Analysis of the Use of Probe Vehicles for Road Infrastructure Data Collection

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ABSTRACT

This thesis explores the concept of using sensors found in normal vehicles, also known as probe vehicles, to collect road infrastructure data. This concept was demonstrated by measuring vertical acceleration using in-vehicle sensors in order to describe road ride quality. Data collection was performed at the Virginia Smart Road using two instrumented vehicles. The gathered information was compared to road profile data collection, which is the current state-of-the-practice in ride quality assessment. Following the concept validation, the acceleration measurements were further analyzed for repeatability and effect of various independent variables (vehicle speed and type). A network-level simulation was completed using the robust set of measurements from the experiment. In addition, methodology for identifying rough sections and locations were established. Results show that under controlled testing conditions, roadway profile can accurately be estimated using probe vehicle acceleration data and may provide a more practical way to measure road smoothness. The analysis also showed that vertical acceleration data from a fleet of probe vehicles can successfully identify poorly-conditioned pavement areas. This suggests that instrumented probe vehicles might be a viable and effective way of implementing a network level roadway health monitoring program in the near future.
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<td>A.B.S.</td>
<td>Anti-lock Braking System</td>
</tr>
<tr>
<td>A.S.T.M.</td>
<td>American Society for Testing and Materials</td>
</tr>
<tr>
<td>B.i.F.i</td>
<td>Bearing Information through Vehicle Intelligence</td>
</tr>
<tr>
<td>C.A.N.</td>
<td>Controller Area Network</td>
</tr>
<tr>
<td>C.R.C.P.</td>
<td>Continuously Reinforced Concrete Pavement</td>
</tr>
<tr>
<td>D.A.S.</td>
<td>Data Acquisition System</td>
</tr>
<tr>
<td>D.O.T.</td>
<td>Department of Transportation</td>
</tr>
<tr>
<td>D.S.R.C.</td>
<td>Dedicated Short-Range Communications</td>
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<tr>
<td>F.H.W.A</td>
<td>Federal Highway Administration</td>
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<tr>
<td>G.P.S.</td>
<td>Global Positioning System</td>
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<tr>
<td>H.P.M.S.</td>
<td>Highway Performance Monitoring System</td>
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<tr>
<td>I.N.T.R.O.</td>
<td>Intelligent Roads</td>
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<tr>
<td>I.Q.L.</td>
<td>Information Quality Level</td>
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<tr>
<td>I.R.I.</td>
<td>International Roughness Index</td>
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<tr>
<td>J.R.C.P.</td>
<td>Joint Reinforced Concrete Pavement</td>
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<tr>
<td>M.I.T.</td>
<td>Massachusetts Institute of Technology</td>
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<tr>
<td>N.H.S.</td>
<td>National Highway System</td>
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<tr>
<td>N.C.A.T.</td>
<td>National Center for Asphalt Technology</td>
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<tr>
<td>N.C.H.R.P.</td>
<td>National Cooperative Highway Research Program</td>
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<td>N.D.S.</td>
<td>Naturalistic Driving Studies</td>
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<tr>
<td>O.B.E.</td>
<td>On-Board Equipment</td>
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<td>O.G.F.C.</td>
<td>Open-Graded Friction Course</td>
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<tr>
<td>P.O.C.</td>
<td>Proof of Concept</td>
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<tr>
<td>R.A.M.</td>
<td>Random Access Memory</td>
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<tr>
<td>R.I.T.A.</td>
<td>Research and Innovative Technology Administration</td>
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<tr>
<td>T.T.C.</td>
<td>Time to Collision</td>
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<tr>
<td>V.I.I.</td>
<td>Vehicle Infrastructure Integration</td>
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<tr>
<td>V.D.O.T.</td>
<td>Virginia Department of Transportation</td>
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CHAPTER 1 - INTRODUCTION

