CVI UTC

CONNECTED VEHICLE/INFRASTRUCTURE UNIVERSITY TRANSPORTATION CENTER (CVI-UTC)

Infrastructure Pavement Assessment & Management Applications Enabled by the Connected Vehicles Environment – Proof-of-Concept

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Infrastructure Pavement Assessment & Management Applications Enabled by the Connected Vehicles Environment – Proof-of-Concept

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Disclaimer

Connected Vehicles-Infrastructure UTC

The mission statement of the Connected Vehicle/Infrastructure University Transportation Center (CVI-UTC) is to conduct research that will advance surface transportation through the application of innovative research and using connected-vehicle and infrastructure technologies to improve safety, state of good repair, economic competitiveness, livable communities, and environmental sustainability.

The goals of the Connected Vehicle/Infrastructure University Transportation Center (CVI-UTC) are:

- Increased understanding and awareness of transportation issues
- Improved body of knowledge
- Improved processes, techniques and skills in addressing transportation issues
- Enlarged pool of trained transportation professionals
- Greater adoption of new technology

Abstract

The objective of this project was to develop prototypes and conduct a field test of system level applications of a connected vehicle pavement condition measurement system. This allowed the research team to: (1) investigate different approaches to a connected vehicle pavement measurement system; and (2) determine the optimum procedures for collecting, processing, aggregating, and storing the data to support engineering and management decisions.

The study found that roughness measures obtained from probe vehicles are comparable to roughness measures obtained from the profile, when the appropriate parameters that affect roughness were taken into account. A sensitivity analysis suggested that data sampling and quarter-car parameters were the most critical parameters. Finally, the results of the network-level simulations showed that the probe vehicle vertical acceleration measurements (collected from a mobile smart phone application) have the potential to be used for network-level prescreening of deficient pavement sections.

Acknowledgements

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Introduction

A fundamental role of transportation agencies is to effectively manage the enormous public investment in pavement. This includes developing strategies and systems to periodically assess pavement condition, developing maintenance plans to maximize pavement life within limited budgets, and making tactical decisions regarding treatment necessary during adverse weather conditions to keep roadways functional. This management activity is supported by data collected to assess the condition of the pavement. The current state-of-the-practice in pavement condition data collection requires the use of specialized sensors and equipment to support this activity. This represents a significant cost burden on the agencies involved, and the technical approach to data collection also scales poorly. Given the need for specialized equipment and sensors, it is very difficult to collect data at many locations in a timely, cost effective manner.

A potential advantage offered by connected vehicles is that this program promises to closely tie the infrastructure to the vast vehicle fleet that uses it. Given the large set of sophisticated sensors integrated in modern vehicles, it is possible that these vehicular sensors may be used as a means to assess pavement conditions. In this setting, the entire vehicle fleet can be transformed into probes measuring pavement conditions at all locations in frequent time intervals.

Objectives

The overall objective of this project was to develop prototypes and use them to conduct a field test of system-level applications of a connected vehicle pavement condition measurement system. This allowed the research team to: (1) investigate different approaches to a connected vehicle pavement measurement system; and (2) determine procedures for collecting, processing, aggregating, and storing the data to support engineering and management decisions.

Specific objectives of this study are summarized as follows:

1. To gain experience in a system-level probe-vehicle-based pavement condition measurement applications to determine feasibility;
2. To compare a Dedicated Short-Range Communications (DSRC) (versus a smart phone-based approach to this application); and,
3. To investigate the utility of the data produced for supporting pavement/asset management decisions.

Background

Roughness Measurement

Currently, pavement roughness (or ride quality) is obtained from the roadway profile by simulating the effect of this profile on the vertical acceleration of a standard (quarter-) car traveling along the roadway (**Figure 1**). In this model, $\mathbf{z_{road}}$ represents the profile, $\mathbf{z_{tire}}$ the vertical movement of the tire, and $\mathbf{z_{body}}$ the vertical movement of the vehicle body, while k_b represents the suspension stiffness coefficient, C_b the suspension damping coefficient, and k_t the tire stiffness. Within the connected vehicle environment, the car acceleration response can be directly measured rather than just being simulated. In fact, some cars are already collecting this information for other purposes, such as improving the driver experience. This data can be used directly to estimate user perception of ride quality and identification of areas that need maintenance.

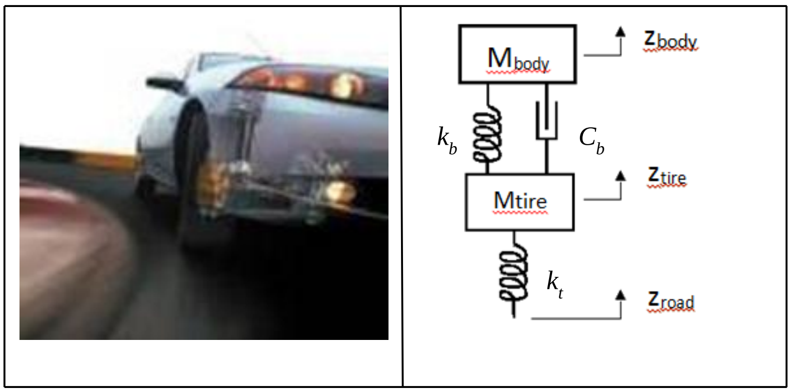


Figure 1. Schematic of quarter-car model used to measure roughness.

The core hypothesis of this project is that Vehicle-to-Infrastructure (V2I) technology can be used to collect and integrate pavement roughness information from connected vehicles into a pavement management system (PMS). That information will provide uniform, continuous, immediate, and cost-effective data about transportation infrastructure health and level of service, which, in turn, can be used to support pavement management decisions.

