EVALUATING ROADWAY SURFACE RATING TECHNOLOGIES

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16. Abstract

The key project objective was to assess and evaluate the feasibility and accuracy of custom software used in smartphones to measure road roughness from the accelerometer data collected from smartphones and compare results with PASER (Pavement Surface and Evaluation Rating System) and IRI (International Roughness Index) measurement values collected from the same roadway segments. This project is MDOT's first large implementation of a customized Android smartphone to collect road roughness data using a methodology developed from previous research work performed by UMTRI. Accelerometer data collection was performed via Android-based smartphones using a customized software application called DataProbe. During the project's initial phase smartphones were installed in each of nine Michigan Department of Transportation (MDOT) vehicles driven by MDOT employees. These same vehicles also were used during 2012 and 2013 to

collect data on road distress using PASER Ratings for comparison.

The DataProbe software application was used to collect data and transmit it to a University of Michigan Transportation Research server, where it was sorted, stored, and analyzed. All MDOT regions are represented in this analysis that compares road roughness ratings for nearly 6000 one tenth of a mile road segments. For the second phase of the project, road distress (PASER Rating) data was collected in 2014 simultaneously with an MDOT vehicle equipped with an IRI device and two DataProbe smartphones and two UMTRI vehicles equipped with five DataProbe smartphones.

The analysis of the 2012 and 2013 data found that there were a number of significant predictors of IRI road roughness including: the phone and the vehicle used to collect the data, the speed of the vehicle collecting the data, the type of road surface, date of data collection, and accelerometer variance. By including quadratic terms to adjust for non-linear relationships and interactions among the predictors studied in this project, the multiple regression model predicted nearly 45 percent and 43 percent of the variance in IRI scores, respectively. An analysis of commonly used IRI categories (3 level/5 level) using ordinal logistic regression found that DataProbe accurately predicted these categories 68/71 percent of the time (2012 data), 77/76 percent of the time (2013 data).

Analysis of the data collected in 2014 showed multiple regression models with variance among accelerometer measurements and speed accounting for 37 percent of the variance, while the ordinal logistic regression accurately predicted the IRI (3 level/5 level) categories 86/83 percent of the time. These results are promising when considering the near term application of the DataProbe technology for smaller locales that drive over their local roads more often, generating web-based road roughness visuals of each of the roads in their jurisdiction. In the longer term, state-wide road roughness measurement may be performed through the crowd-sourcing model available through Connected Vehicle initiatives, where all vehicles will be equipped with devices that support safety applications as well as other applications such as those that measure road roughness.

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Executive Summary

This project is a follow-up to a previous MDOT research project [1] conducted by UMTRI in 2012. This work will hopefully compliment an on-going innovation initiative to identify how state DOTs might use and benefit from the large quantities of data generated by future connected vehicle programs and to assist in refining connected vehicle system requirements.

For the current project UMTRI used technology developed from the “Slippery Road Detection and Evaluation” project to gather accelerometer data from the smartphone(s) and subsequently transmit the collected data to an UMTRI server via a wireless cell phone service. Phones were placed in nine vehicles driven by Michigan Department of Transportation (MDOT) employees across the state and used to collect accelerometer data while at the same time Pavement Surface Evaluation Rating (PASER) system data (a pavement condition measurement) was collected.

The original purpose of this research study was to compare accelerometer readings from the DataProbe program collected in 2012 and 2013 to the PASER rating measurements collected in 2012 and 2013 on the same segments of the state’s roadway system. Meetings with the MDOT team early in the project revealed that comparing the DataProbe accelerometer readings to the International Roughness Index (IRI), which is used by all states to measure road roughness, would be a better test of the DataProbe program than comparing them to PASER ratings that focused on road distress. The primary focus of this project was to determine if a reliable and repeatable comparison between the DataProbe measurements and those from the IRI data collection system could be made.

The main variables used in the analyses included variance among accelerometer measurements gathered by DataProbe, the speed of the vehicle, the date of data collection, surface type, and the individual phones.

The analysis of the 2012 and 2013 found that the nine phones themselves differed in how they predicted IRI scores for the road segments common to both IRI and the individual phone. This model accounted for 45 percent of the variance in IRI scores for the common road segments in the analysis for the 2012 data collection and 43 percent of the variance for the 2013 data collection.

The analysis of the 2014 data took advantage of having DataProbe and IRI readings collected simultaneously rather than during different timeframes. The same routes were also driven multiple times to gather more data per road segment. The results show predictive power using just the variance among accelerometer measurements and the speed of the vehicle as the two main independent variables, accounting for 39 percent of the variance in IRI scores for common road segments. The phones themselves were found to be significant predictors, but their contribution to the explained variance was negligible.

Because many departments of transportation use IRI scores grouped into three categories to make decisions on road maintenance, the 2012, 2013, and 2014 data was also analyzed using

[1] Robinson, R., Cook, S., *Slippery Road Detection and Evaluation Final Report*, 2012, University of Michigan Transportation Research Institute.

logistic regression to predict the three categories. A five level IRI category model that provides more differentiation among the "good" and "fair" IRI ratings was also analyzed.

3 Categories of IRI Scores		5 Categories of IRI Scores	
Good	000 - 095	Good	000 – 048
			049 – 095
Fair	096 – 169	Fair	096 – 138
			139 – 169
Poor	170+	Poor	170+

- The results for the 2012 data show that the model using variance among accelerometer measurements and controlled for the speed of the vehicle, accurately predicted the three level IRI score 68 percent of the time and the five level IRI variable 71 percent of the time.

- For the 2013 data, variance among accelerometer measurements accurately predicted the three level IRI score 77 percent of the time and the five level IRI score 76 percent of the time.

- The 2014 analysis showed variance among accelerometer measurements predicting the three level IRI score 86 percent of the three and the five level score 83 percent of the time. The slight differences between the three and five level predictions show that the model is able to predict a three level and a more specific five level independent variable equally well.

These results provide a number of important insights into the use of smartphone accelerometers to measure road roughness.

1) More DataProbe data collected per IRI road segment increases the predictive power of the smartphone when predicting categories rather than exact IRI readings.
2) Phones differ from each other even if they are the same model of phone across different vehicles, though their effects are mitigated in the categorical analysis
3) As the speed of the vehicle increases, the IRI predicted IRI ratings tend to be lower, meaning the roads seem smoother.
4) Smartphones accelerometers do not predict IRI road segment scores to the degree necessary to replace the IRI ratings, but they predict IRI categories very well.

If in fact, decision-makers uses IRI categories to make road repair decisions then the DataProbe system can provide a quick, inexpensive tool for <u>continually</u> keeping track of all the roads in the state, assuming the roads are driven multiple times.

Introduction

The United States Department of Transportation's (USDOT) Federal Highway and Safety Administration (FHWA) and Michigan's Department of Transportation have many focused efforts in the area of connected vehicle application and development. The connected vehicle research with FHWA and MDOT includes the Integrated Mobile Operations (IMO) project (2014)[2] that uses technology similar to the previously completed Slippery Road project[3], where an Android-based smartphone is used to collect external sensor, vehicle, and phone-based data, and transmit it via cell phone to a server based at the University of Michigan Transportation Research Institute.

This project differs from the previous projects in that its focus is primarily on the accelerometer data that is collected directly from the phone in order to see how well this data predicts road roughness data compared to data collected via the International Roughness Index system deployed throughout the US. There are a number of other studies that use cell phone accelerometers to inform state DOTs of road conditions. Samer Katicha et al[4] (2014), from Virginia Tech, presented a paper at the 2014 Transportation Research Board conference that compared the use of probe vehicle data to IRI data to measure road roughness. They conclude that it is possible to determine road roughness using cell phones if you use multiple vehicles over the same road. They also try to create a "one size fits all" approach to create a standard model for the use of accelerometer data, though they admit that each vehicle has to be analyzed independently.

Luis Amador-Jimenez and Nagham Matout (2014)[5] found that different vehicles provide different readings when driven over the same road and that the faster the vehicle drove over the route, the worse the correlation with IRI data for the same road. Viengnam Douangphachanh and Hiroyuki Oneyama (2013)[6] in one study found that the orientation of the phone in the vehicle, the phone, the sampling frequency, and the vehicle all affected the accelerometer readings. In their other study (2013)[7], they found differences in the phone and the vehicles when comparing accelerometer readings to IRI data and that the faster a vehicle drove over a route, the worse the correlation with IRI data, especially driving over 37 miles per hour.

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[2] Belzowski, B. and Cook, S. *Integrated Mobile Observations 2.0,* 2014, University of Michigan Transportation Research Institute and the Michigan Department of Transportation.
[3] Robinson, R., Cook, S., *Slippery Road Detection and Evaluation Final Report*. (2012). University of Michigan Transportation Research Institute.
[4] Katicha, Samer W., Gerardo W. Flintsch, and Luis G. Fuentes. "Use of Probe Vehicles to Measure Road Ride Quality." In *Transportation Research Board 93rd Annual Meeting*, no. 14-2836. 2014.
[5] Amador-Jiménez, Luis, and Nagham Matout. "A low cost solution to assess road's roughness surface condition for Pavement Management." In *Transportation Research Board 93rd Annual Meeting*, no. 14-3086. 2014.
[6] Douangphachanh, Viengnam, and Hiroyuki Oneyama. "Estimation of road roughness condition from smartphones under realistic settings." In *ITS Telecommunications (ITST), 2013 13th International Conference on*, pp. 433-439. IEEE, 2013.
[7] Douangphachanh, Viengnam, and Hiroyuki Oneyama. "A Study on the Use of Smartphones for Road Roughness Condition Estimation." In *Proceedings of the Eastern Asia Society for Transportation Studies*, vol. 9. 2013.

Kongyang Chen, et al (2013)[8] used taxis in China to test the use of externally placed accelerometers on vehicles to find potholes. They found they had to calibrate the accelerometer readings based on the type of vehicle driven. Finally, Girts Strazdins et al. (2011)[9] tried to use smartphone based accelerometers to develop a year round map of potholes. They found differences among the phones they used for gathering the data and that winter roads change too quickly for reliable detection of potholes.

The analysis of the data collected for this project during 2012 and 2013 within the seven MDOT regions also uses smartphone technology to collect accelerometer data from MDOT vehicles. In this analysis a number of key variables are used to predict IRI scores for common road segments: *variance among accelerometer measurements*, *speed* of the vehicle, the *phone* (which is also a proxy for the vehicle), the *date of data collection*, and the *road surface type*.

The main variable that measures the vertical movement of the phone in the vehicle (and the roughness of the road) is the *variance among accelerometer measurements*. Because 100 X (vertical), Y (horizontal), and Z (longitudinal forces) coordinates are generated every second by the accelerometer and are measured on a continuous scale, a variance measure was created that summarized each second of vertical accelerometer data (X). This measure describes how the vertical accelerometer reading varies over a one second interval. The formula is shown below:

$$\sum_{i=1}^{100} \frac{(Xi - Xavg)^2}{n-1}$$

Where:
i is one of the one hundred readings per second,
X is the vertical accelerometer reading for one of the one hundred readings per second
Xavg is the average of all 100 accelerometer readings for each second
n is the total number of readings per second (i.e. 100)

For data collected during 2014 using simultaneous measurements from a MDOT IRI device and several smartphones equipped with DataProbe across different vehicles, the analysis looks at the effects of *variance among accelerometer measurements*, *phones*, *vehicles*, and *speed*. These analyses provide FHWA and MDOT with detailed knowledge of the applicability of using Android-based smartphones to measure road roughness.

The analyses of the data for each year measure the capability of accelerometers to predict individual IRI road segment scores as well as their capability of predicting IRI road segment categories as defined by department of transportation professionals.

[8] Chen, Kongyang, Mingming Lu, Guang Tan, and Jie Wu. "CRSM: Crowdsourcing based Road Surface Monitoring." In *Proc. of the 11th IEEE/IFIP International Conference on Embedded and Ubiquitous Computing (EUC)*. 2013.
[9] Strazdins, Girts, Artis Mednis, Georgijs Kanonirs, Reinholds Zviedris, and Leo Selavo. "Towards vehicular sensor networks with android smartphones for road surface monitoring." In *2nd International Workshop on Networks of Cooperating Objects (CONET'11), Electronic Proceedings of CPS Week*, vol. 11. 2011.

The report is divided into six main sections: 2012, 2013, and 2014 Data Collection; 2012, 2013, and 2014 Data Management; 2012, 2013, and 2014 Data Analysis, Lessons Learned, Conclusions, and Recommendations.

Scope

Because the goal of the project is to see if road roughness data collected via phone accelerometers during 2012 and 2013 predicts data gathered on the same road segments via the system using the International Roughness Index(IRI), UMTRI used the technology developed in the Slippery Road project, a customized Android-based smartphone called DataProbe, to measure road roughness by using the phone's accelerometer. Data collected by DataProbe is sent via the cell phone to an UMTRI server. Phones are installed in vehicles from all seven MDOT regions, and drivers, who are measuring road distress for the MDOT PASER data collection, collect the data while coding PASER road segments.

DataProbe accelerometer data for 2012 and 2013 is merged with IRI data and PASER road surface type data for the same years to create separate analysis datasets for each year. From these datasets, variance among accelerometer measurements and other key variables were used to predict IRI road roughness scores for both 2012 and 2013. Besides these analyses, in 2014 data was simultaneously collected with an MDOT IRI vehicle and the DataProbe phone to see if the type of phone, the type of vehicle, or the speed of the vehicle affects accelerometer readings. It also determined whether many passes must be made across a road segment using DataProbe to generate readings that better predict IRI readings.

2012, 2013, and 2014 Data Collection

Data Sources

Data was collected separately in 2012, 2013, and 2014, and three independent datasets were created in order to analyze them separately. The 2012 and 2013 data used to measure the relationship between the Android-based smartphone accelerometer data and the International Roughness Index score included data from the:

- DataProbe application used with the Android-based smartphone and collected via MDOT Pavement Surface and Evaluation Rating System (PASER) data collectors
- International Roughness Index scores gathered via MDOT data collection (see Appendix A)
- Pavement Surface and Evaluation Rating System (PASER) data collected via MDOT data collectors (See Appendix A)

The 2014 data used to measure the relationship between the Android-based smartphone accelerometer data and the International Roughness Index score included data from the:

- DataProbe application used with the Android-based smartphone and collected via UMTRI and MDOT vehicles simultaneously over five specific routes in southeastern Michigan
- International Roughness Index scores gathered via MDOT data collection simultaneous with the DataProbe data collection

Data from 2012 and 2013 was collected between April and December of each year, and the 2014 data collection took place during June and July of 2014. For 2012 and 2013, the Android phones were introduced to MDOT drivers and installed into their vehicles as they rated road distress of Michigan roads throughout the state for the Pavement Surface Evaluation and Rating (PASER) project. MDOT divides the state into seven regions: Superior, North, Bay, Grand, University, Metro, and Southwest.

