the sampling rate of the Basic Safety Message under the connected vehicle environment (USDOT, 2012), a sample of 20% of the original acceleration readings was generated using systematic sampling method for each run. All data were collected within a month and the pavement condition during this period was considered unchanged. Note that different pavement sections may have different required numbers of trips depending on the variation of their test run RMS results.

Considering that rougher pavement sections may have a different level of variations than smoother pavement sections, another interesting question is whether rougher sections require more (or fewer) data collection trips. To answer this question, pavement sections were divided into two groups: a lower IRI group with IRI values less than 90 in/mile and a higher IRI group with IRI values greater than 90 in/mile. For I-64 sections, the lower IRI group includes 463 (80% of the total sections) pavement sections, while the higher IRI group contains 117 pavement sections. Among US-250 sections, there are 116 sections for a

Table 3. Number of Data Collection Trips Required for I-64 W Sections

| | Trips Needed | 50 HZ Collecting Rate | | 10 HZ Collecting Rate | |
|---|---|---|---|---|---|
| | | # of Sections | Cumulative % | # of Sections | Cumulative % |
| IRI <= 90 in/mile | 0-4 | 132 | 28.51% | 67 | 14.47% |
| | 5-6 | 197 | 71.06% | 146 | 46.00% |
| | 7-8 | 76 | 87.47% | 106 | 68.90% |
| | 9-10 | 23 | 92.44% | 66 | 83.15% |
| | 11-12 | 16 | 95.90% | 31 | 89.85% |
| | 13-14 | 4 | 96.76% | 16 | 93.30% |
| | 15-16 | 10 | 98.92% | 8 | 95.03% |
| | 17-18 | 2 | 99.35% | 7 | 96.54% |
| | 19-20 | 1 | 99.57% | 3 | 97.19% |
| | 21+ | 2 | 100.00% | 13 | 100.00% |
| IRI > 90 in/mile | 0-4 | 34 | 29.06% | 17 | 14.53% |
| | 5-6 | 53 | 74.36% | 32 | 41.88% |
| | 7-8 | 13 | 85.47% | 29 | 66.67% |
| | 9-10 | 7 | 91.45% | 20 | 83.76% |
| | 11-12 | 8 | 98.29% | 10 | 92.31% |
| | 13-14 | 1 | 99.15% | 4 | 95.73% |
| | 15-16 | 0 | 99.15% | 2 | 97.44% |
| | 17-18 | 1 | 100.00% | 2 | 99.15% |
| | 19+ | 0 | 100.00% | 1 | 100.00% |

Table 4. Number of Data Collection Trips Required for US-250 E Sections

| | Trips Needed | 50 HZ Collecting Rate | | 10 HZ Collecting Rate | |
|---|---|---|---|---|---|
| | | # of Sections | Cumulative % | # of Sections | Cumulative % |
| IRI <= 90 in/mile | 0-4 | 30 | 41.38% | 13 | 19.83% |
| | 5 | 37 | 73.28% | 14 | 31.90% |
| | 6 | 20 | 90.52% | 18 | 47.41% |
| | 7 | 7 | 96.55% | 16 | 61.21% |
| | 8 | 2 | 98.28% | 17 | 75.86% |
| | 9 | 1 | 99.14% | 11 | 85.34% |
| | 10 | 0 | 99.14% | 4 | 88.79% |
| | 11 | 0 | 99.14% | 5 | 93.10% |
| | 12 | 1 | 100.00% | 4 | 96.55% |
| | 13 | 0 | 100.00% | 2 | 98.28% |
| | 14+ | 0 | 100.00% | 2 | 100.00% |
| IRI > 90 in/mile | 0-4 | 43 | 66.00% | 18 | 27.00% |
| | 5 | 22 | 88.00% | 16 | 43.00% |
| | 6 | 5 | 93.00% | 19 | 62.00% |
| | 7 | 2 | 95.00% | 10 | 72.00% |
| | 8 | 0 | 95.00% | 8 | 80.00% |
| | 9 | 0 | 95.00% | 6 | 86.00% |
| | 10 | 0 | 95.00% | 3 | 89.00% |
| | 11 | 0 | 95.00% | 5 | 94.00% |
| | 12 | 1 | 96.00% | 0 | 94.00% |
| | 13 | 2 | 98.00% | 1 | 95.00% |
| | 14+ | 2 | 100.00% | 5 | 100.00% |