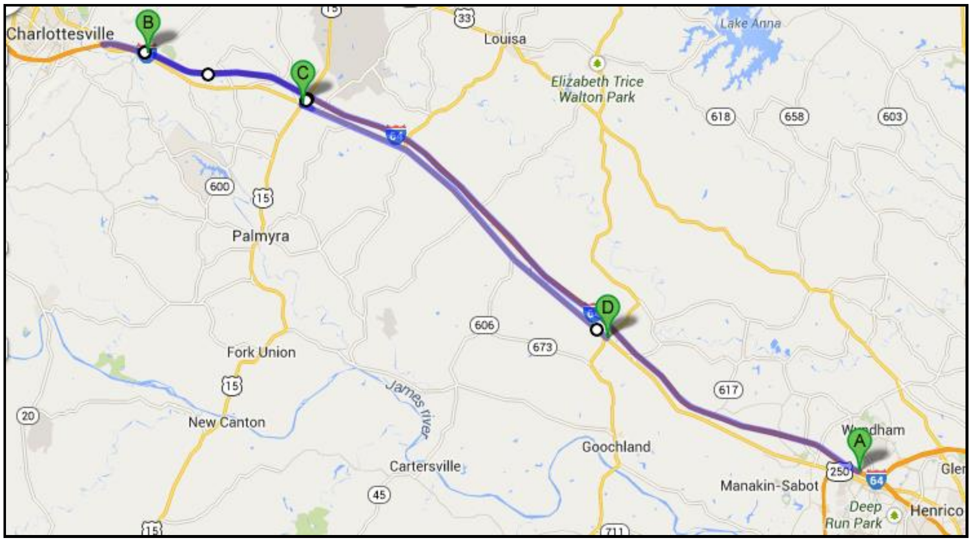
Methods

Roughness Measurements

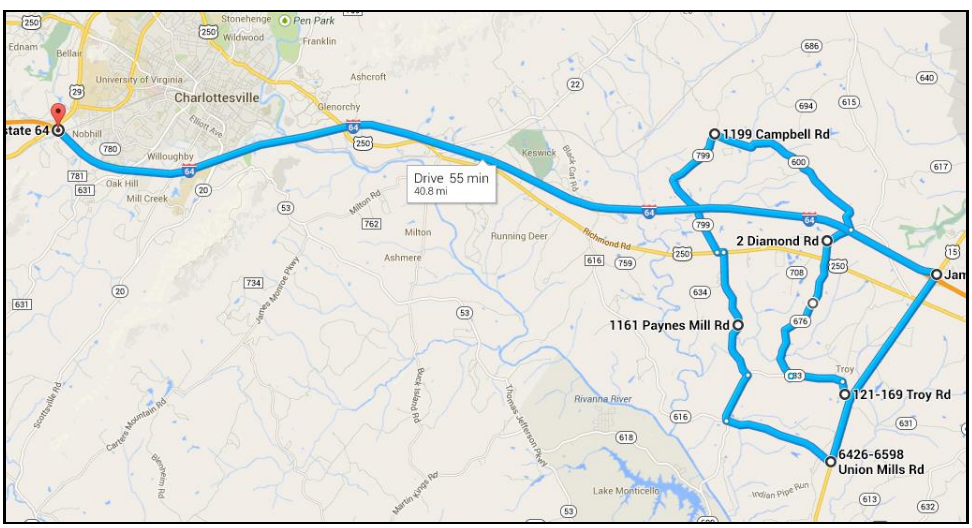
Testing was performed on the Virginia Smart Road in Blacksburg, Virginia and on roadways near Charlottesville, Virginia. The Smart Road testing validated the use of probe vehicle measurements to estimate pavement roughness. This was done by developing a numerical procedure to calculate the International Roughness Index (IRI) from the probe vehicle and comparing that IRI with the IRI calculated from an inertial profiler. The next step was comparing the measured probe vehicle acceleration with vehicle acceleration predicted from the inertial profiler measurements.

The inertial profiler is the name of the device used to measure pavement roughness by state Departments of Transportation (DOTs). The validation of the numerical procedure included evaluating the accuracy of the numerical calculations, determining the effect of data sampling frequency on the calculations, performing a sensitivity analysis on the quarter-car parameters (mass, stiffness, and damping parameters) that most affect the calculation results.

Additional field testing was performed to validate the use of in-vehicle acceleration measurement with a mobile smart phone to predict pavement IRI. In-vehicle acceleration measurements were obtained using a mobile smart phone application, while pavement IRI was obtained using an inertial profiler. Field testing was performed in 2013 and 2014 in an area around Charlottesville, Virginia, as shown in **Figure 2**. A correlation between normalized smart phone measured acceleration with the IRI was developed. The normalization of the acceleration measurements was performed with respect to vehicle speed.



(a) 2013 [A-B: I-64 W, MP 178- 121; C-D: US-250 E, MP 113.2- 134.8]



(b) 2014

Figure 2. Data collection routes around Charlottesville, VA (Map data ©2014 Google).

Calculation of IRI from Acceleration Measurements

The standard method to determine roadway roughness is to calculate the IRI from roadway profile measurements using the quarter-car model. The quarter-car model is basically a set of differential equations which are practically solved numerically (using a finite difference discretization). The numerical solution also gives the vehicle's vertical acceleration. **Figure 1** presented a schematic which illustrates that the IRI and vertical acceleration can be obtained from profile measurements. To calculate the IRI from acceleration measurements, we first calculate a roadway profile from the vehicle acceleration measurements, then use the quarter-car model to calculate the IRI. This is necessary since the discretization used to go from the profile to the acceleration cannot be used to go from the acceleration to the profile. The procedure is based on numerical discretization and therefore subject to numerical error. Therefore, the first step was to calculate an upper bound to the error of the discretization developed to calculate the IRI from acceleration measurements. Details on the numerical discretization are given in Katicha et al. [2].