All seven regions are represented in the analysis of 2012 with nine phones reporting data from seven regions. For 2013, eight phones reported data from six regions. For 2014, multiple phones were placed in several vehicles to simultaneously collect data while an MDOT IRI vehicle collected IRI and DataProbe data. This data was collected along five specified routes in southeastern Michigan.

The DataProbe Application used with the Android-based Smartphone

This project is the first large implementation of a customized Android smartphone to collect road roughness data based on the work of UMTRI's Slippery Road project funded by MDOT[10].

The Android smartphones used for the data collection in 2012 and 2013 are manufactured by Motorola which is owned by Google, Inc. The specific phone used for the study was the Droid X2 which uses a Nvidia Tegra 2, gigahertz dual core processor with 8 gigabytes memory expandable to 32 gigabytes. The Droid X2 also includes integrated sensors, functions and services including a GPS receiver, 3-axis accelerometer (100 Hertz), compass, camera, Bluetooth, WiFi, and cellular communications.

For the 2014 data collection, some of the Droid X2 phones were used to compare to the Droid Razr M phone that was used for much of the data collection. The Droid Razr M phone uses a Qualcomm MSM8960, dual-core 1.5 gigahertz Krait processor with 8 gigabytes of memory expandable to 32 gigabytes. The Razr M phone also includes integrated sensors, functions and services including a GPS receiver, 3-axis accelerometer, compass, camera, Bluetooth, WiFi, and cellular communications.

The accelerometer used in the Motorola Droid X2 is the lis331dlh made by STMicroelectronics. The accelerometer used in the Motorola Droid Razr M is the lis2dh also made by STMicroelectronics. It is a three-axis, low power MEMS device. Like all devices of this type, gravity always pulls down on one of the three-axis when a Droid is oriented in one of the positions listed in Figure 1. The quiescent output signals are shown in the chart.

[10] Robinson, R., Cook, S., *Slippery Road Detection and Evaluation Final Report*, 2012, University of Michigan Transportation Research Institute.

The second position listed in the chart (vertical-left side) is the normal position for DataProbe when mounted on the instrument panel. This is similar to a navigation system mounting. In this orientation, the phone's x-axis will measure the vehicle's vertical axis, the phone's y-axis will measure the vehicle's lateral axis and the phone's z-axis will measure the vehicle's forward or longitudinal forces.

Position	X	Y	Z
vertically – facing user	0	9.81 m/s^2	0
vertical - left side	9.81 m/s^2	0	0
vertical – upside down	0	-9.81 m/s^2	0
vertical – right side	-9.81 m/s^2	0	0
laying on back – facing up	0	0	9.81 m/s^2
laying on face – upside down	0	0	-9.81 m/s^2

Figure 1 – DataProbe phone orientation

The phone is somewhat sensitive to its mounting arrangement in that the windshield mounting bracket used to hold the phone may be subject to 'floating' if it is not mounted rigidly between the windshield and the instrument panel. When the phone is suspended on the plastic mount it will lose fidelity in reading all of the vehicle's body vibrations due to the flexibility of the plastic bracket. Further, vibration resonances can be generated by a cantilevered mounting. It is necessary to mount the phone on a windshield with a suction cup, extend the arm such that the base of the phone can touch the instrument panel with some pressure. It doesn't require much pressure to work adequately. The vehicle itself is a far greater source of error in measuring vibration.

The smartphone included a car mounting bracket that mounted flush to the top of the instrument panel, while attaching to the windshield via a suction device. An example of proper placement is seen in Figure 2. The initial installation of the mounting bracket does require some care to assure the bracket and the subsequent mounting of the phone is square with the axis of the vehicle. Within a few degrees error, the software can correct the data.

Figure 2 – Proper placement of the Android-based smartphone

The phone car mount contains a magnet that triggers the activation of the DataProbe application when it is placed in the mount. Figure 3 displays what the driver sees on the screen.

Figure 3 – The information screen on the Android-based smartphone

The DataProbe application was developed to create a file based on five minutes of data collection. Each file contains one reading of the :

- Vehicle ID
- Date of data collection.

It also contains one second readings of the following data:

- time of data collection
- latitude and longitude
- vehicle altitude
- number of satellites connected to the phone
- vehicle heading
- vehicle speed
- one hundred 3-axis accelerometer readings.

Data files accumulate on the phone using the DataProbe program in five minute intervals and are then transferred to the UMTRI MS SQL Server. Figure 4 shows a typical DataProbe data file:

Size:			1164138												
File Name:			4840_05302012_111550												
VIN:			10001												
Date:			5/30/2012												
Air Temp:			10001												
Barometer			10001												
Coolant Te			10001												
Odometer			10001												
TIME	LAT	LONG	ALT	SAT	HEAD_G	SPD-G	X1	Y1	Z1	X2	Y2	Z2	X3	Y3	Z3
11:15:50	42.83978	-84.2182	895.77	6	0	0	10.14008	0.156906	-3.90305	10.13027	-0.22555	-3.91285	9.943943	-0.22555	-3.69711
11:15:51	42.83978	-84.2182	895.77	6	0	0	10.35582	-0.15691	-3.29503	10.35582	-0.15691	-3.29503	10.35582	-0.15691	-3.29503
11:15:52	42.83978	-84.2182	895.77	6	0	0	10.35582	-0.15691	-3.29503	10.35582	-0.15691	-3.29503	10.35582	-0.15691	-3.29503
11:15:53	42.83981	-84.218	896.75	6	78.2	17.8	10.35582	-0.15691	-3.29503	10.35582	-0.15691	-3.29503	10.35582	-0.15691	-3.29503
11:15:54	42.83984	-84.2178	896.75	10	81	29.1	10.77751	-0.06865	-2.22611	10.48331	-0.28439	-3.53039	10.48331	-0.28439	-3.25581
11:15:55	42.83985	-84.2176	897.74	10	83.2	32.8	9.139797	-0.16671	-3.55001	9.296704	-0.16671	-3.55001	9.365351	-0.16671	-3.55001
11:15:56	42.83987	-84.2174	898.06	10	83.2	35.2	10.88538	0.156906	-2.58896	11.16977	0.156906	-1.37293	11.17958	1.372931	-0.90221
11:15:57	42.83989	-84.2172	897.74	10	81.6	40.6	10.58138	0.039227	-2.09862	8.316039	-0.04903	-2.19669	9.610517	0.009807	-1.01989
11:15:58	42.83992	-84.217	898.39	10	81.8	44	9.218251	-0.03923	-0.43149	11.96411	0.17652	-1.96133	8.786758	0.11768	-0.90221
11:15:59	42.83994	-84.2167	898.72	10	81.7	47.6	11.57185	0.098066	-1.84365	10.86577	-0.12749	-1.84365	10.80693	-0.12749	-2.90277
11:16:00	42.83997	-84.2165	898.72	10	81.4	50.5	9.728196	-0.27459	-1.15718	10.43428	-0.07845	-0.99047	10.70886	-0.07845	-0.91202
11:16:01	42.84	-84.2162	898.72	10	81.9	52.8	10.35582	-0.63743	-1.34351	10.13027	-0.04903	-2.86354	10.05182	-0.04903	-1.25525
11:16:02	42.84003	-84.2159	898.72	10	82.3	54.4	10.19892	-0.21575	-1.52984	11.72875	-0.21575	-1.29448	11.72875	-0.21575	-1.29448
11:16:03	42.84006	-84.2156	898.06	10	82.8	57.7	10.15969	0.019613	-0.62763	10.15969	0.019613	-0.62763	10.15969	0.019613	-0.62763
11:16:04	42.84009	-84.2153	897.74	10	82.4	59	10.29698	-0.11768	-1.14738	9.257478	-0.11768	-1.01008	10.43428	-1.21602	-1.01008
11:16:05	42.84012	-84.2149	897.74	10	82.8	62.1	10.35582	-0.06865	-0.74531	10.97364	0	-0.66685	10.79712	-0.23536	-1.88288
11:16:06	42.84016	-84.2146	898.39	10	82.7	63.1	10.43428	-0.03923	-0.82376	10.43428	-0.03923	-0.82376	10.43428	-0.03923	-0.82376
11:16:07	42.84019	-84.2142	898.72	10	82.5	65	8.472945	-0.39227	-0.78453	8.472945	-0.39227	-0.78453	9.198637	-0.49033	0.137293
11:16:08	42.84023	-84.2139	899.05	10	82	66.1	10.39505	-0.2942	-0.23536	9.218251	-0.24517	-0.39227	9.218251	-0.24517	-0.39227

Figure 4 – Sample DataProbe data file

The International Roughness Index

As its name implies, the International Roughness Index (IRI) is used throughout the world to measure road roughness by creating a road profile using a laser that measures the depth of any cracks, pot holes, or other undulations in a road.[11] It has been used in the U.S. as the standard for road roughness since 1986. MDOT typically collects IRI data during the April to August timeframe. National Highway System designated routes are measured every year, while Michigan roads/highways (M-routes) are measured in even numbered years and US roads/highway and some interstate roads (I-routes) are measured in odd numbered years. For

[11] Federal Highway Administration, Policy Information, Highway Performance Monitoring System Field Manual: http://www.fhwa.dot.gov/ohim/hpmsmanl/appe.cfm . Last referenced 12/16/2014.

these analysis, IRI data was collected by MDOT in 2012 and 2013 and by MDOT and UMTRI in 2014.

Using an algorithm developed by road roughness researchers, the IRI device creates a road profile for a specific length of road (for these analysis, it is a tenth of a mile) and assigns a score from 0 to 700, with a higher score meaning a rougher road. In general, scores from 0 to 95 represent a "Good" road, 96 to 170 represent a "Fair" road, and greater than 170 represent a "Poor" road. The data collection rate for IRI has a higher frequency than the data sample rate used in the smartphones.

The data provided by MDOT for these analyses included the:

- year the data was collected
- name of the route that was rated
- latitude and longitude of the beginning and the end of the tenth of a mile segment
- date and time when the data was collected
- average IRI score for that segment
- average speed driven when scoring the road segment

The Pavement Surface and Evaluation Rating System (PASER)

The Pavement Surface and Evaluation Rating System (PASER) is used by MDOT to measure road distress. It uses a 10 point scale to rate road segments with 0 to 4 representing a "Poor" road, 5 to 7 representing a "Fair" road, and 8 to 10 representing a "Good" road. For the purpose of this study, only the following data sources were used:

- Latitude and longitude of the starting and ending PASER road segments
- Road surface type coding of road segments: asphalt, concrete, or composite

2012, 2013, and 2014 Data Management

For 2012 and 2013 data collection, consolidating the data from the three data sources (DataProbe, IRI, and PASER) was a challenging project. The basic process included:

- Incorporating the PASER data with the IRI data in order to include the road surface type variable
- Deleting parts of DataProbe files or some incomplete files
- Matching road segments in the combined PASER and IRI dataset with the DataProbe dataset
- Deleting some non-matching road segments

Incorporating the surface type variable from the PASER dataset into the IRI dataset was performed by matching the tenth of a mile road segments in the IRI data based on the beginning and ending latitude/longitude readings with the same readings in the PASER datasets. For this matching process the ARC-GIS mapping software was used.

Whole DataProbe files were deleted if :

- Three or less satellites are reported for 75 percent of the file, showing undependable location information from the Global Positioning System (GPS)
- More than 325 columns are reported in the file, which indicates a corrupted file or a data collection error
- The file does not show movement from one location to another, based on no change in the latitude/longitude variables

Within a DataProbe file, some rows of data were deleted if the average variance among accelerometer measurements across the 100 accelerometer samples in a row of data was zero or if rows of data showed no change in the latitude and longitude from one second to the next.

After deleting files or rows of DataProbe data, the updated IRI dataset that includes the road surface type variable was matched to the DataProbe dataset based on vehicle bearing and latitude/longitude for the beginning and end of a road segment. The bearing measurement was used to make sure the DataProbe and IRI vehicles used to rate road roughness were moving in the same direction within a road segment. The bearing had to be within five degrees to be considered valid or else the road segment was deleted.

The resulting dataset of matching IRI and DataProbe road segments and determining the number of DataProbe readings per IRI road segment was subjected to a final test where matching road segments were deleted if the vehicle was not driving at least 15 mph.

The resulting analysis dataset for the 2012 analysis found 5,999 IRI road segments common to both IRI and DataProbe readings, while the 2013 analysis found 1119 IRI road segments common to both IRI and DataProbe readings. Using the data integrated from the various data sources, data management of the 2012 and 2013 data yielded the following variables for analysis:

- The phone used in each region (DataProbe)
- The average speed of the vehicle during data collection (DataProbe)
- The date of data collection (DataProbe and IRI)
- The variance among accelerometer measurements
- Road surface type (PASER)

Data management for the 2014 data collection was similar to the 2012 and 2013 data management except that road surface type was not added to the final dataset because in 2014, the specific routes used for this data collection were primarily concrete, so there were not enough differences in pavement to perform separate analyses on them.

2012, 2013, and 2014 Data Analysis

2012 Analysis

Main Effects Variables

The analysis is defined by five main predictor variables:

- The phone(s) used in each region
- The speed of the vehicle during data collection
- The date of data collection
- Road surface type
- The variance among accelerometer measurements

The analysis begins by examining the frequencies of the analysis variables and the bivariate relationships between the predictor variables and the dependent variable (IRI score). Figure 5 shows the distribution of the 5,999 road segments by the different phones that represent each MDOT region.

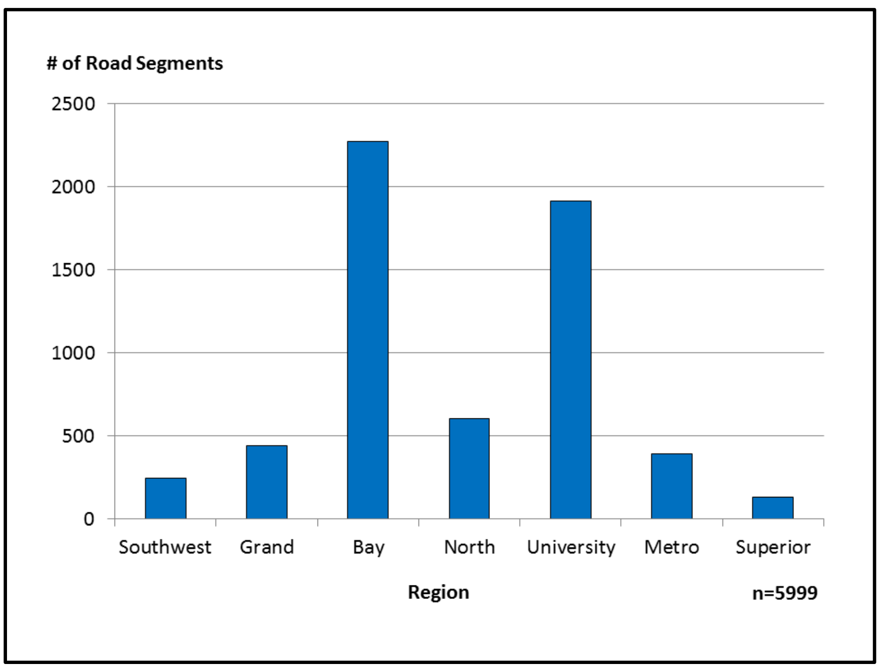

Figure 5 – The number of DataProbe and IRI matching road segments by MDOT region (2012)

Figure 6 shows the number of road segments for each phone, the average IRI score for the segments for that phone, and the minimum, maximum, and median IRI scores for road segments for each phone. Note that some regions have more than one phone used to gather data because these regions had more road segments to rate. Though each of the phones in the study was identical, this analysis could not tell if any differences or similarities between IRI and DataProbe readings were due to the phone or to the vehicle where the phone is placed or both. The 2014 data analysis attempts to answer this question.