BACKGROUND

Pavement Condition Assessment

Pavement condition assessment is a key asset management business process that allows Department of Transportation (DOT) personnel and other transportation agencies to make cost-effective decisions regarding the preservation and renewal of pavement assets. Effective asset management, as any decision support tool, requires reliable and sufficient data, calibrated analysis models and procedures, and tools that help visualize and quantify the impact of the possible solutions considered. The 2001 AASHTO Pavement Management Guide discussed in detail the technologies and processes used for the selection, collection, reporting, management, and analysis of data used in pavement management at the state level (1). While there is an extensive range of data that is needed in a Pavement Management System (PMS), a specific emphasis is placed on the robust collection of pavement condition data. Pavement condition data, if collected efficiently and accurately, provides indication of road performance in relation to safety, ride comfort, and structural integrity. The main parameters that are collected include ride quality, surface distress, friction, and structural capacity. The asset management processes include decisions supported by the pavement condition data at the strategic, network, and project levels. For example, at the national level, the Highway Performance Monitoring System (HPMS) requires states to submit pavement condition data periodically for a sample of roads on the National Highway System (NHS). This data is collected by the state DOTs using automated, semi-automated and, in some cases, visual methods. The system is used by the Federal Highway Administration (FHWA) for apportionment, performance measures, highway statistics, and condition reporting. The pavement condition data is stored, along with road classification and travel vehicle by type (2).

However, the current process is often limited in its overall effectiveness. The use of new technologies has in some cases led agencies to collect larger amounts of data and create vast databases that have not always been useful or necessary for supporting decision processes. It is important that the agencies tailor the data collection practices to the use of the data and the level of decisions being supported. The issue of uniformity of the data is particularly challenging at the national level because state, regional, and local agencies have often independently developed data collection practices and standards (3). In addition, the actual task of collecting the data can be onerous and time-consuming. Agencies must utilize a small fleet of data collection vehicles to cover a large amount of road mileage. This creates issues with prioritizing infrastructure projects and can lead to decision making that is not completely thorough. One positive development is the more frequent use of automated data collection methods. For example, NCHRP Synthesis 334 found that essentially all North American highway agencies are collecting pavement condition data through some automated means. Furthermore, the synthesis also found that 33 out of 56 agencies use service providers (also called vendors or contractors) to collect at least some of the automated data (4). While processes to evaluate this data has presented new challenges (data collected is different in nature than previous manual methods), the use of automated equipment increases safety and speed of the data capture and may facilitate the development of more uniform data collection practices. This thesis provides a logical next step in the evolution of data collection technologies by examining the foundation of a data collection methodology that could provide wide coverage and uniformity across jurisdictions.
Probe Vehicle Concept

The way in which transportation agencies collect, store, and analyze data has evolved along with advances in technology, such as mobile computing, advanced sensors, imaging technologies, distributed databases and spatial technologies. These technologies have enabled necessary data collection and integration procedures to support the comprehensive analyses needed for asset management (5). These data collection procedures often require investment in application-specific vehicles whose cost means that pavement inspection intervals are rather large and coverage (in terms of roadway mileage) is rather low. The concept of using on-board sensors in newer production vehicles to collect traffic and infrastructure information has the potential to alleviate this problem. These vehicles, also known as probe vehicles, could provide agencies with a much larger fleet of data collection devices using sensors that are already installed in today’s passenger cars and trucks. By measuring pavement condition with these built-in, inexpensive vehicle sensors and transmitting data via available wireless connection, a large amount of data can be collected at a relatively low cost. The technology uses current items, some of which are already installed in many vehicles, to collect data, to communicate with infrastructure and other vehicles, and to relay information to satellite locations. In most probe vehicle systems, these tasks are achieved by on-board sensors, such as accelerometers, GPS, and a wireless communication device (6). The majority of tests and research conducted in this area rely on these basic concepts.