Results

Accuracy of Calculations from Probe Vehicle Acceleration Measurements

Figure 3 shows two methods of calculating the IRI. The first method requires calculating the IRI directly from the profile (red line in **Figure 3**). The second method calculates the vertical acceleration from the profile, recalculates the profile from the vertical acceleration, and finally calculates the IRI from the recalculated profile (dotted black line in **Figure 3**).

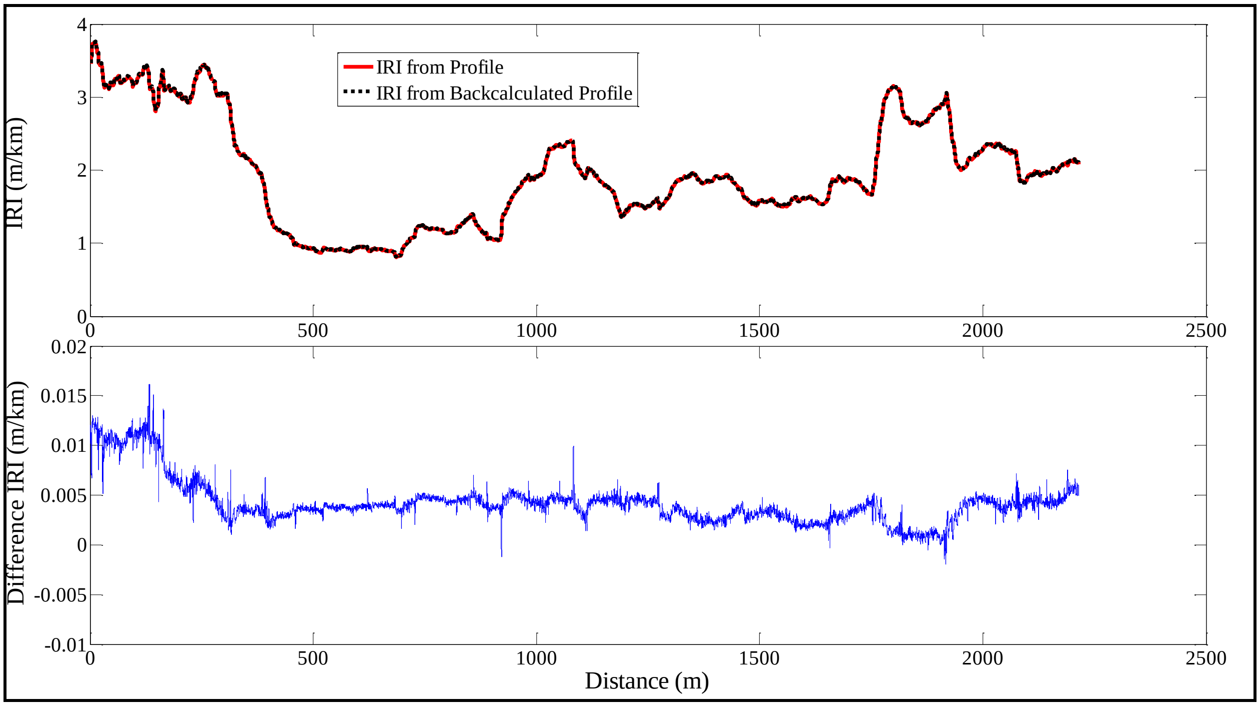


Figure 3. Accuracy of IRI calculation; calculated IRI (top) and difference between calculated IRI (bottom).

Clearly, in practice, the two steps of calculating the vertical acceleration from the profile and then recalculating the profile from the vertical acceleration represent wasted and unnecessary circular effort. The reason it is performed is to evaluate the total error of this circular effort that has been caused by the numerical approximations in the discretization. The total error of this process is shown in the bottom of **Figure 3**. In this example, the maximum error incurred in the calculation of the IRI is less than ±0.02 m/km. This is at least an order of magnitude lower than the accuracy of inertial profilers, in terms of IRI calculation.

Effect of Data Sampling Rate and of the Quarter-Car Simplification

The instrumented vehicle used as the probe vehicle for the data collection on the Smart Road is equipped with an accelerometer that measures vertical acceleration at a 10 Hz frequency. With testing performed at a speed of 50 mph, this corresponds to a measurement approximately every 2 m (2.235 m, to be more exact). However, profile measurements are obtained at every 0.03 m. Therefore, the effect that a lower sampling rate of probe vehicle acceleration can have on the calculation of the IRI was evaluated.

Another issue with the calculation of the IRI from the probe vehicle is that the IRI uses a quarter-car model, whereas the accelerometer in the probe vehicle measures the response of the full car (not just a quarter of it). The difference can be explained by considering a car traveling on a smooth road that is about to hit a bump. In the quarter-car model, when the quarter-car hits the bump, the acceleration felt by the quarter-car is the response to the bump. In the probe vehicle (full car), when the front tires hit the bump, the back tires are still on the smooth road and do not completely feel the effect of the bump. The accelerometer, which is affected by the response of both the front and back tires, will therefore measure a response that is different than that of a quarter-car. Modeling a full car can become fairly challenging (which was determined not worth the effort for this application), therefore a rough approximation to the full car was used to average the response of four quarter-cars, which represents the front/back and left/right portions of the car. **Figure 4** shows the effect of the sampling rate on the calculated IRI. Details of how the sampling rate was changed can be found in Katicha et al. [2]. The red curve represents the calculated IRI from the inertial profiler using the vehicle sampling distance of 0.03 m, while the green line shows the calculated IRI using a sampling distance of 2 m. In general, reducing the sampling rate (increasing the sampling distance) resulted in lowering the IRI. The IRI calculated from the probe vehicle is shown in blue. The figure shows that the sampling rate explains some of the discrepancies between the IRI calculated from the inertial profiler and the IRI calculated from the probe vehicle acceleration measurements.