Phone / Region	Number of Segments	Mean IRI Score	Min	Max	Median
Metro1	104	123	54	216	112
Metro2	291	117	42	450	97
Southwest	245	94	41	293	88
Grand	439	82	32	227	81
Superior	130	64	34	182	56
University1	769	81	33	381	75
University2	1143	83	36	267	76
Bay	2274	93	30	400	81
North	604	68	36	267	58
Totals	**5999**	**87**	**30**	**450**	**78**

Figure 6 – Descriptive statistics for each phone (2012)

Figure 7 shows the distribution of IRI scores for the 5,999 road segments in the analysis by each region. IRI road segment ratings range from 0 to 95 for a "Good" road, 96 to 170 for a "Fair" road, and greater than 170 for a "Poor" road.

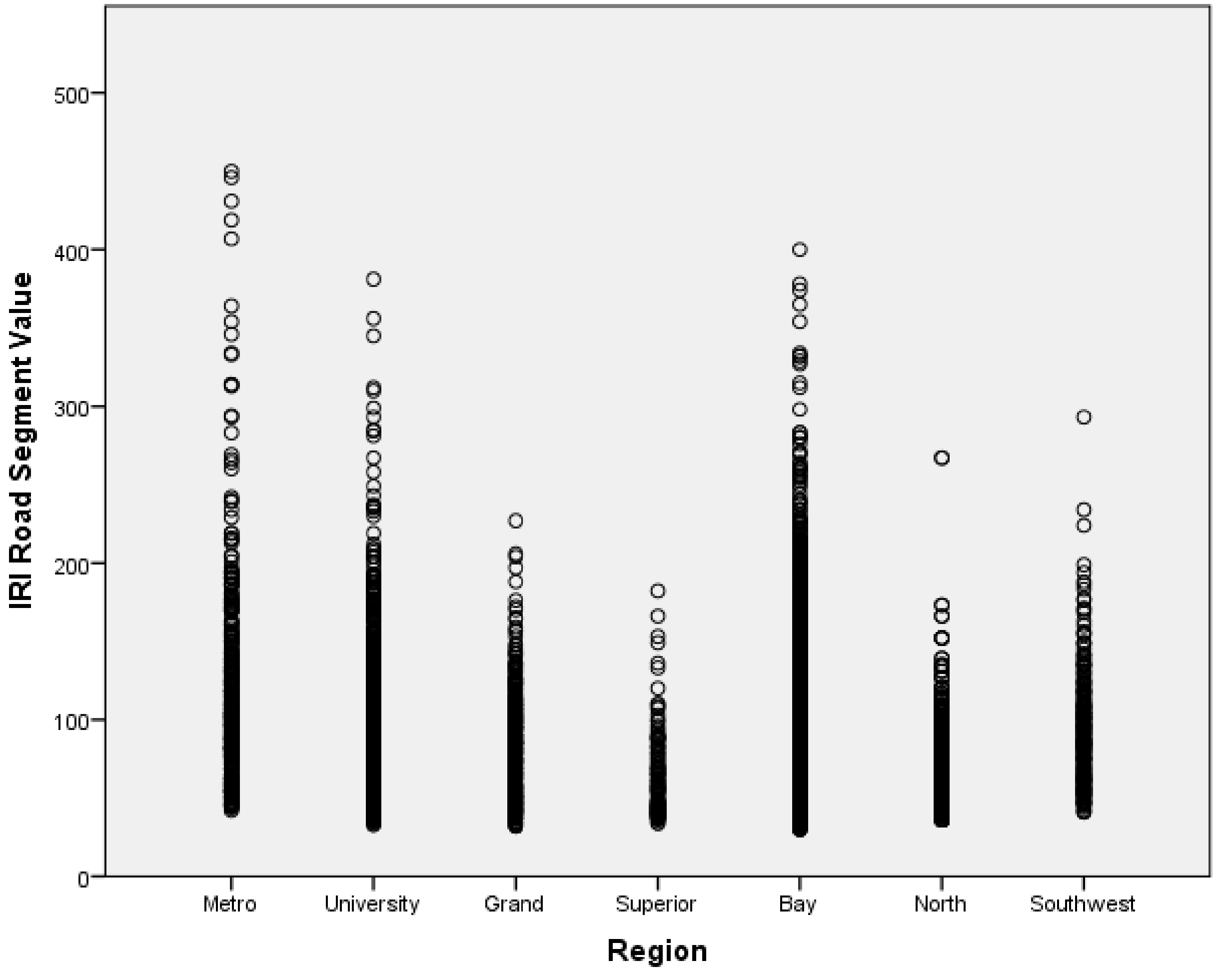

Figure 7 – IRI road segment ratings by region (2012)

The key variable in the analysis is the *variance among accelerometer measurements* which is based on the 100 accelerometer readings taken every second by the DataProbe program. The accelerometer variance variable is based on the vertical/left side position (X axis) reading from the accelerometer. In an inactive state this reading is 9.86 meters per second squared. For the purposes of this research, readings were accepted at plus or minus 2 meters per second squared from the inactive state. If readings were outside this range, the case was dropped from analysis. The formula for the variance among accelerometer measurements is:

$$\sum_{i=1}^{100} \frac{(Xi - Xavg)^2}{n-1}$$

Where:

i is one of the one hundred readings per second,
X is the vertical accelerometer reading for one of the one hundred readings per second
Xavg is the average of all 100 accelerometer readings for each second

n is the total number of readings per second (i.e. 100)

Figure 8 shows the variance among accelerometer measurements, as well as the minimum, maximum, and median for the entire dataset.

Average Variance Among Accelerometer Measurements	Min	Max	Median
.86	0	17	.68

Figure 8 – Descriptive statistics for the Average Variance Among Accelerometer Measurements (2012)

Figure 9 shows the bivariate relationship between IRI road segment ratings and the variance among accelerometer measurements. Note that the relationship between these two variables is not linear.

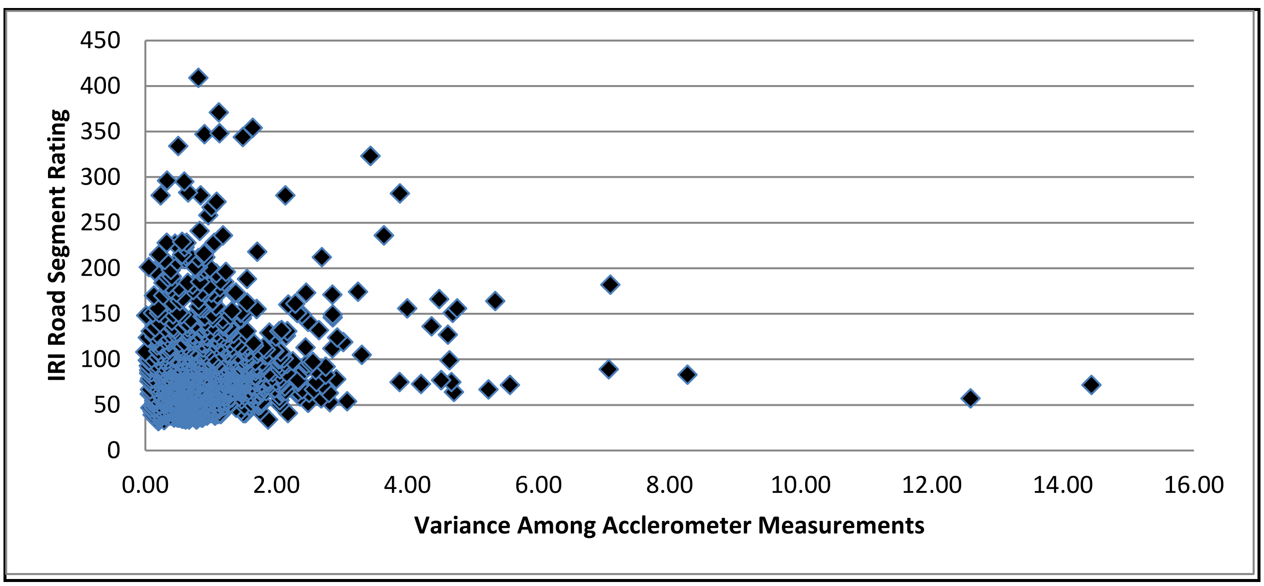

Figure 9 – IRI road segment ratings variance among accelerometer measurements (2012)

The date of data collection was also examined to determine its relationship to IRI road segment scores. The difference date variable was created by subtracting the date DataProbe was collected from the IRI road segment collection date. The average number of days difference as well as the minimum, maximum, and median are seen in Figure 10. If the number of days is positive, then DataProbe data was collected before IRI data, and if the number of days is negative, then IRI data was collected before DataProbe data. One of the concerns was that the collection dates might be so far apart that the road would change over that period of time. But the average difference between the two collections of less than two months allays those concerns.

Mean Difference Date (days)	Min	Max	Median
-58 (~ 2 months)	-157 (~5 months)	56 (~1.5 months)	-52 (~1.5 months)

Figure 10 – Descriptive statistics for difference date (2012)

The speed of a vehicle when it gathers data can also affect road roughness data collection, so the average speed of DataProbe segments was included to predict IRI road segment scores. Figure 11 shows the average speed of 57 miles per hour as well as the minimum, maximum, and median speed of data collected via DataProbe for the 5,999 road segments in the analysis.

Average DataProbe Speed (MPH)	Min	Max	Median
57	15	90	60

Figure 11 – Descriptive statistics for average DataProbe speed (2012)

The final variable, road surface type, has three main surfaces: asphalt, concrete, or composite, and the distribution of these three surfaces across the road segments in the analysis is shown in Figure 12. Each surface type is well represented in the analysis.

Surface Type	Number of Road Segments
Asphalt	1632
Concrete	2546
Composite	1821

Figure 12 – Distribution of road surface type (2012)

Quadratic Terms

Preliminary analysis showed significant non-linearity between IRI road segment ratings and the predictor variables. One method of managing the non-linear nature of relationships between predictor and dependent variables is to include quadratic terms. For the purposes of this analysis three terms were created:

- Difference date * difference date
- Speed of the DataProbe vehicle * Speed of the DataProbe vehicle
- Variance among accelerometer measurements * Variance among accelerometer measurements

Interactions

In order to improve the explanatory power of the model, interaction terms were also included that allow the main variables to interact in unique ways. The following variables were included in this analysis:

- Difference date * Speed of the DataProbe vehicle
- Difference date * Variance among accelerometer measurements
- Speed of the DataProbe vehicle * Variance among accelerometer measurements

Centered Variables

Because variables are used singly and in combination with other variables, centering the variables was performed by subtracting the mean from the original value of the variable. This process keeps the variances of the variables and the model itself stable.

Transformations

Based on previous plots of the relationship between the IRI road segment rating and the variance among accelerometer measurements, the relationship was seen as non-linear. One way of adjusting for this non-linearity is to transform the dependent variable in the regression model, IRI road segment rating, using a log transformation. In general, the log transformation minimizes outliers that can have a negative effect on the regression model, as well as maintaining the homogenous nature of the variance across the dataset. All of these issues affect the fit of the model, and the log transformation thus increases the predictive quality of the model.

The Single Variable Regression Model: Predicting IRI Road Segment Ratings

The goal of using the accelerometer in a smartphone (variance among accelerometer measurements) to predict IRI road segment ratings was tested by using a multiple regression model that allows a better understand of the relationship among a variety of predictors including the variance among accelerometer measurements. The analysis begins by looking exclusively at the variance among accelerometer measurements as a single predictor of log IRI road segment ratings. The variance among accelerometer measurements by itself is not a strong predictor of IRI road segment ratings, as shown in Figure 13. The single variable regression model with independent variable, variance among accelerometer measurements, predicts about 10 percent of the variance in the log IRI road segment rating.

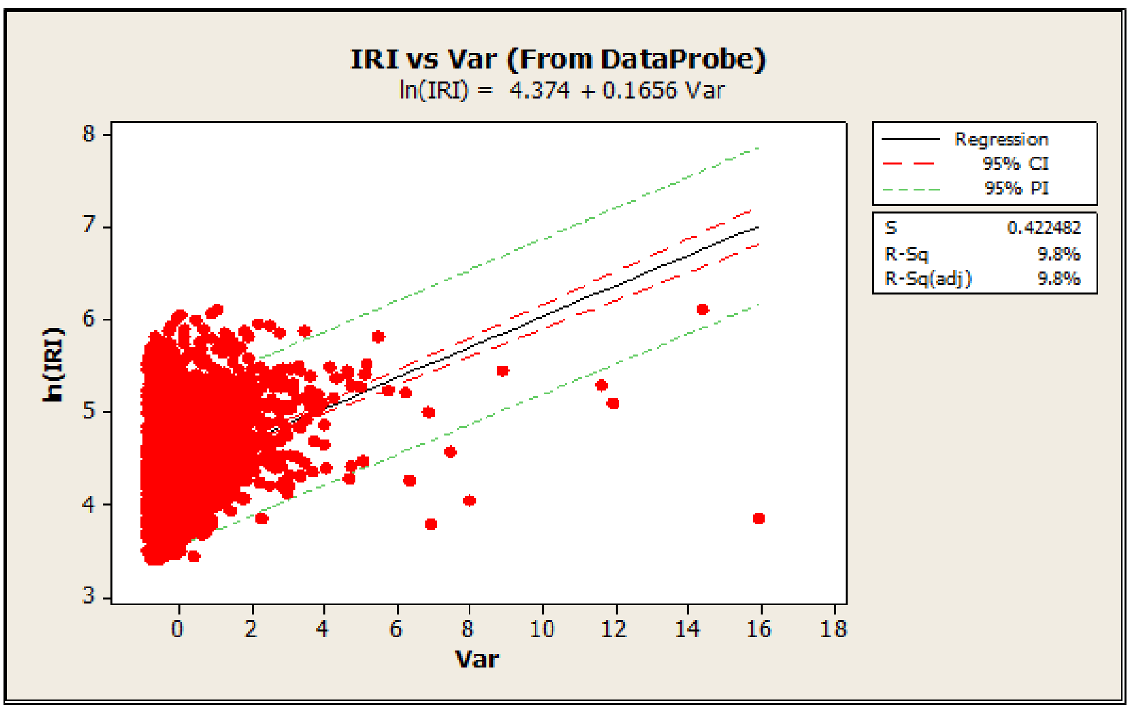

Figure 13 – Regression of the variance among accelerometer measurements on IRI road segment ratings (2012)

The Multiple Regression Main Effects Model: Predicting IRI Road Segment Ratings

The next analysis examines the predictive power of a combination of main effects variables on log IRI road segment ratings using multiple regression. The main effects variables include:

- Variance among accelerometer measurements
- Speed of the DataProbe vehicle
- Date difference between the date of IRI data collection and DataProbe data collection
- Individual phones (in relation to one of the phones left out of the analysis)
- Road surface type (in relation to one of the surface types left out of the analysis)

Figure 14 shows the results of the multiple regression using only the main effects variables. The model predicts nearly 37 percent of the variance of log IRI road segment ratings, with all of the variables significant at the .02 level. The fit statistic for this model shows that there is a lack of fit at the .03 of significance.