Table 5. t-test Results

| Compared Groups | DoF | Average of Min. Trips # | *t*-statistic | *P*-value |
|---|---|---|---|---|
| 50 Hz Vs. 10 Hz on I-64 | 579 | 6.04 vs. 8.06 | -12.51 | 0.000 |
| 50 Hz Vs. 10 Hz on US-250 | 215 | 4.75 vs. 6.95 | -9.72 | 0.000 |
| Smooth Vs. Rougher Pavement Sections on I-64 at 50 Hz | 270 | 6.13 vs. 5.98 | 0.55 | 0.583 |
| Smooth Vs. Rougher Pavement Sections on I-64 at 10 Hz | 352 | 8.16 vs. 7.68 | 1.14 | 0.256 |
| Smooth Vs. Rougher Pavement Sections on US-250 at 50 Hz | 157 | 4.85 vs. 4.64 | 0.80 | 0.424 |
| Smooth Vs. Rougher Pavement Sections on US-250 at 10 Hz | 148 | 6.97 vs. 6.94 | 0.06 | 0.952 |
| I-64 Vs. US-250 at 50 Hz | 564 | 6.04 vs. 4.75 | 7.81 | 0.000 |
| I-64 Vs. US-250 at 10 Hz | 564 | 8.06 vs. 6.95 | 3.03 | 0.003 |

lower IRI group and 100 sections for a higher IRI group. Minimum number of data collection trips was calculated for each 0.1-mile section based on RMS results from multiple trips. Tables 3 and 4 summarize the number of sections in each minimum trip number bin and cumulative percentages for all pavement sections on I-64 and US-250 based on sampling rates and pavement roughness levels.

To satisfy the requirement for most pavement sections, the 95 percentile minimum number of required trips is first discussed here. For the lower IRI group of I-64 W, 95 percent of sections require fewer than 12 data collection trips at a 50 Hz sampling rate and fewer than 16 trips at a 10 Hz sampling rate. For the higher IRI group on I-64, the 95 percentile numbers of minimum trips required are 11 and 14 under 50 Hz and 10 Hz sampling rate, respectively. For sections on US-250, fewer trips are required than I-64 sections for both IRI groups and for both sampling rates (50 Hz and 10 Hz). The 95 percentile numbers of minimum trips are 7 and 12 for 50 Hz and 10 Hz rate, respectively, for both IRI groups.

To further investigate the impacts of sample rates, roughness levels, and routes on the required number of data collection trips, *t*-tests were conducted to compare the means for eight paired groups. The null hypothesis is that the two compared groups have the same average minimum number of trips. Table 5 shows the *t*-test results in terms of degree of freedom, group average number of minimum trips, *t*-statistic and *P*-value for each comparison, with the numbers in bold indicating that they are significant at a 0.05 confidence level.

A summary interpretation of the results is provided below:

- As expected, collecting data at 50Hz requires statistically significantly fewer trips than at 10Hz for both the I-64 and US-250 routes. In addition, one interesting thing to note is that applying a 10Hz sampling rate could actually reduce the total amount of data required for robust roughness estimations. For example, an average pavement section on I-64 requires six 50Hz data collection trips, or eight 10Hz trips. Considering that a 50Hz trip will generate five times the amount of data than a 10Hz trip, the total size of data from 50Hz trips will be larger than the 10Hz trips at the end. Therefore, there is a trade-off between required number of trips and the resulting amount of data when considering which sampling rate to apply.
- Although the raw acceleration dataset collected from a higher IRI group with rougher pavement sections is likely to contain a higher within-section variation than a smoother section, when the aggregated RMS acceleration was examined, it is interesting to note that rougher pavement sections do not necessarily require significantly more data collection trips than smoother sections. This could be explained by the fact that the RMS acceleration measurement is the aggregated result of all acceleration readings in the studied section. Generally speaking, rougher pavement sections result in larger RMS acceleration values, which are less sensitive to the within-section variation and noisy data inputs of different data collection trips. As a result, it is possible for rougher pavement sections to generate consistent RMS acceleration results as smoother sections with the same number of data collection trips.
- According to Table 5, the US-250 E route requires significantly fewer data collection trips than the I-64 W route. The main reason may be that there is only one travel lane on US-250 in one direction, while there are two lanes on I-64. As a result, unlike data collection on I-64, the acceleration collection was always from the same lane on US-250. Another possible reason could be the travel speed on US-250 was less than on I-64. Since the data collection rate did not change, more acceleration data were collected for each 0.1-mile section on US-250. It points to the necessity of designing sampling strategies based on facility type or number of lanes.

It is important to note that the resulting minimum number of trips is based on the two studied facilities: a four-lane divided freeway and a two-lane undivided primary road in Virginia. The results are expected to be transferable to similar type roadways if data collection is conducted on a dry pavement surface with vehicles that have similar dynamic characteristics.

## 5. Benefit Assessment

In this section, a case study of Virginia is provided to demonstrate a “rough” cost saving estimate that can be achieved by using the proposed smartphone-based application, rather than specialized profiler vans. First, in the current practice, it was estimated that VDOT spends about $1.8 million per year in pavement condition data collection (Sauerwein and Smith, 2011) as briefly mentioned in the introduction section. Note that, VDOT uses profiler vans with specialized equipment and sensors to collect pavement roughness information only for limited roadways at a longer (one or more year) time interval, i.e. once every year for the interstate and primary highways and every five years for the secondary roads.