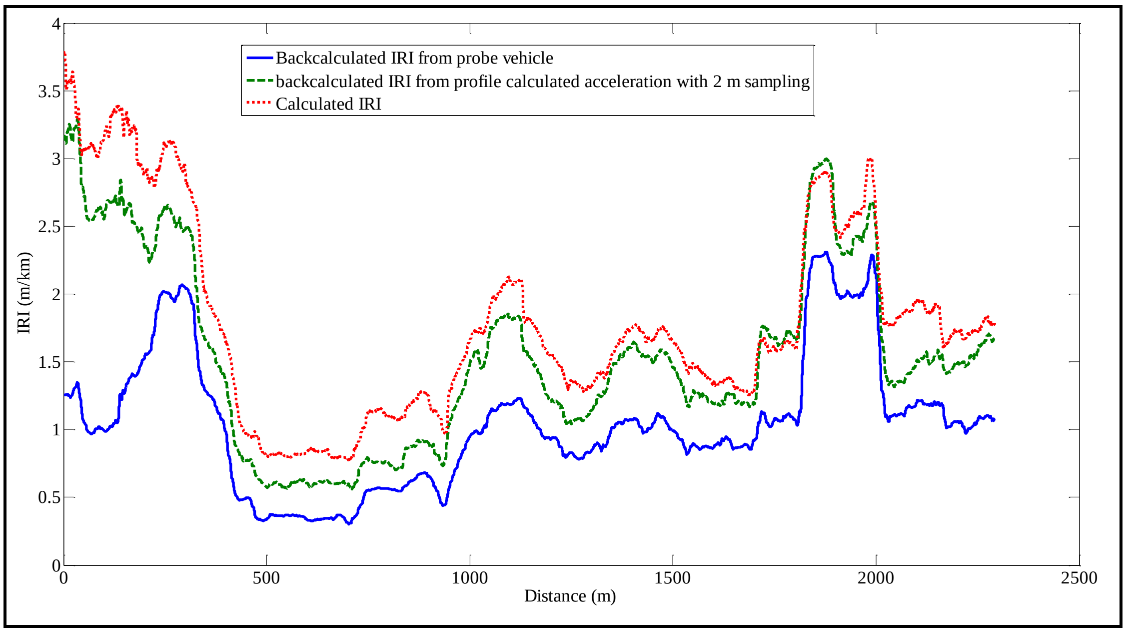


Figure 4. Effect of sampling rate on the calculated IRI.

Figure 5 shows the effect of approximating the response of the full car by averaging the left and right profile measurements and also averaging the response of the four tires to better represent the response of a full car. The Measured IRI (labeled MIRI in the figure) calculated from the inertial profiler and the IRI calculated from the Probe Vehicle Roughness Index (PVRI) are much closer, except for the first 250 m. It is believed that this could be due to the fact that the probe vehicle had not yet reached the speed of 50 mph.

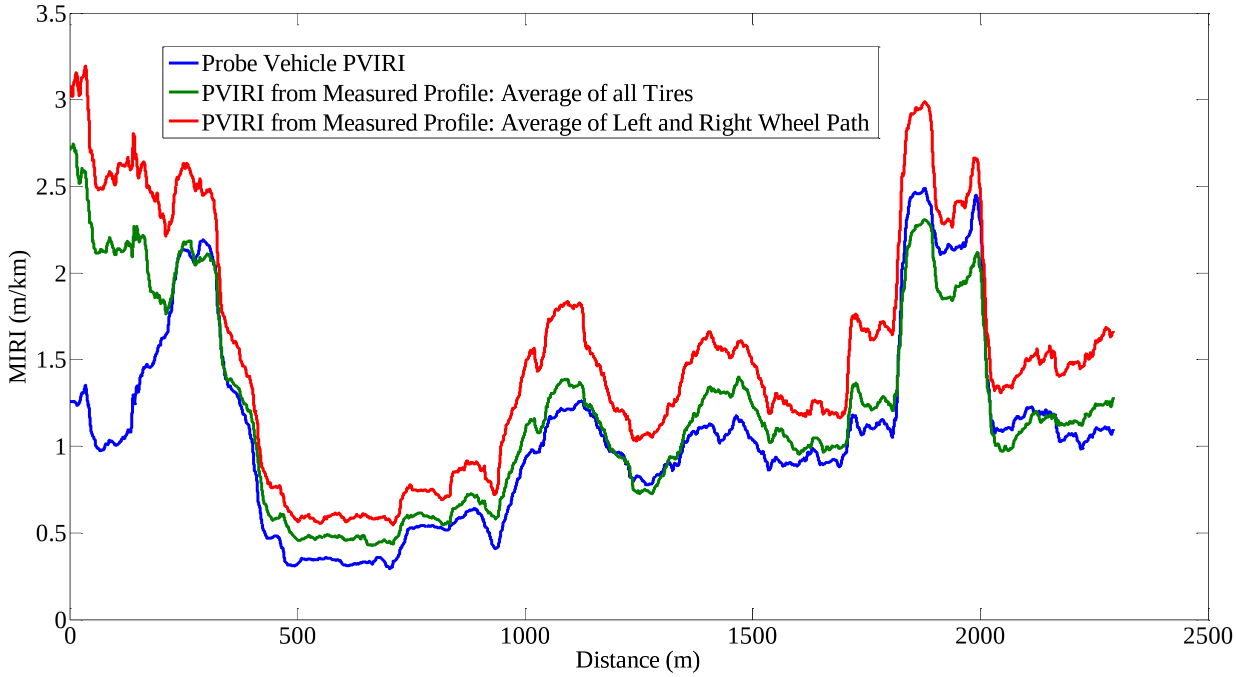


Figure 5. Effect of approximating full car model with average quarter car models.