Term	Coef	P	Term	Coef	P
Constant	4.420	0.000	Diff Date	0.001	0.000
Surface Type	(Compared to Concrete)		Speed	-0.013	0.000
Asphalt	-0.090	0.000	Variance Among Accelerometer Measurements	0.212	0.000
Composite	-0.065	0.000	Std Dev	0.354	
Phone	(Compared to Metro2)		R^2(adj)=	36.720	
Metro1	0.279	0.000	R^2(Pred)=	36.220	
Southwest	0.113	0.000	Lack of Fit	Yes	0.025
Grand	-0.039	0.020			
Superior	-0.094	0.001			
University2	-0.640	0.000			
Bay	-0.560	0.000			
North	-0.130	0.000			
University1	-0.091	0.000			

Figure 14 – Main effects regression model results (2012)

The Multiple Regression Full Model: Predicting IRI Road Segment Ratings

The full model that predicts log IRI road segment ratings includes all the main effects variables from the main effects model, while also including the following interactions and quadratic terms:

Interactions:

- Difference date * Speed of the DataProbe vehicle
- Difference date * Variance among accelerometer measurements
- Speed of the DataProbe vehicle * Variance among accelerometer measurements

Quadratic terms:

- Difference date * difference date
- Speed of the DataProbe vehicle * Speed of the DataProbe vehicle
- Variance among accelerometer measurements * Variance among accelerometer measurements

The result of the multiple regression that includes all of these variables is shown in Figure 15. The addition of the quadratic terms to account for the non-linearity of the relationships, and the interaction terms to help explain more about the relationship with log IRI road segment ratings increased the explanatory power of the model by 8 percent to nearly 45 percent of explained variance. Again the model fit statistic is significant, showing a lack of fit at the .03 level.

Term	Coef	P		Term	Coef	P
Constant	4.320	0.000		Diff Date	0.002	0.000
Sur Type	(Compared to Concrete)			Spd	-0.013	0.000
Asphalt	-0.065	0.000		Variance Among Accelerometer Measurements	0.381	0.000
Composite	-0.057	0.000		Diff Date^2	0.000	0.610
Phone	(Compared to Metro2)			Spd^2	0.000	0.000
Metro1	0.301	0.000		Var^2	-0.028	0.000
Southwest	0.085	0.000		Diff Date*Spd	0.000	0.000
Grand	0.017	0.279		Diff Date*Var	-0.002	0.000
Superior	-0.114	0.000		Spd*Var	-0.003	0.000
University2	-0.065	0.000		Std Dev	0.330	0.000
Bay	-0.078	0.000		R^2(adj)=	44.830	
North	-0.146	0.000		R^2(Pred)=	44.160	
University1	-0.091	0.000		Lack of Fit	Yes	0.038
Var =Variance Among Accelerometer Measurements						

Figure 15 – Full model regression results (2012)

The Ordinal Logistic Regression Model: Predicting IRI Categories for 2012 data

Another way of approaching the IRI road segment ratings is by viewing them as decision-makers do, as categories that help define if a road segment is considered “good”, “fair”, or "poor." Many departments of transportation take the raw IRI scores and put them into these categories considering an IRI road segment with a 0 to 95 rating as "good", a rating of 96 to 170 as "fair", and a rating of greater than 170 as "poor."

In talking with transportation officials about these categories, they suggested that just being in one category or another is not by itself enough of a factor to determine whether a road needs attention. There may be quite a difference between a road with a 97 rating and one with a 165 rating, even though they are in the same category. Taking this into account was a factor in creating a second categorical IRI variable that divides the "good" and "fair" roads into four categories, such that the "good" rating has two categories ranging from 0 to 48 and 49 to 95, and the "fair" rating has two categories ranging from 96 to 133 and 134 to 170. All roads with ratings greater than 170 were considered "poor" roads.

Another advantage of using a categorical dependent variable is that if there are many outliers (IRI road segment ratings more than three standard deviations from the mean) these can have a dramatic effect on a multiple regression model that tries to predict the continuous IRI road segment ratings dependent variable.

Using ordinal logistic regression to predict the 3 level and 5 level IRI category variables allows measurement from another perspective: a categorical one. By focusing on the two main predictor variables, speed and variance among accelerometer measurements, the following results for the 2012 data show an interesting relationship between these two variables and the IRI road segment ratings. Figure 16 shows the results for the three level IRI categorical dependent variable. Though the model does not fit the data particularly well based on the Summary Measures of Association of .37, it does provide insight into how the three IRI levels are predicted in the Concordant, Discordant, and Ties table.

This table provides measures of association to assess the quality of the model. These measures are based on an analysis of individual pairs of observations with different responses. In this table there are 1550 good roads, 889 fair roads, and 86 poor roads; hence, there are 1550 times 889 times 86 pairs or 1,587,704 pairs. A pair is considered *concordant* if the observation with the higher response, in this case the poor roads (2), also has the higher estimated probability (i.e. a poor road has a higher probability of having a higher speed and variance among accelerometer measurements), *discordant* if the poor road has a higher probability of having a lower speed and lower variance among accelerometer measurements, and *tied* if the estimated probabilities are identical. The numbers given are the percentages of pairs in each of the groups; obviously, the higher the percentage of concordant pairs the better is the fit of the model. In this case, speed and variance among accelerometer measurements account for 68 percent of concordant pairs, showing that they are properly predicting the IRI group 68 percent of the time.

Ordinal Logistic Regression							
Variable	*Value*	*Count*					
Group	(0) Good Roads (IRI: 0-95)	1550					
	(1) Fair Roads (IRI: 96-170)	889					
	(2) Poor Roads (IRI: 171+)	86					
	Total	2525					
Logistic Regression Table							
					Odds	95% CI	
Predictor	Coef	SE Coef	Z	P	Ratio	Lower	Upper
Speed of DataProbe Vehicle	- 0.0443284	0.0029039	15.27	0.000	1.05	1.04	1.05
Variance Among	0.469474	0.0558082	-8.41	0.000	0.63	0.56	0.70
Accelerometer Measurements							
Log-Likelihood = -1844.258							
Test that all slopes are zero: G = 261.592, DF = 2, P-Value = 0.000							
Goodness-of-Fit Tests							
Method	Chi-Square	DF	P				
Pearson	7821.57	3962	0.000				
Deviance	3681.93	3962	0.999				
Measures of Association:							
(Between the Response Variable and Predicted Probabilities)							
Pairs	Number	Percent	Summary Measures				
Concordant	1084317	68.3	Somers' D	0.37			
Discordant	496856	31.3	Goodman-Kruskal Gamma	0.37			
Ties	6531	0.4	Kendall's Tau-a	0.18			
Total	1587704	100.0					

Figure 16 – Ordinal logistic regression results for the three level IRI dependent variable (2012)

The results from the five level IRI categorical dependent variable shown in Figure 17 also provide insight into the predictive power of speed and DataProbe variance. The model fits the data slightly better than the three level IRI categorical dependent variable based on the Summary Measures of Association of .42. It also improves the number of correctly predicted pairs of data in the Concordant, Discordant, and Ties table.

Because it has more groups, this analysis also has more pairs of data to compare. In this table there are 437 good roads group 1, 1559 good roads group 2, 361 fair roads group 1, 82 fair roads group 2, and 86 poor roads; hence, there are 437 times 1559 times 361 times 82 times 86 pairs or 1,804,167 pairs. In this case speed and variance among accelerometer measurements account for 71 percent of concordant pairs, showing that they are properly predicting the IRI group 71 percent of the time.

Ordinal Logistic Regression								
Variable Value		*Count*						
Category	(0) Good Roads 1 (IRI: 0-48)	437						
	(1) Good Roads 2 (IRI: 49-95)	1559						
	(2) Fair Roads 1 (IRI: 96-133)	361						
	(3) Fair Roads 2 (IRI: 134-170)	82						
	(4) Poor Roads (IRI: 171+)	86						
	Total	2525						
Logistic Regression Table								
					Odds	95% CI		
Predictor	Coef	SE Coef	Z	P	Ratio	Lower	Upper	
Speed of DataProbe Vehicle	-0.0561155	0.0029253	19.18	0.000	1.06	1.05	1.06	
Variance Among	0.675489	0.0557181	-12.12	0.000	0.51	0.46	0.57	
Accelerometer Measurements								
Log-Likelihood = -2582.482								
Test that all slopes are zero: G = 419.324, DF = 2, P-Value = 0.000								
Goodness-of-Fit Tests								
Method	Chi-Square	DF	P					
Pearson	773218	7926	0.000					
Deviance	5156	7926	1.000					
Measures of Association:								
(Between the Response Variable and Predicted Probabilities)								
Pairs	Number	Percent	Summary Measures					
Concordant	1281907	71.0	Somers' D	0.42				
Discordant	516443	28.6	Goodman-Kruskal Gamma	0.43				
Ties	6517	0.4	Kendall's Tau-a	0.24				
Total	1804867	100.0						

Figure 17 – Ordinal logistic regression results for the five level IRI dependent variable (2012)

2012 Analysis Conclusions

Using multiple independent variables to predict IRI road segment ratings using multiple regression yields a model that does not account for enough of the variance in IRI road segment ratings. An ordinal logistic regression does a better job of predicting both the three level and five level categorical IRI dependent variable. One can summarize the difference in predicting IRI using the speed of the vehicle and variance among accelerometer measurements and using multiple regression and ordinal logistic regression in this way: It is similar to trying to predict what percentage a student will get for a final grade compared to predicting if the student will receive a good grade (A or B), a "passing" grade (C or D) or fail completely (F). The five level categorical analysis showed whether the student would receive an "A", a "B", a "C", a "D", or a "F". Predicting the exact percentage (exact IRI road segment rating) is more difficult than predicting the actual grade (IRI 3 or 5 level category) a student will receive.

2013 Analysis

Main Effects Variables

Similar to the 2012 analysis, the 2013 analysis is defined by five main predictor variables:

- The phone(s) used in each region
- The speed of the DataProbe vehicle during data collection
- The date of data collection
- Road surface type
- Variance among accelerometer measurements

The analysis begins by examining the frequencies of the analysis variables and the bivariate relationships between the predictor variables and the dependent variable (IRI score). Figure 18 shows the distribution of the 1,119 road segments by the different phones that represent each MDOT region. The number of road segments and the distribution of road segments differs significantly from the 2012 data collection.

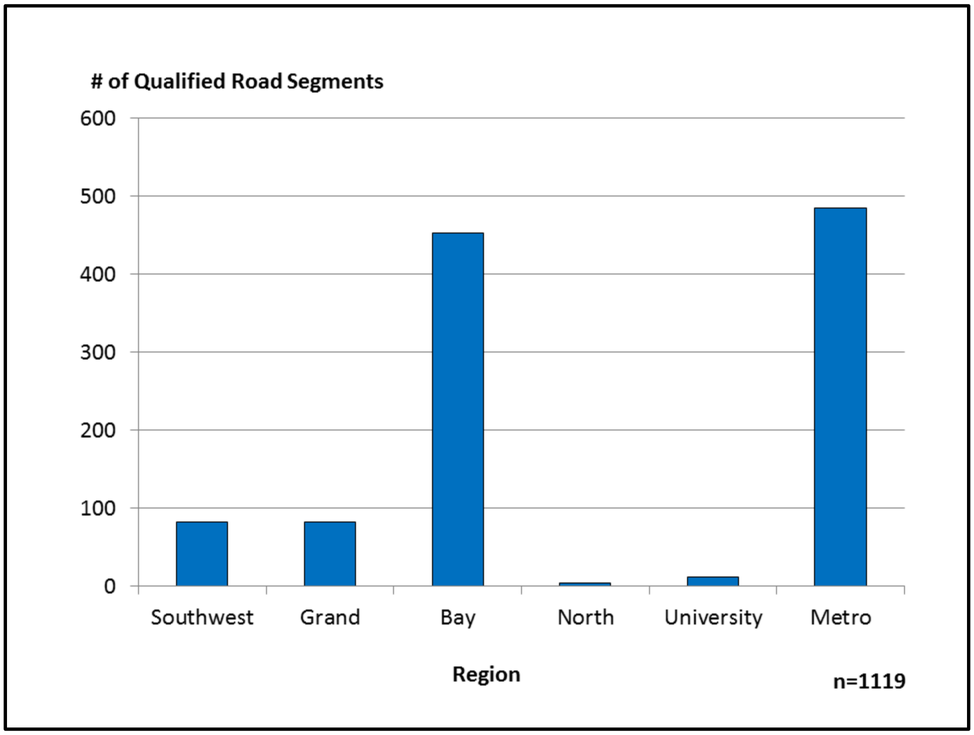

Figure 18 – The number of DataProbe and IRI matching road segments by MDOT region (2013)

Figure 19 shows the number of road segments for each phone, the average IRI score for the segments for that phone, and the minimum, maximum, and median IRI scores for road segments for each phone. Note that some regions have more than one phone used to gather data because these regions had more road segments to rate. Though each of the phones in the study was identical, this analysis could not tell if any differences or similarities between IRI and DataProbe readings were due to the phone or to the vehicle where the phone is placed or both. The 2014 data analysis attempts to answer this question.