The idea for probe vehicles as useful traffic and infrastructure tools has been explored for several years. In a fully integrated network, the passenger cars would essentially become the data collection devices (7). In the United States, the U.S. Department of Transportation (DOT) and Federal Highway Administration (FHWA) launched a nationwide initiative in 2003 known as the Vehicle Infrastructure Integration (VII). The VII program supervised multiple research projects aimed at using wireless communication between vehicles and infrastructure to improve safety and mobility (8). Probe vehicles naturally played a major role in a majority of the research. This program was later engulfed by IntelliDrive℠ and is currently controlled by the Research and Innovative Technology Administration (RITA) under the title Connected Vehicle Research. Pavement condition monitoring continues to be a recurring component of the research involved (8). While a large scale, fully-integrated system may not exist for some time, the general consensus is that the data collection and asset management processes would be significantly improved. The data collected by probe vehicles would be dynamic and would cover a large scope of the networks in which the vehicles are deployed to provide a constantly updating condition database (9).

Evaluating Ride Quality

Based on preliminary research, the most practical and easily deployable probe vehicle application for pavement assessment is relating on-board sensors to ride quality. Ride quality, or smoothness, is one of the most vital condition indicators. When state agencies program maintenance, repair, and rehabilitation work of their road networks, they do so by measuring road smoothness, as it has significant influence on the performance as perceived by the users of the pavements and is directly linked to the costs assumed by these roadway users. Smoothness can have a great effect on vehicle performance. Fuel consumption, tire wear, and vehicle durability are all greatly influenced by the smoothness of the road. A road with more bumps will have a negative impact on the performance of the vehicle. While smoothness is only one of many condition indicators used by data collection agencies, it is the driving indicator in the public eye. Typical road users have a much keener perception of road smoothness than other aspects such as friction and structural capacity. Therefore, it is important for a road to have an acceptable level of smoothness (3).
Smoothness measurement techniques have evolved since the 1960’s when the smoothness of a road was first computed by measuring the vertical deviations of the road surface along a longitudinal line of travel in a wheel path (i.e. a longitudinal profile). Since then, many different devices have been developed with an aim to capture those aspects of a longitudinal profile that affect ride quality, vehicle dynamic loading, and safety. Currently, the most commonly used measuring devices are the laser-based inertial profilers, which measure longitudinal profiles at highway speeds and compute the International Roughness Index (IRI) which was developed by the NCHRP and the World Bank. The procedure for determining the IRI is described in ASTM E1926. The IRI is the accumulation (usually expressed in in/mi) of all the vertical differences of a simulated vehicle trajectory from an otherwise smooth surface across a given length of road. If the sum of these differences is large, the surfaces are described as rough, creating an uncomfortable experience for roadway users. However, if the sum is small, the surfaces are usually very smooth and travel is not as disruptive, either to the vehicle or its passengers. The IRI has become the standard for measuring ride quality on the nation’s pavements.

While modeling the response of a theoretical vehicle to the longitudinal profile is one way of quantifying smoothness, the basic concept relating vertical acceleration to ride quality as initially conceived is still valid. This provides an opportunity to evaluate roadway condition using probe vehicles. From a physical perspective, road profile (i.e., a measure in the pavement profile of vertical distance variations experienced by a vehicle) has a direct influence on the vertical acceleration of a vehicle traveling along the roadway. The vehicle travel speed (horizontal speed) influences the speed (vertical speed) at which it traces this profile and the changes in speed determine the acceleration. Therefore, the profile of the road directly influences the vertical acceleration experienced by the vehicle. Unlike the longitudinal profile, which requires sophisticated lasers, vertical acceleration can be measured by sensors found in many of today’s production vehicles. Most vehicles with a higher center of gravity, including small trucks and sport utility vehicles, are equipped with rollover stability control, supported by vertical accelerometers. Newer passenger cars are also outfitted with accelerometers for electronic stability control. When placed perpendicular to the traveled surface on the vehicle, and when combined with several transducers, an accelerometer establishes an inertial reference for the vehicle. This can then be translated into road smoothness as a longitudinal profile is created. The setup of an accelerometer on a profiling vehicle is outlined in the ASTM Standard E 950-98. The methodology tailored towards probe vehicles is still being improved and studied. The ability to interpret the data that are collected depends on variables such as network size, fleet size, road type, and environmental conditions.