Effect of Car Parameters

In the quarter-car model, the car parameters (mass, stiffness, and damping) determine response. Misspecification of these parameters will affect the calculated IRI. **Figure 6** shows the effect of a ±25% change in the car parameters. The results showed that the suspension damping ratio, C, and the tire stiffness ratio, k_2, had the most significant effect on the calculation of the IRI.

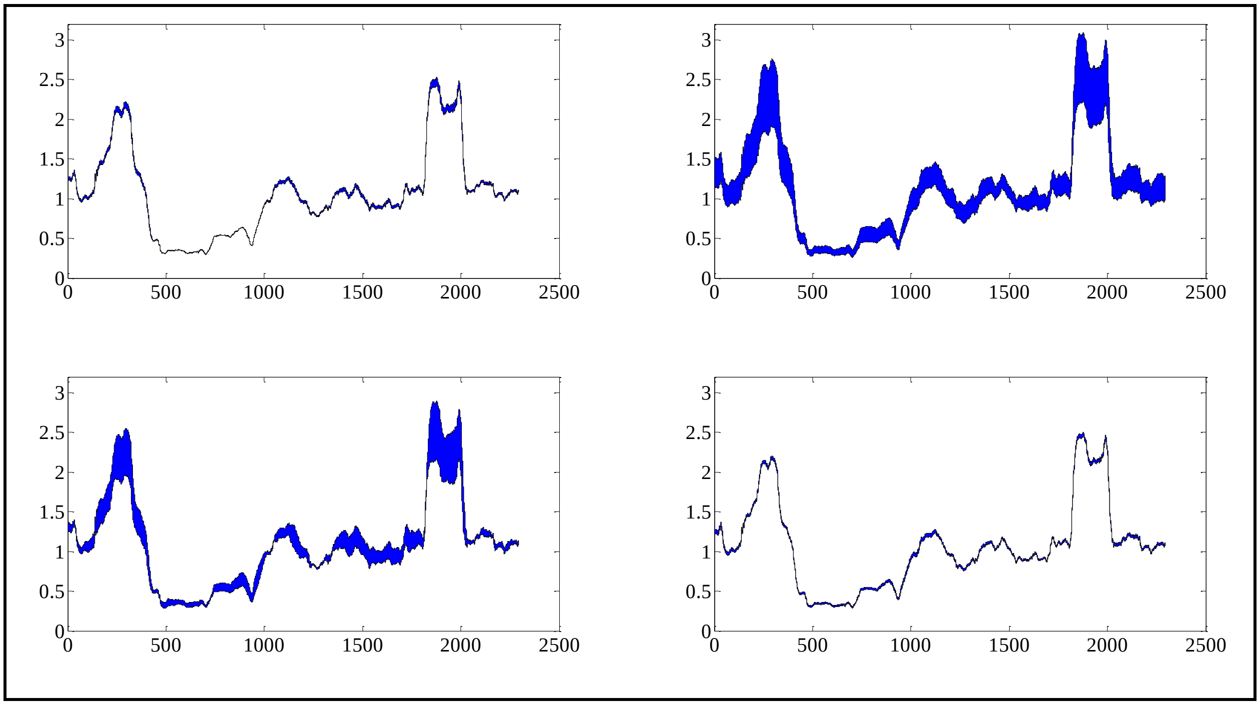


Figure 6. Effect of quarter-car parameters on PVRI;
Top Left k_1; Top Right: C; Bottom Left: k_2; Bottom Right: μ.

Network-level Data Collection Simulations

This section presents the methodology of using an acceleration-based metric for the identification of deficient pavement sections at the network level. Exploratory analyses were conducted based on data collected under naturalistic driving conditions on interstate, primary, and secondary roadways near Charlottesville, VA. According to Dawkin et al. [1], a Root Mean Squared (RMS) vertical acceleration, which is calculated with the equation below, represented a better scenario for matching the IRI with acceleration measurements under a constant speed.

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

Where:

$a_{z,\ RMS}$ = the RMS vertical acceleration for the studied pavement section N = the number of acceleration readings among the studied pavement section

$a_{z,i}$ = the i^{th} vertical acceleration reading among the studied section g = the contribution of the force of gravity

Figure 7 and **Figure 8** show the correlation between RMS vertical acceleration and the actual IRI, based on mile posts on I-64W and US-250E. Note that the acceleration data were collected with relatively steady vehicle speeds.