Phone / Region	Number of Segments	Mean IRI Score	Min	Max	Median
Metro1	330	138	38	919	113
Metro2	155	113	31	316	106
Southwest1	78	91	41	358	75
Southwest2	4	90	81	102	88
Grand	83	106	42	230	106
University	12	136	79	229	109
Bay1	173	120	38	377	98
Bay2	280	132	48	329	127
North	4	61	34	85	62
Totals	**1119**	**124**	**31**	**919**	**107**

Figure 19 – Descriptive statistics for each phone (2013)

Figure 20 shows the distribution of IRI scores for the 1119 road segments in the analysis by each region. IRI road segment ratings range from 0 to 95 for a “Good” road, 96 to 170 for a “Fair” road, and greater than 170 for a “Poor” road.

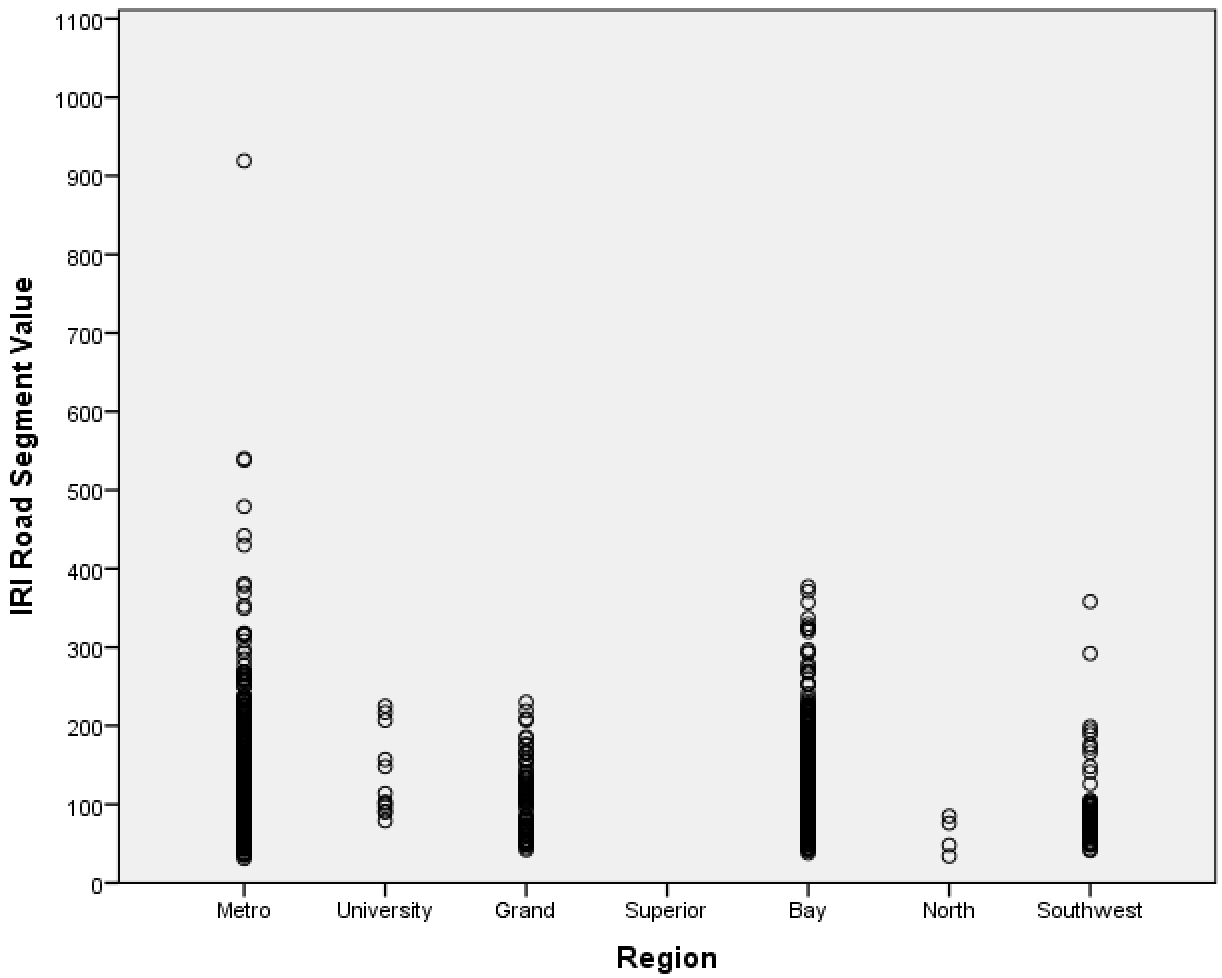

Figure 20 – IRI road segment ratings by region (2013)

The key variable in the analysis is the *variance among accelerometer measurements* which is based on the 100 accelerometer readings taken every second by the DataProbe program. The phones used for the 2013 data were exactly the same phones used in the 2012 data collection. The accelerometer variance variable is based on the vertical/left side position (X axis) reading from the accelerometer. In an inactive state this reading is 9.86 meters per second squared. For the purposes of this research, readings were accepted at plus or minus 2 meters per second squared from the inactive state. If readings were outside this range, the case was dropped from analysis.

Figure 21 shows the average variance among accelerometer measurements, as well as the minimum, maximum, and median for the entire dataset. These statistics vary significantly from the 2012 data.

Average Variance Among Accelerometer Measurements	Min	Max	Median
1.45	.034	14	1.04

Figure 21 – Descriptive statistics for variance among accelerometer measurements (2013)

Figure 22 shows the bivariate relationship between IRI road segment ratings and average variance among accelerometer measurements. Note that the relationship between these two variables is not linear.

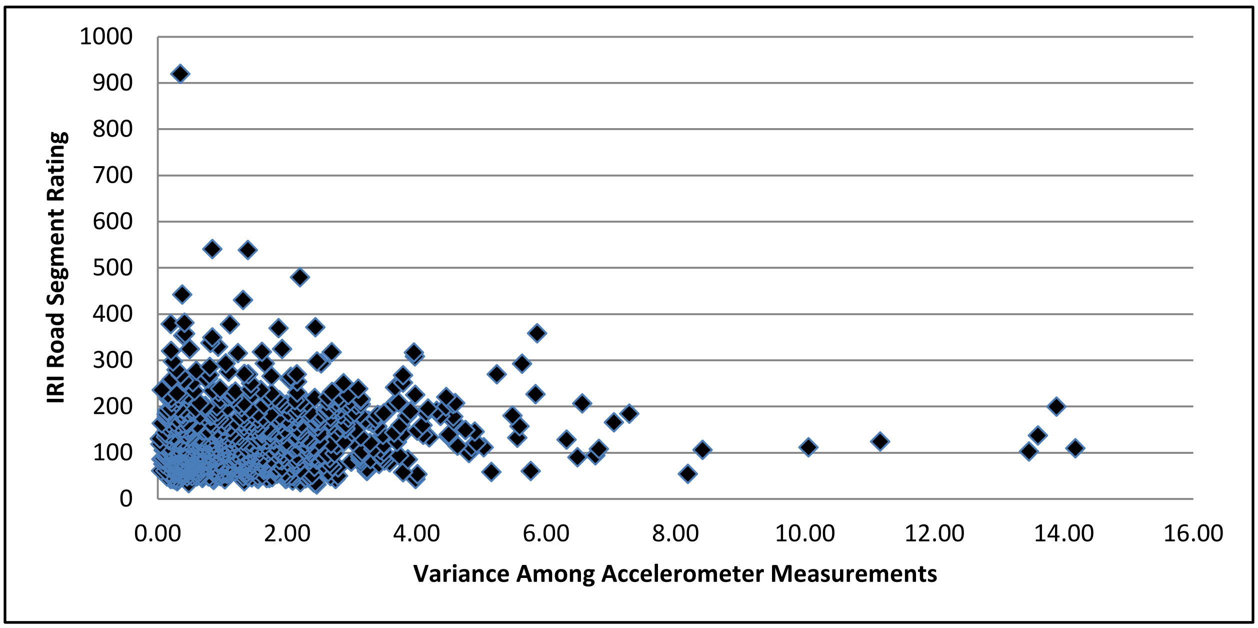

Figure 22 – IRI road segment ratings by variance among accelerometer measurements (2013)

Date of data collection was also included to examine its relationship to IRI road segment scores. The difference date variable was created by subtracting the variance among accelerometer measurements collected date from the IRI road segment collection date. The average number of days difference as well as the minimum, maximum, and median are seen in Figure 23. If the number of days is positive, then DataProbe data was collected before IRI data, and if the number of days is negative, then IRI data was collected before DataProbe data. One concern was that the collection dates might be so far apart that the road would change over that period of time. But the average difference between the two collections of slightly more than two months allays those concerns.

Mean Difference Date (days)	Min	Max	Median
-80 (~ 2.5 months)	-169 (~5.5 months)	0 (0 months)	-74 (~2.5 months)

Figure 23 – Descriptive statistics for difference date (2013)

The speed of a vehicle when it gathers data can also affect road roughness data collection, so the average speed of DataProbe segments was included to predict IRI road segment scores. Figure 24 shows the average speed of 50 miles per hour as well as the minimum, maximum, and median speed of data collected via DataProbe for the 1,119 road segments in the analysis.

Average DataProbe Speed (MPH)	Min	Max	Median
50	15	76	53

Figure 24 – Descriptive statistics for average DataProbe speed (2013)

The final variable, road surface type, has three main surfaces: asphalt, concrete, or composite, and the distribution of these three surfaces across the road segments in the analysis is shown in Figure 25. Each surface type is well represented in the analysis.

Surface Type	Number of Road Segments
Asphalt	449
Concrete	445
Composite	225

Figure 25 – Distribution of road surface type (2013)

Quadratic Terms

The preliminary analysis showed significant non-linearity between IRI road segment ratings and the predictor variables. One method of managing the non-linear nature of relationships between predictor and dependent variables is to include quadratic terms. For these purposes three terms were created:

- Difference date * difference date
- Speed of the DataProbe vehicle * Speed of the DataProbe vehicle
- Variance among accelerometer measurements * Variance among accelerometer measurements

Interactions

In order to improve the explanatory power of the model, interaction terms were also included that allow the main variables to interact in unique ways. For the analysis the following interaction terms were included:

- Difference date * Speed of the DataProbe vehicle
- Difference date * Variance among accelerometer measurements
- Speed of the DataProbe vehicle * Variance among accelerometer measurements

Centered Variables

Because variables were used singly and in combination with other variables they are centered by subtracting the mean from the original value of the variable. This process keeps the variances of the variables and the model itself stable.

Transformations

Based on the previous plots of the relationship between the IRI road segment rating and the variance among accelerometer measurements, the relationship is non-linear. One way of adjusting for this non-linearity is to transform the dependent variable in the regression model, IRI road segment rating, using a log transformation. In general, the log transformation minimizes outliers that can have a negative effect on the regression model, as well as maintaining the homogenous nature of the variance across the dataset. All of these issues affect the fit of the model, and the log transformation thus increases the predictive quality of the model.

The Single Variable Regression Model

The goal of using the accelerometer in a smartphone (variance among accelerometer measurements) to predict IRI road segment ratings was tested by using a multiple regression model that allows a better understanding of the relationship among a variety of predictors including variance among accelerometer measurements. The first analysis looks exclusively at variance among accelerometer measurements as a single predictor of log IRI road segment ratings. Variance among accelerometer measurements by itself is not a strong predictor of IRI road segment ratings, as shown in Figure 26. The single variable regression model with independent variable, variance among accelerometer measurements, predicts only 3 percent of the variance in the log IRI road segment rating.

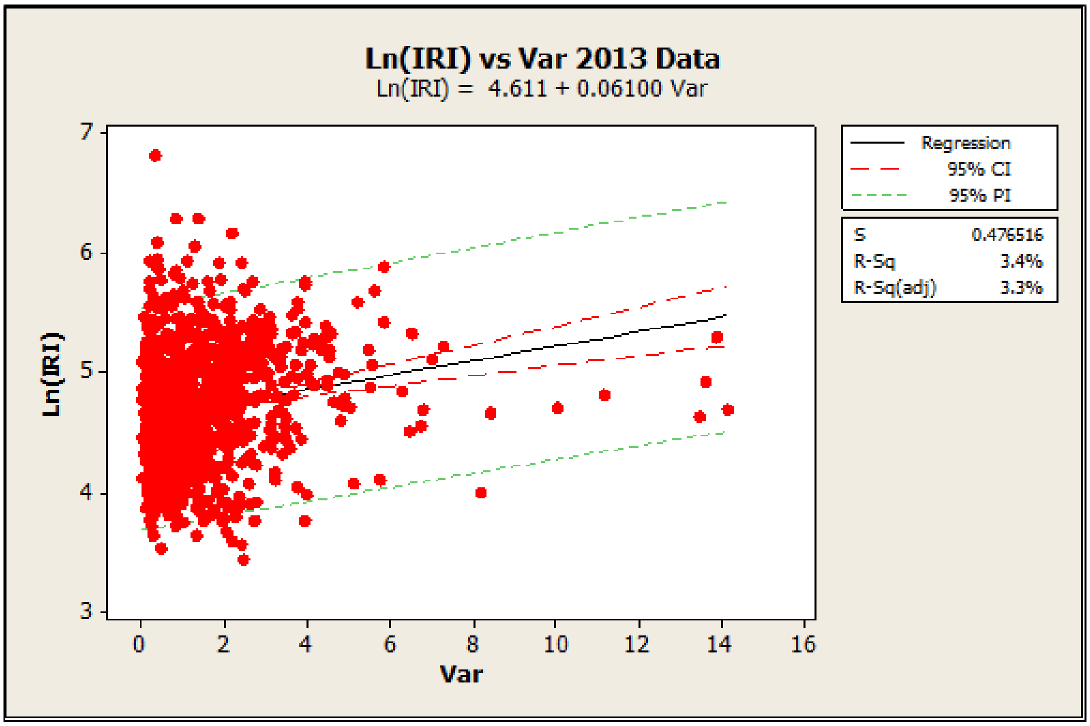

Figure 26 – Regression of variance among accelerometer measurements on IRI road segment ratings (2013)

The Multiple Regression Main Effects Model

The predictive power of a combination of main effects variables on log IRI road segment ratings using multiple regression is examined next. The main effects variables include:

- Variance among accelerometer measurements
- Speed of the DataProbe vehicle
- Date difference between the date of IRI data collection and DataProbe data collection
- Phones

Figure 27 shows the results of the multiple regression using only the main effects variables. The model predicts nearly 34 percent of the variance of log IRI road segment ratings, with all of the variables, except date difference, significant at the .00 level.