**PROBLEM STATEMENT**

Pavement condition assessment, in particular the assessment of ride quality, could potentially be made more efficient by utilizing new on-board technology installed in vehicles. In the long term, this could provide transportation agencies with a new method for evaluating the functional condition of its pavement assets by identifying areas of poor ride quality through the use of accelerometers. The hypothesis is that we can use data collected from probe vehicles to extract information that could be used to remotely and continuously determine road infrastructure condition. This thesis evaluates the extraction of useful road surface condition and performance information from vehicles instrumented for Naturalistic Driving Studies (passenger cars and large trucks). Commercial heavy vehicles could be particularly useful as probe vehicles for nation-wide data collection because they typically follow longer routes along the main highways than regular passenger cars (providing a better coverage of the National Highway System), and
are more consistently maintained and operated. Preliminary analysis, outlined in Flintsch et al (12) and further documented at the beginning of Chapter IV, suggests that this approach is feasible and useful information can be extracted from the specially-instrumented vehicles.

OBJECTIVES

This thesis focused on using data from vehicle acceleration sensors and relating them to pavement ride quality. The overall goal was to establish a methodology for collecting and processing probe vehicle data to provide an alternative to transportation agencies for measuring the condition of their network. Specific objectives include the following:

✓ Conduct a thorough literature review on previous and on-going uses of probe vehicles
✓ Use preliminary data to compare acceleration and smoothness profile measurements
✓ Collect a large amount of data using two different instrumented vehicles on the Virginia Smart Road
✓ Assess the accuracy and repeatability of acceleration measurements
✓ Evaluate the effect of vehicle type and vehicle speed on acceleration measurements
✓ Develop a way to identify areas of poor pavement condition through acceleration measurements
✓ Simulate a large scale probe vehicle deployment with the processing of multiple test runs; and
✓ Comment on the future development of probe vehicle technology

RESEARCH SCOPE

New technology has made the possibilities for probe vehicle applications both practical and wide-ranging. It was important at the onset of the experimental design to concentrate the study to a single probe vehicle application. Therefore, the data collection and analysis in this thesis is concentrated on vertical acceleration measurements from probe vehicle accelerometers. This thesis focuses on examining the feasibility of using accelerometers to describe ride quality. The assessment of the collection procedures and data quality includes a comparison to current ride quality measurement techniques, analysis of repeatability, and experimentation with various speeds and vehicles. These techniques are all included in the objectives stated above. All experimental data collection was taken from the same test section. The acceleration measurements obtained from instrumented vehicles were limited to the Virginia Smart Road, which provides an ideal closed circuit for data collection. A small amount of data was also collected on a stretch of highway for preliminary analysis. The goal of the thesis was to prove the concepts behind acceleration data collection and later allow for expansion of the study. The results obtained were positive and warrant further investigation on public highways. This would preferably be completed using a fleet of instrumented probe vehicles. The data collected provides a logical step towards an actual implemented probe vehicle system that could constantly measure ride quality over a large road network.
CHAPTER 2 - LITERATURE REVIEW

BACKGROUND

Introduction

Pavement asset management practices related to ride quality assessment and probe vehicle usage were researched as part of the literature review. Reports, articles, and presentations were reviewed and related to the thesis objective. The sources were taken from online databases, conference publications, and resources at the Virginia Tech Transportation Institute (VTTI). Each study that is included in this section contributed to the development of this thesis. The major results and findings from the literature review are summarized at the end of the section.

Beginning Concepts

The benefits of a successfully deployed probe system have been imagined by several organizations and researchers. The current pavement evaluation system has limited potential due to high cost and lack of availability (3). Budgets for road surface monitoring and management in most locations are constrained. Therefore, there is need for a new system that can determine roads which need maintenance and map potential driver hazards. Local roads are especially prone to deterioration due to weathering, heightened traffic load, and typical wear and tear. It is important to accurately locate these deteriorations and control the problems in a cost efficient manner (9). An efficiently deployed fleet of probe vehicles, equipped with pavement condition sensors, could serve as a major improvement to asset management and road safety.