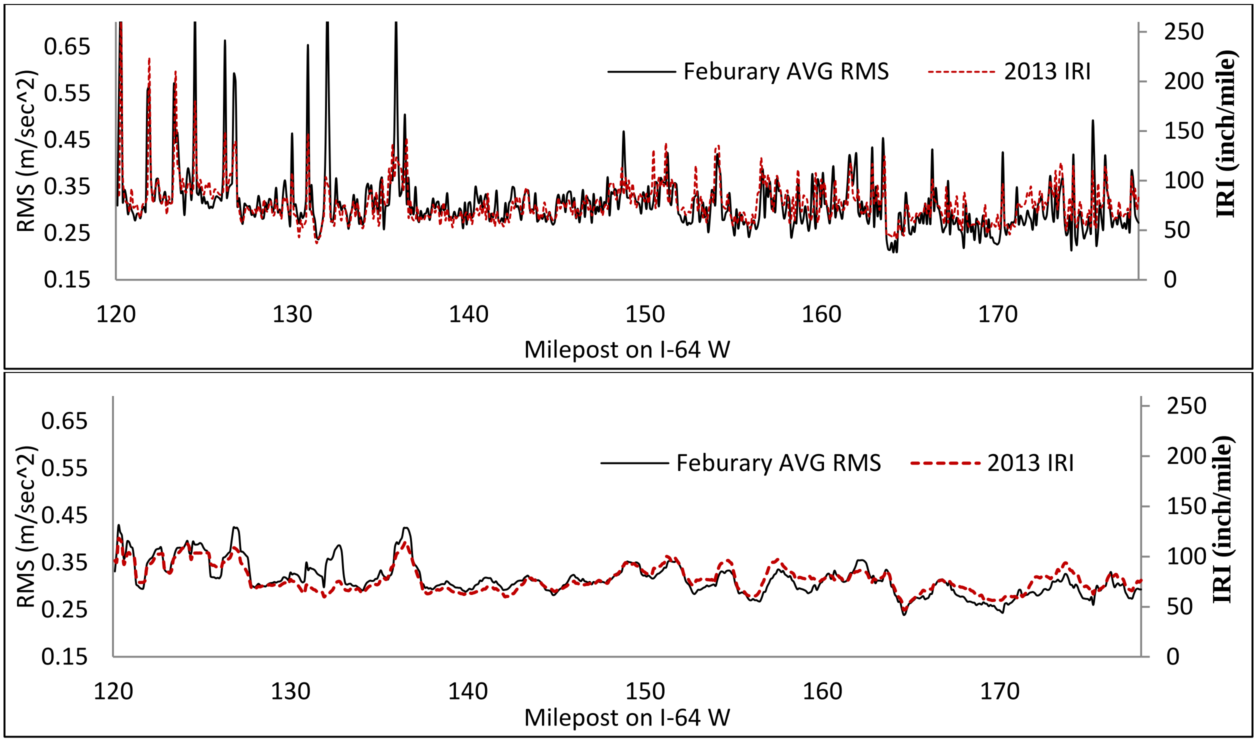


Figure 7. IRI Compared to RMS Acceleration on I-64 W; Top: Original 0.1-mile data; Bottom: Moving average using a 1-mile window.

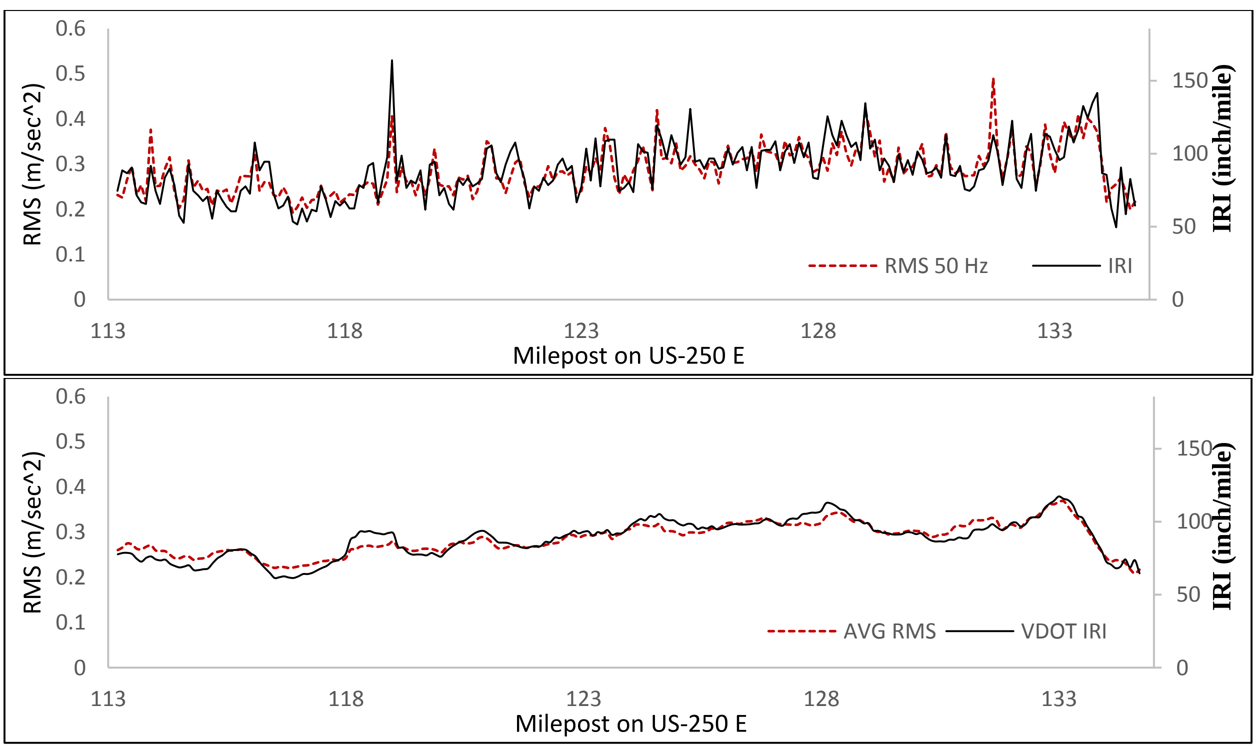


Figure 8. IRI Compared to RMS Acceleration on US-250 E; Top: Original 0.1-mile data; Bottom: Moving average using a 1-mile window

Under naturalistic driving conditions where there is a good variety of driving speeds, the vehicle vertical acceleration measurements need to be normalized to account for the effect of vehicle speeds. A normalized acceleration-based metric (NRMS) was introduced by incorporating vehicle operating speed in a previous study [3], as presented in the following equations. NRMS indicates the vibration level that a vehicle is expected to experience at the speed of 80 km/h. Note that this metric is designed for network screening purposes, i.e., to pre-identify deficient pavement sections, which does not require a high degree of accuracy.

$$NRMS = (80/v)^w a_{z,RMS}$$

Where:

w = an exponent that relates to pavement PSD characteristics and its default value is 1.3,

v = the speed of the vehicle, and

$a_{z,RMS}$ = the measured RMS vertical acceleration.