Term	Coef	P
Constant	5.5974	0.000
Diff Date	0.000063	0.883
Variance Among Accelerometer Measurements	0.1371	0.000
Phone	-0.000061	.0000
Speed	-0.0165	0.000
R^2(adj)=	33.6%	
R^2(Pred)=	33.5%	

Figure 27 – Main effects regression model results (2013)

The Multiple Regression Full Model

The full model that predicts log IRI road segment ratings includes all the main effects variables from the main effects model, while also including the following interactions and quadratic terms:

Interactions:

- Difference date * Speed of the DataProbe vehicle
- Difference date * Variance among accelerometer measurements
- Speed of the DataProbe vehicle * Variance among accelerometer measurements

Quadratic terms:

- Difference date * difference date
- Speed of the DataProbe vehicle * Speed of the DataProbe vehicle
- Variance among accelerometer measurements * Variance among accelerometer measurements

The results of the multiple regression that includes all of these variables is shown in Figure 28. The addition of the quadratic terms to account for the non-linearity of the relationships, and the interaction terms to help explain more about the relationship with log IRI road segment ratings increased the explanatory power of the model by 6 percent to nearly 43 percent of explained variance.

Term	Coef	P		Term	Coef	P
Constant	5.720	0.000		Diff Date	0.71	0.1408
Surface Type	(Compared to Asphalt)			Speed	-0.23	0.000
Composite	-0.065	0.000		Variance Among Accelerometer Measurements	0.55	0.000
Concrete	0.019	0.1220		Diff Date^2	0.078	0.3877
Phone	(Compared to Southwest2)			Speed^2	-0.13	0.0051
Grand	-0.17	0.4850		Var^2	-0.73	0.0000
Bay2	-0.063	0.0010		Diff Date*Speed	0.075	0.2176
North	0.032	0.3860		Diff Date*Var	0.73	0.0009
University	-0.038	0.0170		Speed*Var	0.36	0.0038
Metro1	0.26	0.000		Std Dev	0.330	0.000
Southwest1	0.17	0.2520		R Squared(adj)=	43.10%	
Bay1	-0.026	0.0700		R Squared (Pred)=	41.93%	
Metro2	-0.089	0.2320				
Var=Variance Among Accelerometer Measurements						

Figure 28 – Full model regression results (2013)

The Ordinal Logistic Regression Model: Predicting IRI Categories for 2013 data

Similar to the use of ordinal logistic regression to model the 2012 data, the 2013 data was also modeled using ordinal logistic regression for both the 3-level and 5-level IRI road segment ratings.

Using ordinal logistic regression to predict the 3 level and 5 level IRI category variables allows measurement from another perspective: a categorical one. By focusing on the two main predictor variables, speed and variance among accelerometer measurements, the following results for the 2013 data show an interesting relationship between these two variables and the IRI road segment ratings. Figure 29 shows the results for the three level IRI categorical dependent variable. The model fits the data better than the 2012 data based on the Summary Measures of Association of .55, and it provides insight into how the three IRI levels are predicted in the Concordant, Discordant, and Ties table.

This table provides measures of association to assess the quality of the model. These measures are based on an analysis of individual pairs of observations with different responses. In this table there are 303 good roads, 559 fair roads, and 257 poor roads; hence, there are 330 times 559 times 257 pairs or

390,911 pairs. A pair is considered *concordant* if the observation with the higher response, in this case the poor roads (2), also has the higher estimated probability (i.e. a poor road has a higher probability of having a higher speed and variance among accelerometer measurements), *discordant* if the poor road has a higher probability of having a lower speed and lower variance among accelerometer measurements, and *tied* if the estimated probabilities are identical. The numbers given are the percentages of pairs in each of the groups; obviously, the higher the percentage of concordant pairs the better is the fit of the model. In this case, speed and variance among accelerometer measurements account for 77 percent of concordant pairs, showing that they are properly predicting the IRI group 77 percent of the time.

Ordinal Logistic Regression							
Variable	*Value*	*Count*					
Group	(0) Good Roads (IRI: 0-95)	303					
	(1) Fair Roads (IRI: 96-170)	559					
	(2) Poor Roads (IRI: 171+)	257					
	Total	1119					
Logistic Regression Table							
					Odds	95% CI	
Predictor	Coef	SE Coef	Z	P	Ratio	Lower	Upper
Speed of the DataProbe Vehicle	-0.0684971	0.0045168	15.16	0.000	1.07	1.06	1.08
Variance Among	0.646047	0.0582376	-11.09	0.000	0.52	0.47	0.59
Accelerometer Measurements							
Log-Likelihood = -1006.085							
Test that all slopes are zero: G = 311.634, DF = 2, P-Value = 0.000							
Goodness-of-Fit Tests							
Method	Chi-Square	DF	P				
Pearson	6032.73	2228	0.000				
Deviance	2012.17	2228	1.000				
Measures of Association:							
(Between the Response Variable and Predicted Probabilities)							
Pairs	Number	Percent	Summary Measures				
Concordant	302657	77.4	Somers' D	0.55			
Discordant	87208	22.3	Goodman-Kruskal Gamma	0.55			
Ties	1046	0.3	Kendall's Tau-a	0.34			
Total	390911	100.0					

Figure 29 – Ordinal logistic regression results for the three level IRI dependent variable (2013)

The results from the five level IRI categorical dependent variable shown in Figure 30 also provide insight into the predictive power of speed and variance among accelerometer measurements. The model fits the data about the same as the three level IRI categorical dependent variable based on the Summary Measures of Association of .52. It also predicts the same percentage of pairs of data in the Concordant, Discordant, and Ties table.

Because it has more groups, this analysis also has more pairs of data to compare. In this table there are 40 good roads group 1, 424 good roads group 2, 281 fair roads group 1, 155 fair roads group 2, and 219 poor roads; hence, there are 40 times 424 times 281 times 155 times 219 pairs or 459,919 pairs. In this case, speed and variance among accelerometer measurements account for 76 percent of concordant pairs, showing that they are properly predicting the IRI group 76 percent of the time.

Ordinal Logistic Regression							
Variable Value	*Count*						
Category (0) Good Roads 1 (IRI: 0-48)	40						
(1) Good Roads 2 (IRI: 49-95)	424						
(2) Fair Roads 1 (IRI: 96-133)	281						
(3) Fair Roads 2 (IRI: 134-170)	155						
(4) Poor Roads (IRI: 171+)	219						
Total	1119						
Logistic Regression Table							
					Odds	95% CI	
Predictor	Coef	SE Coef	Z	P	Ratio	Lower	Upper
Speed of the DataProbe Vehicle	-0.0689356	0.0042298	16.30	0.000	1.07	1.06	1.08
Variance Among	0.667470	0.0551367	-12.11	0.000	0.51	0.46	0.57
Accelerometer Measurements							
Log-Likelihood = -1424.369							
Test that all slopes are zero: G = 344.533, DF = 2, P-Value = 0.000							
Goodness-of-Fit Tests							
Method	Chi-Square	DF	P				
Pearson	17239.4	4458	0.000				
Deviance	2846.0	4458	1.000				
Measures of Association:							
(Between the Response Variable and Predicted Probabilities)							
Pairs	Number	Percent	Summary Measures				
Concordant	348391	75.8	Somers' D	0.52			
Discordant	110368	24.0	Goodman-Kruskal Gamma	0.52			
Ties	1160	0.3	Kendall's Tau-a	0.38			
Total	459919	100.0					

Figure 30 – Ordinal logistic regression results for the five level IRI dependent variable (2013)

2013 Analysis Conclusions

Similar to the 2012 results, using multiple independent variables to predict IRI road segment ratings using multiple regression yields a model that does not account for enough of the variance in IRI road segment ratings. An ordinal logistic regression does a better job of predicting both the three level and five level categorical IRI dependent variable. One can summarize the difference in predicting IRI using the speed of the vehicle and variance among accelerometer measurements and using multiple regression and ordinal logistic regression in this way: It is similar to trying to predict what percentage a student will get for a final grade compared to predicting if the student will receive a good grade (A or B), a "passing" grade (C or D) or fail completely (F). The five level categorical analysis showed whether the student would receive an "A", a "B", a "C", a "D", or a "F". Predicting the exact percentage (exact IRI road segment rating) is more difficult than predicting the actual grade (IRI 3 or 5 level category) a student will receive.

2014 Analysis

The 2014 data collection differed from the 2013 and 2013 data collections in a five main ways:

1) In the 2014 data collection, DataProbe accelerometer measurements and IRI road ratings were performed simultaneously with DataProbe phones in the same vehicle that was measuring road segments using the IRI device.
2) A selected number of road segments were traveled multiple times to measure the effects of multiple measurements of the same road segments.
3) For analysis purposes, the average was taken of all the passes through a single IRI segment by each phone . So, ten passes through an IRI segment counts as one data point per phone. This yielded 1100 data points for analysis.
4) As many as six DataProbe phones per vehicle were used to measure road segments simultaneously as shown in Figure 31.
5) The data collection area in southeastern Michigan was limited to only five roads.

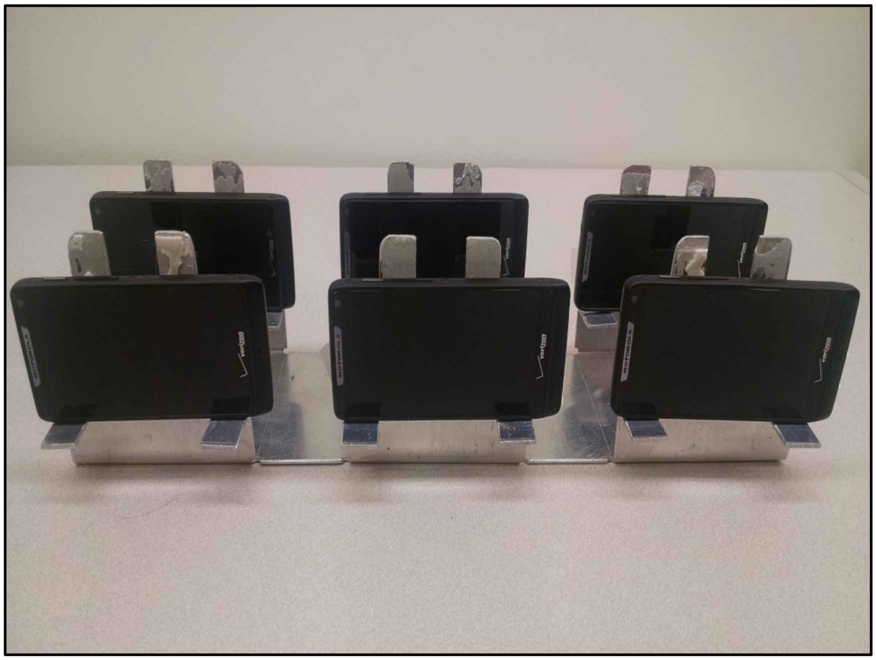

Figure 31 – Six Phone Rack

Figures 32 to 36 show the five roads and the road segments that make up each analysis road in southeastern Michigan.

Figure 32 – Eastbound and Westbound Ford Road in Ann Arbor, MI (2014)

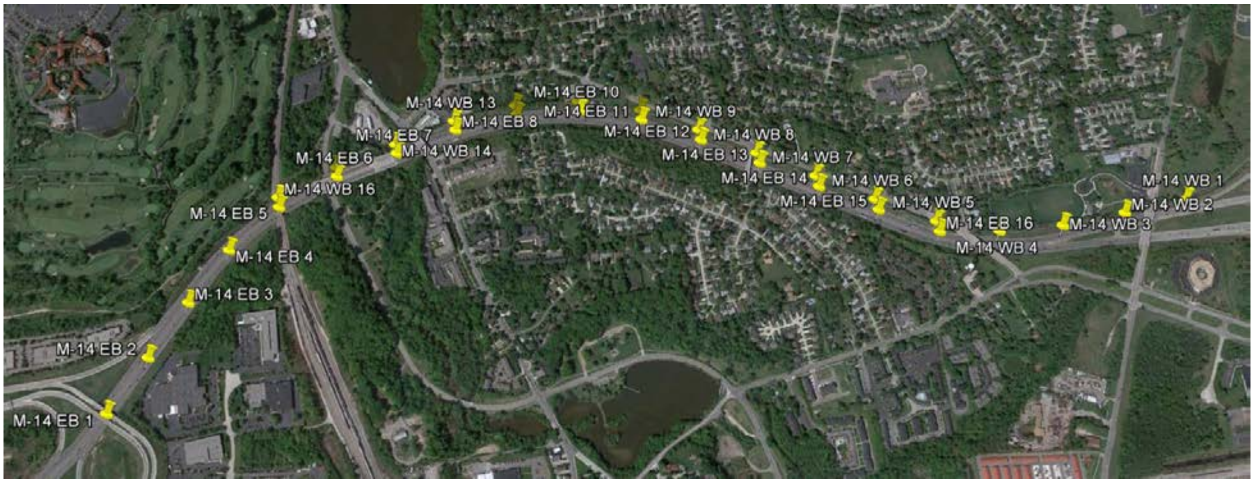

Figure 33 – Eastbound and Westbound M-14 in Plymouth, MI (2014)

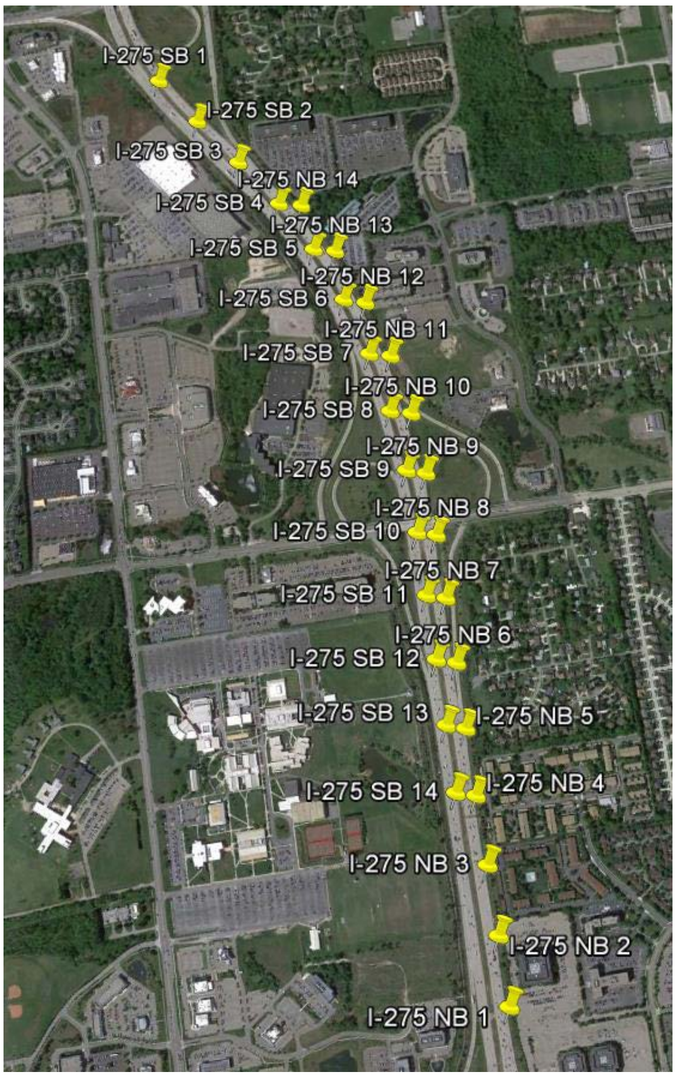

Figure 34 – Northbound and Southbound I-275 in Livonia, MI (2014)