Some of the concept’s major advancements have been led by the United States DOT and FHWA. Four years after the creation of the Vehicle Infrastructure Integration initiative, the FHWA launched a proof of concept project to identify the feasibility of a vehicle-to-infrastructure collaboration process. The proof of concept focused mainly on probe vehicles as a suitable data collection and communication system. Data collection works by gathering the vehicle data and position in order to create a snapshot of the current state of the vehicle. By saving a large amount of snapshots along the route of the vehicle, data and position information can be readily collected. The technology uses current devices, some of which are already installed in vehicles, to collect data, communicate with infrastructure and other vehicles, and relay information to satellite locations. The majority of tests and research conducted in this area rely on the basic concepts demonstrated in the proof of concept by the FHWA (13).

A more extensive look at the VII methodology shows the various components needed for a successful deployment system. The VII system revolves around on board equipment (OBEs). OBEs exchange messages with each other and with roadside terminals via wireless communication, which, in this case, is the DSRC radio system. This is an extremely large scale project that would involve millions of data exchanges every second. A typical service delivery node would be expected to support over 1000 roadside terminals. The FHWA estimates that in order to achieve nationwide deployment, 100 to 200 of these nodes would need to be created. The technology of the proof of concept system aims to achieve the following: transmit messages from network providers to OBEs, transmit messages from traffic signals to OBEs, transmit messages between OBEs, collect data from OBEs and distribute where necessary, provide security, and ensure privacy of vehicle operator. A typical OBE would be equipped with the following: a vehicle Interface, which provides a common referencing scheme and means for accessing vehicle data.
(also allows the OBE to be used in a variety of vehicle types without needing to customize each application to interface with each vehicle type); positioning services, which provide vehicle position and time information for applications, including notifications about geographic events; communications management, which provides an interface between applications and security and DSRC Radio subsystems; security services, which provide specialized security functions (signing, verification, encryption and decryption) for use directly by applications and for use on behalf of applications by the communications manager. In this thesis, the OBE is equipped with the technology necessary to collect pavement condition data. Through the DSRC radio system, the data collected can be relayed to an outside terminal for processing (6).

Asset Management Data Collection

To help tailor data collection practices to the uses of the data, the World Bank introduced the concept of Information Quality Levels (IQL) for road management (14). This concept helps highway agencies structure road management information into different levels that correlate to the degree of sophistication required for decision making and, thus, the appropriate methods for collecting and processing data. Within the proposed framework, very detailed data (low-level data) can be condensed or aggregated into progressively simpler forms (higher-level data). Bennett and Paterson (15) defined five levels that ranged from very detailed data in an IQL-1 (research and benchmark data for other measurement methods) to a very general IQL-5 (top-level data, such as key performance measures or indicators, which typically might combine key attributes from several pieces of information) (15). These IQLs have been associated with different level of asset management decision-making, as shown in Figure 1.

Figure 1 Information Quality Levels and Asset Management Decision Making

Based on available current technology, an integrated probe vehicle system may provide a practical and cost effective alternative for collecting comprehensive and uniform data. This data collection approach can support collection at the highest IQLs, appropriate to support strategic and possibly network-level decisions, while also providing more frequent condition assessment at the lower IQLs.

Probe vehicle collected condition data can support the condition assessment of the road infrastructure systems by providing objective, wide-ranging and frequent pavement (and possibly bridge deck) condition data at the national, regional, and local levels. The approach using probe vehicles could be used to collect data with IQLs 3 or 4, providing a very cost effective tool for state highway agencies, local governments, and regional planning organizations to collect the road surface condition information for
supporting network-level asset management business processes. The amount of data collected on a given network would exponentially increase since an integrated vehicle fleet would be collecting information at every instant of travel. Given the right penetration percentage, data collection could be an ongoing process. This would result in a much more robust data set and, in turn, a more accurate depiction of the quality of the road infrastructure.