Figure 9 shows the scatter plots of IRI with RMS acceleration or NRMS acceleration when the exponent w values are 0.5, 1.0, and 1.5, respectively. According to the figure, the RMS accelerations before normalization did not show consistent relationships with the IRI values between different routes. However, after normalization, the NRMS values appear to share a similar relationship with the IRI between different routes. It indicates that incorporating vehicle speed in the acceleration-based metric makes it possible to generalize the results to different functional classes of highway. An optimal value of w = 1.3 was found to minimize the prediction error based on the collected data using the cross validation method.

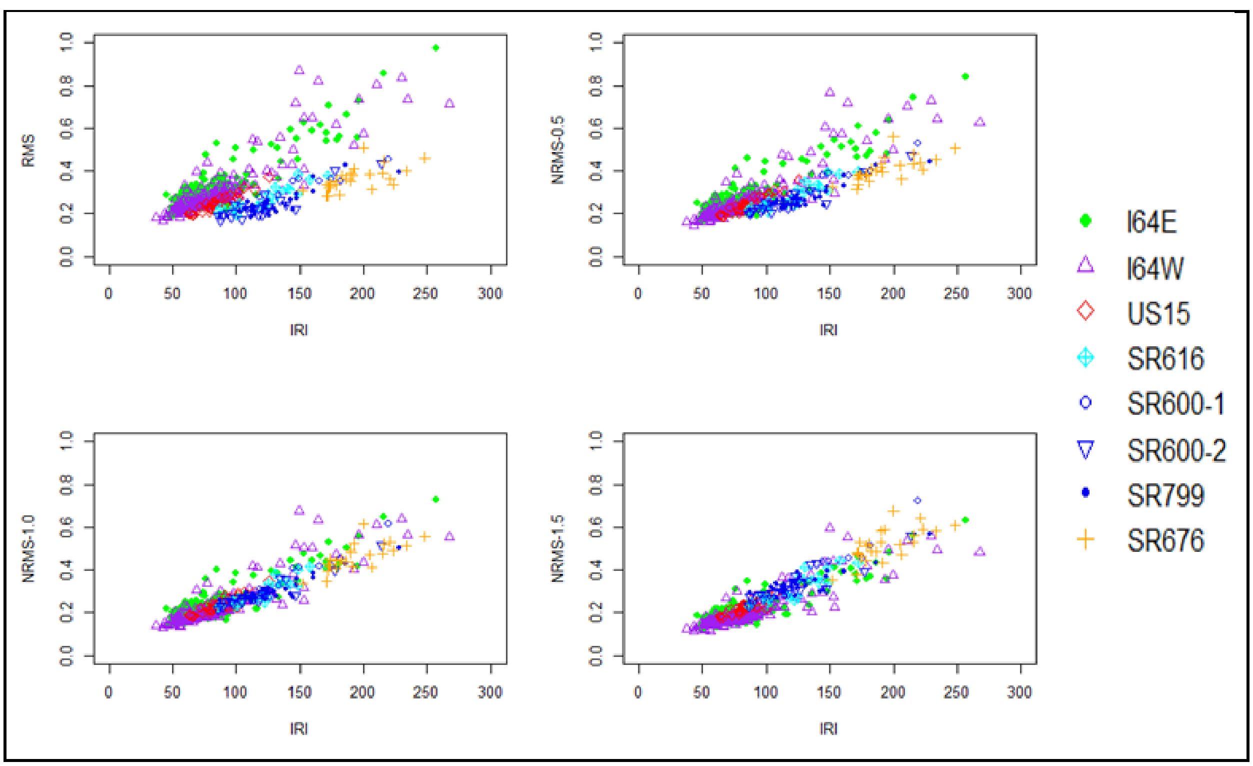


Figure 9. Scatter plots of IRI vs. RMS/NRMS acceleration.

Identification of Deficient Pavement Sections

A logistic regression model, as shown in the equation below, was developed to identify deficient pavement sections (IRI>=140 in/mile).

$$logit(p) = \log\left(\frac{p}{1-p}\right) = -14.2 + 39.04 * NRMS$$

Where:

p = the probability of the studied section being deficient, and

NRMS = the NRMS acceleration of the studied section

According to the developed model, a pavement section with a NRMS value greater than 0.36 is expected to be deficient with a probability of greater than 0.5, and thus should be flagged as a deficient section. **Table 1** shows that the model can correctly identify 80 percent of deficient pavement sections. Note that the total number of misclassified sections is nine (six deficient and three non-deficient). It was found that all nine sections that were misclassified by the model (**Figure 10**) had IRI values between 130 and 150 in/mile. Specifically, this model missed six sections that were near the deficient threshold while picking up three sections that soon would be deficient.

Table 1. Classification Results Summary

	Testing Data Predicted		
Observed	Non-Def.	Deficient	Correct Percentage
Non-Def.	132 (99, 33)[1]	3 (0, 3)	97.78 (100.00, 91.67)
Deficient	6 (3, 3)	24 (13, 11)	80.00 (81.25, 78.57)

[1]The first value in the parentheses indicates the number of interstate sections and the latter denotes the number of non-interstate sections.