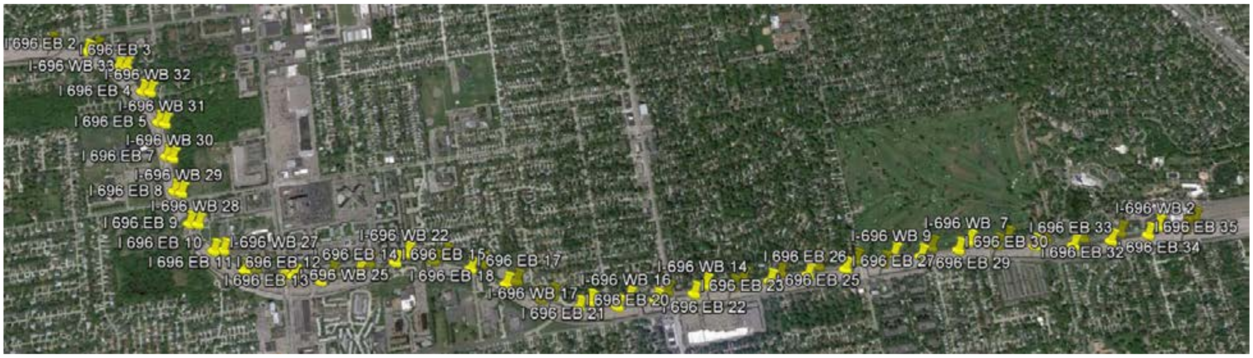

Figure 35 – Eastbound and Westbound I-696 in Southfield, MI (2014)

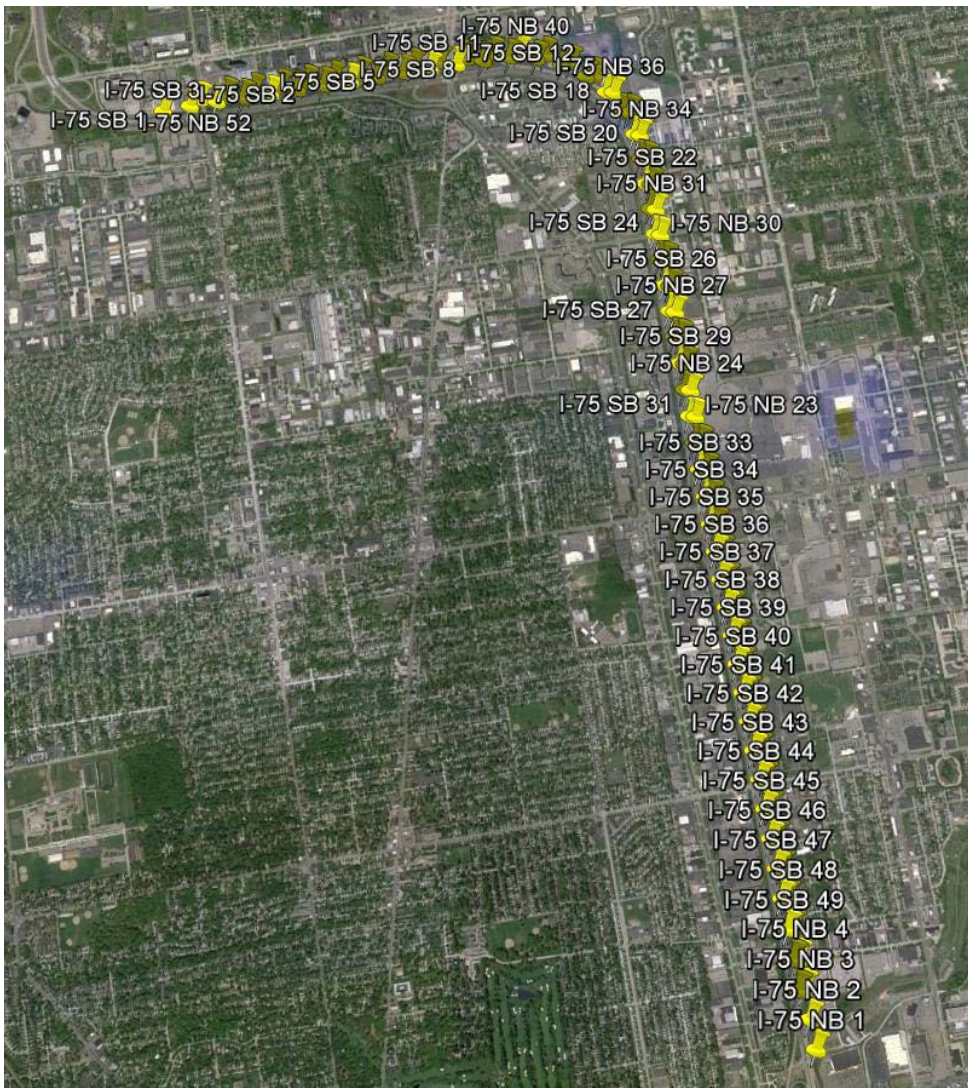

Figure 36 – Northbound and Southbound I-75 in Troy, MI (2014)

Figure 37 displays the roads that were analyzed including the average, minimum, maximum, and median IRI score for that road as well as the speed of the vehicle that gathered the data. In terms of the three level IRI categories (good, fair, poor) used for the ordinal logistic regression, the roads overall are good or fair, though there are segments that are considered poor. These poor segments of roads affect the average rating but have less of an impact on the median. If the median rating is very different from the mean rating, it is most likely due to a number of extreme high or low ratings. Though this occurs in a few of the roads, it does not affect the overall good, fair, or poor ranking for a road; that is, a road does not switch from a good to a fair road or from a fair to a poor road when comparing the means and medians.

Route	Mean IRI Score	Min	Max	Median	Average Speed
Ford Road EB	141	77	200	148	46
Ford Road WB	147	121	188	137	46
M-14 EB	115	65	254	99	58
M-14 WB	138	54	318	106	66
I-275 NB	63	44	108	56	64
I-275 SB	67	36	158	53	68
I-696 EB	139	71	235	137	65
I-696 WB	144	87	219	136	66
I-75 NB	160	102	228	163	63
I-75 SB	143	79	212	142	64

Figure 37 – Descriptive statistics for each road based on direction (2014)

Main Effects Variables

The 2014 analysis differs from the 2012 and 2013 in its focus only on the effects of speed, variance among accelerometer measurements, and to a lesser extent the phones. There is no need to include Difference Date variable, since all the data collection took place within a short period of time. Road surface type is also not considered because nearly all the roads in the analysis are concrete.

The bivariate relationship of variance among accelerometer measurements and IRI road segment ratings is shown in Figure 38. Compared to this same relationship in the 2012 and 2013 data, it seems slightly more linear.

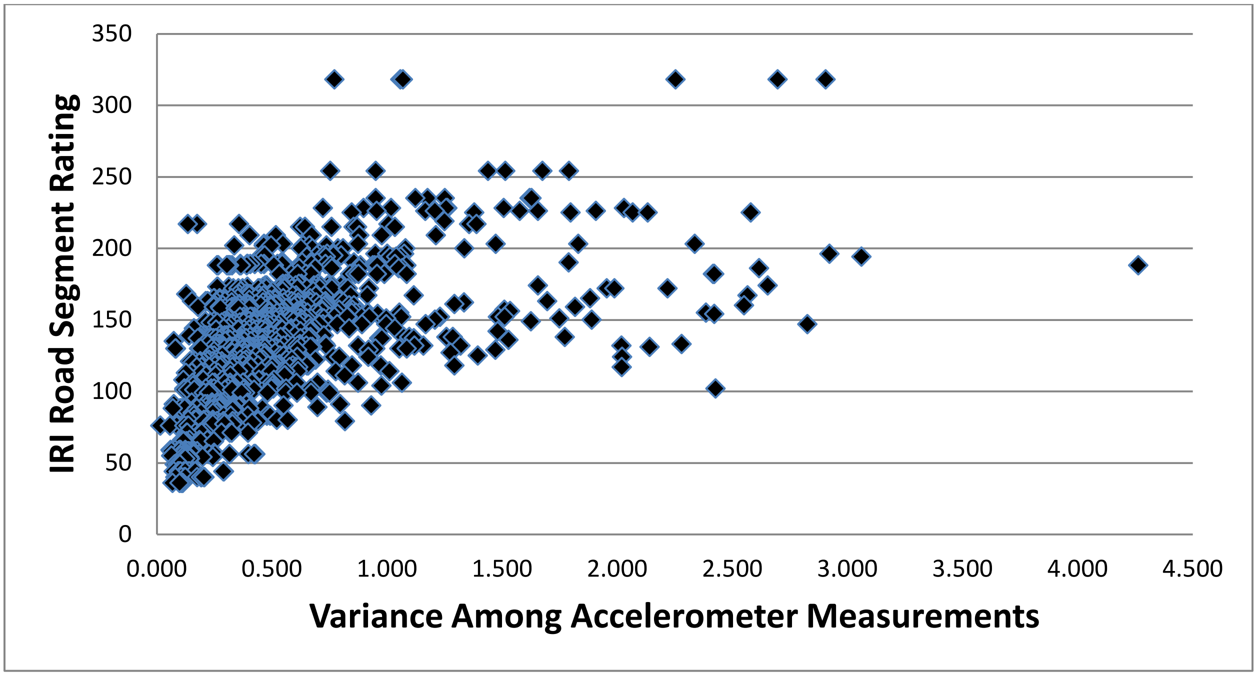

Figure 38 – Bivariate relationship of variance among accelerometer measurements and IRI road segment rating (2014)

The Multiple Regression Main Effects Model

In the 2014 data collection multiple phones were located in multiple vehicles to test the effects of the phones across a number of vehicles. In the following multiple regression analysis output in Figure 39, the effects of the different phones are significantly different from a phone in one of the other vehicles as well as different from each other. This shows significant variability among phones.

Term	Coef	Standard Error of the Coefficient	P
Constant	5.3370		0.000
Variance Among Accelerometer Measurements	1.3966		0.000
Speed	-0.01634		0.000
Phone	(Compared to Phone 1)		
Phone 2	0.0201	0.0227	0.540
Phone 3	-0.0842	0.0319	0.000
Phone 4	-0.1163	0.0320	0.000
Phone 5	-0.0791	0.0326	0.000
Phone 6	-0.1066	0.0329	0.000
Phone 7	-0.6066	0.0559	0.000
			R^2: 39%
			R^2 Adjusted: 38%

Figure 39 – Main effects multiple regression model of 2014 data (2014)

These results tell much about the relationship of each variable to IRI road ratings:

1) An increase in variance among accelerometer measurements increases IRI ratings. Higher IRI scores mean rougher roads, and higher DataProbe scores also mean rougher roads.
2) An increase in speed decreases IRI ratings. Lower IRI scores mean smoother roads, so higher speeds result in lower IRI scores.
3) There are significant differences among the phones on how they measure IRI scores. All phones except one are different than Phone 1, and Phone 2 is not different from Phone 1, which is in another vehicle. These inconsistencies in phones are one of the reasons for moving to the ordinal logistic regression program for measuring the relationship among variance among accelerometer measurements, speed, and IRI road segment ratings.

The Ordinal Logistic Regression Model: Predicting IRI Categories for 2014 data

Similar to the use of ordinal logistic regression to model the 2012 and 2013 data, the 2014 data was also modeled using ordinal logistic regression for both the 3-level and 5-level IRI road segment ratings.

Using ordinal logistic regression to predict the 3 level and 5 level IRI category variables allows measurement from another perspective: a categorical one. By focusing on the two main predictor variables, speed and variance among accelerometer measurements, the following results for the 2014 data show an interesting relationship between these two variables and the IRI road segment ratings. Figure 40 shows the results for the three level IRI categorical dependent variable. The model fits the data much better than the 2012 and 2013 data based on the Summary Measures of Association of .72, and it provides insight into how the three IRI levels are predicted in the Concordant, Discordant, and Ties table.

This table provides measures of association to assess the quality of the model. These measures are based on an analysis of individual pairs of observations with different responses. In this table there are 212 good roads, 678 fair roads, and 211 poor roads; hence, there are 212 times 678 times 211 pairs or 331,526 pairs. A pair is considered *concordant* if the observation with the higher response, in this case the poor roads (2), also has the higher estimated probability (i.e. a poor road has a higher probability of having a higher speed and variance among accelerometer measurements), *discordant* if the poor road has a higher probability of having a lower speed and lower variance among accelerometer measurements, and *tied* if the estimated probabilities are identical. The numbers given are the percentages of pairs in each of the groups; obviously, the higher the percentage of concordant pairs the better is the fit of the model. In this case speed and variance among accelerometer measurements account for 86 percent of concordant pairs, showing that they are properly predicting the IRI group 86 percent of the time.

Ordinal Logistic Regression							
Variable	*Value*	*Count*					
Group	(0) Good Roads (IRI: 0-95)	212					
	(1) Fair Roads (IRI: 96-170)	678					
	(2) Poor Roads (IRI: 171+)	211					
	Total	1101					
Logistic Regression Table							
					Odds	95% CI	
Predictor	Coef	SE Coef	Z	P	Ratio	Lower	Upper
Speed of the DataProbe Vehicle	-0.0876151	0.0088829	9.86	0.000	1.09	1.07	1.11
Variance Among Accelerometer Measurements	3.90939	0.255266	-15.31	0.000	0.02	0.01	0.03
Log-Likelihood = -820.737							
Test that all slopes are zero: G = 411.636, DF = 2, P-Value = 0.000							
Goodness-of-Fit Tests							
Method	Chi-Square	DF	P				
Pearson	3745.36	2198	0.000				
Deviance	1641.47	2198	1.000				
Measures of Association:							
(Between the Response Variable and Predicted Probabilities)							
Pairs	Number	Percent	Summary Measures				
Concordant	283704	85.6	Somers' D	0.71			
Discordant	47024	14.2	Goodman-Kruskal Gamma	0.72			
Ties	798	0.2	Kendall's Tau-a	0.39			
Total	331526	100.0					

Figure 40 – Ordinal logistic regression results for the three level IRI dependent variable (2014)

The results from the five level IRI categorical dependent variable shown in Figure 41 also provide insight into the predictive power of speed and variance among accelerometer measurements. The model fits the data not quite as well as the three level IRI categorical dependent variable based on the Summary Measures of Association of .66. It also predicts a slightly lower percentage of pairs of data in the Concordant, Discordant, and Ties table.