On the other hand, here is an example operation scenario with the proposed smartphone application. The basic idea is to equip agencies' vehicles (maintenance, patrol, other service vehicles, etc.) with a tablet with the proposed smartphone application installed, which will automatically collect and store vertical accelerations while the vehicles are in operation. The collected data will then be retrieved and processed at a preferred interval, i.e. a day, a week, a month, and so on. It is important to note that data collection can be conducted through employees' daily work travel and thus does not incur any additional cost.

There are three cost categories needed to implement the proposed smartphone-based application approach. First, VDOT needs to invest a one-time cost of approximately $400,000 for the initial development tasks. This includes a smartphone application, a database system, a data processing software, and a quality control software. Note that $400,000 was estimated based on the actual effort made by the research team to develop a prototype application. The second category cost is for data collection devices. Each vehicle would require a total of $500 including a tablet with GPS and accelerometer ($400), a mount ($50), and a car charger and cables ($50). Assuming major roadways in the state of Virginia could be monitored with 200 state vehicles, a total cost for data collection devices would be $100,000. If the expected service time for those devices is 5 years, then it will cost $20,000 per year. The third cost category is a labor expense for data retrieval, processing and management. Note that, since data collection will be done through regular work trips, the cost for data collection would be negligible. Assuming two full-time employees for this task, approximately $150,000 is needed per year. Finally, the smartphone-based approach will require a one-time cost of $400,000 at the beginning and then $170,000 per year.

In summary, transportation agencies currently need to spend millions of dollars to collect pavement roughness data only for limited roadway facilities once every (or more) year. However, with the proposed smartphone-based approach, the agencies can collect the similar data for more roadways more frequently with a significantly less cost (only a $400,000 initial cost and a $170,000 annually for Virginia).

## 6. Conclusions

This study evaluates the feasibility of using a prototype smartphone application to estimate pavement roughness. Using an Android-device application developed in this study, data were collected on the I-64 W route (a four-lane divided freeway route) and the US-250 E Route (a two-lane undivided primary road) in Virginia, under naturalistic driving conditions.

The analysis indicates that vehicle vibration response (the RMS acceleration) under naturalistic driving condition can serve as a good indicator of pavement roughness. It correlates well with the VDOT-collected IRI data and is able to capture the trend of pavement roughness. Furthermore, a sample size analysis was performed to find out how many trips are needed to generate robust roughness estimates on two types of study facilities (an interstate and a primary road). The results showed that fewer than 12 data collecting trips are needed for most pavement sections if the application collects data at a rate of 50 Hz, while 16 trips are required at a rate of 10 Hz. It was also found that fewer data collection trips are needed on two-lane undivided roads than four-lane divided freeways. In addition, rougher pavement sections do not necessarily require more data collection trips as their larger RMS acceleration values are less sensitive to the within-section variation of raw acceleration data and the impacts of noisy data inputs from different data collection trips.

Lastly, a benefit assessment showed that the proposed smartphone application-based approach allows for pavement roughness data collection for more roadways (any traveled roadways using a smartphone application vs. limited roadways using profiler vans), more frequently (once any preferred period vs. once every or more years) with much less cost ($400,000 initial cost and $170,000 annually for Virginia vs. several million dollars). This implies that deploying a smartphone-based methodology (or a similar approach taking advantage of advance in mobile technologies) can result in a better practice in various aspects. It would be cheaper (economically beneficial) and more efficient (technologically beneficial), which will culminate into overall societal benefits.

In conclusion, this research demonstrates the feasibility of a smartphone-based pavement roughness assessment application. These results point to the possibility of using such an approach for large scale pavement roughness monitoring using a relatively small fleet of vehicles equipped with smartphone applications to collect data in a cheaper and more frequent manner. In addition, the proposed approach can also serve as a prototype to prepare for the great opportunity to progress pavement assessment practice from the future connected vehicle program.

Some of the recommendations for future research are provided as following. First, it is recommended that future research expands to other types of roadway facilities. Other facilities are likely to need different numbers of data collection trips as they have different numbers of lanes and posted speed limits, which may impact the repeatability of results. Also, given that there will be more variations of speeds for vehicles traveling on those types of highways; a speed factor should be included in the RMS algorithm (Dawkin, 2010). Secondly, this research used only one vehicle for data collection. Considering that there may be different vibration responses due to distinct mechanical and dynamic properties among different classes of vehicles, a sensitivity analysis is recommended to analyze RMS acceleration results from various types of vehicles such as SUVs, passenger cars and commercial trucks. This information will help address whether it is better to collect data using different types of vehicles and how to calibrate RMS acceleration data from different vehicles. Last but not least, research on methodologies to minimize the impacts of noisy data inputs is also recommended.

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