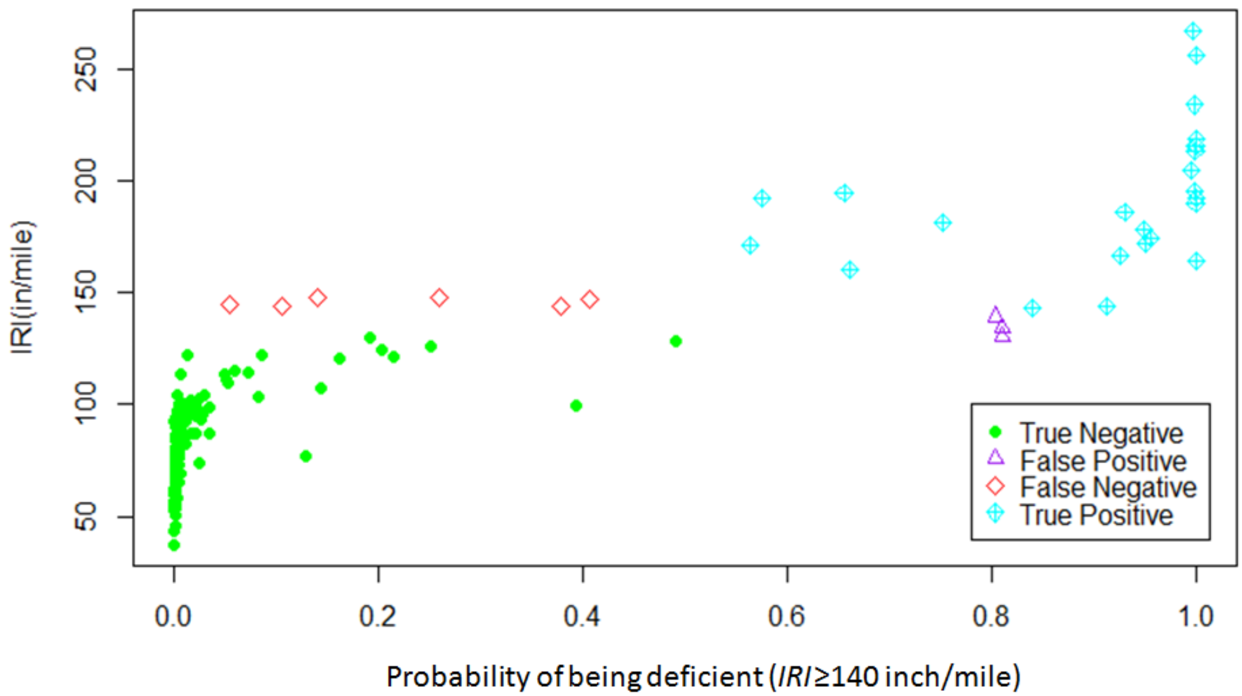


Figure 10. IRI values and the estimated probability

Discussion

The results show that probe vehicle vertical acceleration measurements have the potential to be used for network-level screening of deficient pavement sections. In a classification of deficient and non-deficient sections, the misclassification rate was only 5.5% (nine out of 162 pavement sections). In general, a DOT is interested in finding most (or all) of the deficient sections with a low rate of false positives. For the 30 deficient sections in this study, 24 were identified, while three non-deficient sections were falsely identified. Therefore 80% of the deficient sections were identified. The false discovery proportion, which is the proportion of wrongly classified deficient sections among all sections classified as deficient is 0.11 (3 out of 27).

For the classification, we have used a posterior probability of 0.5 to detect the deficient sections. We can increase the proportion of identified deficient sections by lowering the posterior probability at which we identify deficient sections. This might increase the probability of a false positive; however, it also increases the probability of identifying most of the deficient sections. A practical numerical example can illustrate the usefulness of using probe vehicle data as well as lowering the posterior probability threshold in a relatively well maintained network (i.e., a network with a relatively low proportion of deficient sections). Suppose a roadway network has 10% deficient sections. Without the use of probe vehicle measurements to identify possible deficient sections, the DOT would have to cover all of the network (assuming the agency has no historical data) with an inertial profiler to identify the deficient sections. On the other hand, probe vehicles cover the entire network and therefore acceleration measurements are available for almost 100%

of the network. To identify the deficient sections, general purpose vehicles could be used to collect acceleration, GPS, and vehicle speed data, then calculate the NRMS and finally flag pavement sections that are likely to be deficient. Once a pavement section is flagged, DOTs can send out a profiler van or other data collection tools to obtain the accurate pavement condition data and then decide a proper treatment for that section. Introducing such a prescreening process should be able to reduce the total mileage of pavement sections that need to be measured by the profiler van and still identify locations where maintenance work is necessary.

Conclusions and Recommendations

In general, roughness measures obtained from the instrumented probe vehicle were comparable to roughness measures obtained from the profile (measured with an inertial profiler), when the appropriate parameters that affect roughness are taken into account. One of the most important parameters measured by the probe vehicle that affects roughness is that it represents the response of the full car (i.e., what is felt by all four wheels) and not that of a quarter-car. A sensitivity analysis with respect to the data sampling and quarter-car parameters suggested that data sampling and quarter-car parameters could account for most of the discrepancies observed between the PVRI calculated from the probe vehicle acceleration measurements and the PVRI calculated from the measured profile.

The results of the network-level simulations showed that probe vehicle vertical acceleration measurements with a cell phone have the potential to be used for network-level screening of deficient pavement sections. In a classification of deficient and non-deficient sections, the misclassification rate was only 5.5% (nine out of 162 pavement sections). Therefore, it is recommended that a prototype of a pavement network screening system be developed using state-owned vehicles as probe vehicles to collect data. With the prototype system, a more comprehensive dataset can be generated by collecting data on more routes and in a wider area. It can be then used to validate previous findings, address issues regarding implementation, and assess the network benefit of this system.

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