Because it has more groups, this analysis also has more pairs of data to compare. In this table there are 28 good roads group 1, 161 good roads group 2, 327 fair roads group 1, 380 fair roads group 2, and 205 poor roads; hence, there are 28 times 161 times 327 times 380 times 205 pairs or 446,071 pairs. In this case, speed and variance among accelerometer measurements account for 83 percent of concordant pairs, showing that they are properly predicting the IRI group 83 percent of the time.

Ordinal Logistic Regression								
Variable	*Value*	*Count*						
Category	(0) Good Roads 1 (IRI: 0-48)	28						
	(1) Good Roads 2 (IRI: 49-95)	161						
	(2) Fair Roads 1 (IRI: 96-133)	327						
	(3) Fair Roads 2 (IRI: 134-170)	380						
	(4) Poor Roads (IRI: 171+)	205						
	Total	1101						
Logistic Regression Table								
					Odds	95% CI		
Predictor		Coef	SE Coef	Z	P	Ratio	Lower	Upper
Speed of the DataProbe Vehicle		- 0.0987289	0.0084804	11.64	0.000	1.10	1.09	1.12
Variance Among Accelerometer Measurements		5.87119	0.287849	-20.40	0.000	0.00	0.00	0.00
Log-Likelihood = -1222.708								
Test that all slopes are zero: G = 670.921, DF = 8, P-Value = 0.000								

Goodness-of-Fit Tests			
Method	Chi-Square	DF	P
Pearson	8866.27	4392	0.000
Deviance	2445.42	4392	1.000

Measures of Association:				
(Between the Response Variable and Predicted Probabilities)				
Pairs	Number	Percent	Summary Measures	
Concordant	369944	82.9	Somers' D	0.66
Discordant	75139	16.8	Goodman-Kruskal Gamma	0.66
Ties	988	0.2	Kendall's Tau-a	0.49
Total	446071	100.0		

Figure 41 – Ordinal logistic regression results for the five level IRI dependent variable (2014)

2014 Analysis Conclusions

The 2014 data collection and analysis yielded better predictive models of IRI road segment ratings using variance among accelerometer measurements and speed as the two major predictors than did the 2012 and 2014 data. There were a number of differences in data collection between the 2014 data collection and the 2012 and 2013 data collections, but the main one was that more data was collected for each road segment. This increase in data per road segment allowed for averaging the many readings, generating a better predictor of IRI road segment ratings.

The other important conclusions from the 2014 analysis include the strong relationship between speed and IRI road segment ratings. As speed increases the IRI score decreases showing a smoother road. There also continues to be differences among the phones and vehicles in terms of predicting IRI ratings, but these differences are minimal and can be easily overcome by traveling over the same road segments multiple times.

Lessons Learned

In general, one must take a more experimental approach to measuring the effects of other factors that can play a role in customized programs using smartphones to measure road roughness. This study provided an extensive overview of the issues involved in predicting IRI road roughness scores via smartphones. The 2014 data collection and analysis showed that driving over the same road segment multiple times will increase the power of DataProbe to more accurately predict IRI road segment ratings.

The analysis also showed that accurately predicting a specific IRI rating is difficult. This report argues that predicting an actual IRI score may be an unrealistic or even unnecessary goal. Considering the wide range of IRI scores for the three major categories used to describe road roughness, there seems to be only issues related to predicting road roughness at the margins of these IRI categories. The analyses that examine the prediction of the three level and five level IRI categories display a good alternative to predicting exact IRI scores. The accuracy of predicting the IRI categories using devices such as smartphones allows locales an inexpensive and continuous monitoring of roads as long as the roads are driven over multiple times.

Conclusion

Clearly there are multiple variables affecting the measurement of road roughness when using an Android-based smartphone. Besides variance among accelerometer measurements itself, our analyses show that the type of phones, vehicle speed, road surface type, and the difference date all contribute to explaining the variance of IRI road segment ratings. Though DataProbe does not do an acceptable job of replicating IRI-type ratings of roads, it does a good job of accurately predicting the three and five level categories of road roughness that decision-makers may use to manage their road maintenance.

Despite differences in phones and vehicles, multiple passes over a route may provide an inexpensive and automated system for road maintenance managers' decision-making.

Recommendations

Future collection of large amounts of anonymous data from drivers throughout the state will be part of longer term Connected Vehicle technology projects that will link vehicles' safety systems. This technology will be located in all vehicles, providing a potential crowd-sourcing model for data collection, similar to how traffic information providers use anonymous cell phone data to generate digital traffic/congestion maps.

Road roughness measurements may be part of this future suite of data, but for measuring road roughness in the near term, smartphones may be programmed to accurately gather road roughness data. Two key requirements are needed for accurate smartphone data collection: 1) each road segment must be driven over two to three times, and 2) the analysis of the data collected by the DataProbe unit must use the three or five category level IRI road segment scoring method in order to approximate the accuracy level of the IRI system.

The next level of development for the DataProbe system will have the data gathered by the smartphone using vehicles from the fleet of a small area such as a city or county. The data will be then sent to a server via the cell phone, where the data is processed, analyzed, and color coding for specific road segments of varying lengths applied to constantly updated web-based maps of an area. The phone can also be programmed to automatically take a photo of the road if the level of the accelerometer reading reaches a certain point. The phones can also be used by the drivers to take photos of specific areas they think need to be noted. These photos can become part of the mapping of an area, displaying a visual representation of what the accelerometer is experiencing.

Trying to monitor the whole state in this manner would be too big of a task for this stage of development. It may be more appropriate to choose a number of specific areas across the state where the local officials are willing to fully participate in order to develop and test the data analysis and mapping program. This will provide each locale a continuous update of the condition of its roads, based on the IRI categories (3 or 5 levels). If a road is not traveled enough, the program will not provide a rating, thus showing the managers how much more effort, if any, needs to be put into traveling over their roads in order to generate accurate estimates of the road conditions. DataProbe road ratings can also be tailored to signal how many times a road has been traveled, and as the program evolves, it will be able to determine how many more passes are needed to generate a good estimate of the road roughness/condition.

One issue that is specific to the northern states is gathering data during the winter months. Snow and ice cause very uneven and rough roads. Gathering data during this time may not make sense because DataProbe would not be measuring the true road surface. One option for the winter months might be to change the accelerometer thresholds for the different categories, such that only major road surface changes such as potholes will be measured and reported. This process would continue to provide road maintenance managers information about their roads until the snow melts in the spring and the phones are again measuring the effects of the winter weather on the roads.

Finally, one additional opportunity the smartphone provides is tracking the phones while they are in service via a web portal. The phones in vehicles continuously notify the web portal if they are in service and where they are located on a map. The web portal provides both the data analysts and road supervisors a continuous real-time tracking of vehicles in the fleet. Mangers can also take pictures remotely via the portal and those photos will appear on the portal.

Android-smartphones do not provide the level of granularity that the IRI device provides, but they offer an inexpensive, continuous opportunity to monitor the roads in their jurisdiction, allowing road maintenance managers to be proactive in responding to road issues in their city, county, or state.

This work will hopefully compliment an on-going innovation initiative to identify how state DOTs might use and benefit from the large quantities of data generated by future connected vehicle programs and to assist in refining connected vehicle system requirements. Some of these innovation initiatives include the following:

- **Data Use Analysis and Processing (DUAP)**

The specific purpose of the Data Use Analysis Processing (DUAP) project is to support MDOT and its partners in evaluating uses and benefits of Connected Vehicle-related data in transportation agency management and operations. The DUAP project builds on the work previously done to investigate how the availability of data from Connected Vehicle-equipped vehicles throughout the road network may impact the way transportation agencies do business. DUAP specifically focuses on data uses to enhance safety, improve traffic flow and better manage transportation assets. The work will also support the other Connected Vehicle activities, technology development for MDOT, and economic growth for the state. The overall objective of this project is to demonstrate the use and benefits of vehicle-based probe data to improve transportation safety and mobility through enhancements to MDOTs activities in planning, design, construction, operations, maintenance, and asset management.

- **Vehicle-based Information and Data Acquisition System (VIDAS)**

The VDIAS project studies the collection of probe data from specially instrumented vehicles augmented with other situational data which will be used to determine road surface conditions for improving roadway operations and populate the data stream for the Data Use Analysis Processing (DUAP) project. VIDAS will coordinate with other MDOT Connected Vehicle research projects to evaluate and determine how instrumented vehicles that detect slippery road conditions and pavement roughness can be used to track the environmental state surrounding a vehicle as it moves down the road. Also, it also determines how weather information and road surface conditions can be used to improve various MDOT business processes, practices, and outcomes. This research will bring together dynamic mobility data with other situational data to meet specific use cases and user needs defined in DUAP.

- **Integrated Mobile Observations (IMO) 2.0 (**08-01-2014 Integrated Mobile Observations 2.0 Final Report, link: www.michigan.gov/CV **)**

IMO 2.0 is a project funded by the FHWA Road Weather Management Program, as a grant to MDOT, the lead agency managing the project. UMTRI is the researcher developer of the software system on an Android platform used to gather road condition data from snowplows and light- and medium-duty vehicles. The vehicles are equipped with smartphone technology and monitoring devices that collect data from the vehicle controller area network (CAN) bus and surface monitoring device (atmospheric conditions). The data is sent via cellular communication (4G) to DUAP for post processing then, on to MDOT Transportation Operations Centers (TOC). TOCs will use DUAP shape files to post motorist advisories and warnings to a dynamic message sign, website, or smartphone application for the public and maintenance personnel use.

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Appendix A

Pavement Surface Evaluation Rating (PASER) System

The original project research plan called for measuring the road roughness by comparing the roughness scores generated by the DataProbe system to the Pavement Surface Evaluation Rating (PASER) system. After some initial analyses and discussions with the MDOT Asset Management group, it was determined that the accelerometer readings collected via the phone were better compared to the International Roughness Index than to the PASER scores. PASER scores focus more on road distress rather than road roughness. In fact, the PASER raters, individuals and teams that visually assess rode distress, are trained to not rate the smoothness or roughness of the ride quality of the vehicle. Their focus is on visual road distress.

A road is considered to be in good condition when its PASER ranges from 8-10[12].

A road is in fair condition when PASER ratings fall to 5-7. Although the roads are still structurally sound, they require capital preventative maintenance (CPM) to keep the roads from deteriorating.

The PASER rating of 5 is the lowest rating for a fair road; the last chance to repair the road using CPM. Trends show that 41 percent of roads with a PASER rating of 5 will fail, or fall to poor condition, each year. C Estimates of the cost per mile to apply CPM are at $45,000 to $53,000.

A road is considered to be in poor condition when its PASER rating is 1-4. The structural integrity of these roads has failed. Statistically, 70 percent of poor roads will need to be rehabilitated, while 30 percent will need complete reconstruction.

Estimates of the cost per mile for rehabilitation at $121,000 to $423,000, and the cost per mile for reconstruction are at $328,000 to over $1 million for some freeways.

The details of the data collected via the DataProbe program are noted in Data Sources section of this report. A sample data file of the collected data is shown in Figure 4.

[12] Frequently Asked Questions from the MICountyRoads website: http://www.micountyroads.org/paser/rdcondfaq.pdf

International Roughness Index (IRI)

The definition of the International Roughness Index (IRI) is a scale for roughness based on the simulated response of a generic motor vehicle to the roughness in a single wheel path of the road surface.[13]

Its true value is determined by obtaining a suitably accurate measurement of the profile of the road, processing it through an algorithm that simulates the way a reference vehicle would respond to the roughness inputs, and accumulating the suspension travel. It is normally reported in inches/mile or meters/kilometer.

The IRI is based on continuous research beginning in 1940 and expanded in the 1960's with the introduction of the inertial profilometer. In the 1970's and 1980's work on measuring road roughness was refined resulting in a method for measuring road roughness globally, the IRI, that is reproducible, portable, and stable over time.[14] The IRI methodology is used by the U.S. government and all the States as the standard method to measure road roughness.

The range of values for the IRI is from 0 to infinity with lower values representing smoother roads. For this study, IRI scores were accumulated in one tenth of a mile road segments, a standard used by MDOT. Discussions with MDOT showed that there are three main categories of roads that they designate based on IRI scores: 0 to 95 is considered a good road, 96 to 169 is considered a fair road, and 170 or higher is considered a poor road. Another method for categorizing IRI scores examines a five level division of IRI scores that provides finer detail of the good and fair roads along with equivalent A to F grades: 0 to 45 is considered a very good road (A), 46 to 95 is considered a good road (B), 96 to 138 is considered a high level fair road (C), 139 to 169 is considered a low level fair road (D), and 170 or more is considered a poor road (F). The analyses in this report examine methods for predicting the exact IRI score as well as these three level and five level IRI categories.

As a sample of the results of an IRI analysis, Figure 42 shows a report from the IRI analysis of eastbound Ford Road in Ann Arbor, Michigan where the left and right wheelpaths of the MDOT IRI vehicle generated IRI scores in one tenth of a mile road segments.

[13] "Introduction to the International Roughness Index," Minnesota Department of Transportation, presented at the Bituminous Smoothness Training Workshop, April 11, 2007.
http://www.dot.state.mn.us/materials/smoothnessdocs/IRIIntroduction.pdf

[14] Sayers, M. and Karamihas, S., "The Little Book of Profiling", University of Michigan Transportation Research Institute, Ann Arbor, MI. , September, 1998.

FORD ROAD - EASTBOUND									
Plymouth Road to M-153									
From (feet)	To (feet)	IRI, Left Wheelpath (in/mi)			IRI, Right Wheelpath (in/mi)			Mean IRI (in/mi)	
		Run 1	Run 2	Run 3	Run 1	Run 2	Run 3	Run 1	Run 2	Run 3
0	528	266	248	235	466	446	472	366	347	354
528	1056	136	142	142	294	257	229	215	200	185
1056	1584	127	125	126	115	113	117	121	119	121
1584	2112	140	163	145	168	158	180	154	161	163
2112	2640	168	186	168	199	211	199	184	198	184
2640	3168	117	116	118	113	107	110	115	111	114
3168	3696	151	151	150	168	169	171	160	160	161
3696	4224	143	146	142	133	132	133	138	139	138
4224	4752	218	216	229	171	148	149	194	182	189
4752	5280	163	168	158	135	130	130	149	149	144
5280	5808	164	162	160	133	135	133	148	149	147
5808	6336	160	159	165	142	137	133	151	148	149
6336	6864	151	152	154	136	119	120	144	136	137
6864	7392	132	143	134	129	114	145	130	128	139

Figure 42 – IRI Scores for tenth of a mile segments on eastbound Plymouth Road in Ann Arbor, Michigan