VEHICLE TECHNOLOGY AND SENSORS

Vehicle Sensors

Recent advances in technology have led to more sophisticated digital sensing equipment in vehicles. Utilizing the information from these sensors is the main theory in the probe vehicle approach. While the basic setup is typically the same in all probe vehicle tests, the way those concepts are achieved can vary greatly. The technology being used must be tailored to the project in question. For example, data collection involving ride quality assessment can be achieved with a positioning system and vertical acceleration sensing equipment. The following section takes a closer look at the sensors used in various research projects, the types of data transmission processes, and other equipment that could be included in probe vehicle systems.

VTTI Naturalistic Driving

Current practices at Virginia Tech can be directly linked to a probe vehicle system. VTTI has instrumented many vehicles to support naturalistic driving studies (16). Naturalistic data collection is the collection of driver behavior and performance data in a natural environment. Naturalistic data collection has opened the door for tremendous possibilities in transportation research. Data regarding vehicle position, orientation, speed, acceleration, range, range rate, headway, time to collision (TTC), brake pedal input, as well as qualitative data such as pre-incident maneuvers can be used to describe the driver behavior. Qualitative data such as the roadway type, number of lanes, traffic density, time of day, and weather can be used to describe the driving environment. Tying these data together allows for an understanding of the conditions that exist during events, such as accidents, as well as for attaining baseline data during regular driving. This in situ process uses drivers who operate vehicles that have been equipped with specialized sensors, processing, and recording equipment. In effect, the vehicle becomes the data collection device. The drivers operate and interact with these vehicles during their normal driving routines while the data collection equipment is continuously recording numerous items of interest during the entire driving period (16). The belief is that the data could be very valuable for assessing the condition of the infrastructure, as well as the driver perception of its health and level of service. In a similar manner, the same data could be collected by regular vehicles using the available sensors (e.g. by the trucks comprising a delivery company’s fleet).

Positioning Receivers

In order for the data to be given a unique location (i.e. a point on a road), the condition sensors must be linked somehow with a positioning device. All of the studies that were reviewed used some form of global positioning system (GPS). In the majority of cases, a typical GPS unit was present in the probe vehicle and linked via computer to the condition sensor. This time and location stamp process helps to create a profile of the road as more and more vehicles record similar location stamps (6). For example,
Ndoye et al (2009) used a Garmin GPS receiver. Most of the GPS devices report not only time and position, but speed and heading as well (8).

However, other studies, such as the VII proof of concept, determined that these low cost receivers were not accurate enough for practical use. The VII Consortium used a confidence level of 95% in their location tests. Filtering processes, which included dead reckoning and track smoothing, were applied to the collected data. It was found that this reduced the accuracy in more dynamic driving situations such as turns and constant braking. It did, however, improve accuracy on straight stretches of road where there are fewer road anomalies. It was noted that improvements and refinements could be made to solve the accuracy problem. Since there are an infinite number of operational situations on the road, the system must be developed to improve accuracy. It was also suggested that non-GPS positioning processes be explored (6).

Ndoye et al (2009) explored the idea of filtering GPS data. In order to avoid skewed data by GPS outliers, a model was created to remove any GPS observations that were recorded at an unusual vehicle speed. In addition, any GPS observation that was recorded when the speed of the vehicle was less than 1 mph was removed to account for vehicle stoppages. The estimated composite signal that was created using the recursive algorithm was plotted along with the results from each test run. It was proven that the composite signal kept the integrity of the data plot while filtering out the sensor noise. Composite models for GPS positioning also showed a distinct improvement from the individual paths generated by the GPS receiver. Therefore, it can be concluded that the composite signals display a more accurate description of the location of the probe vehicle (7).

**Pavement Condition Sensors**

Measuring road roughness is the main objective of the probe vehicle system for this thesis. This not only includes obtaining a profile of the road, but also detecting larger road defects, such as potholes. One problem with using probe vehicles is the lack of specialized sensors for data collection. A much more limited set of sensors must be utilized for the project to function (17). To accomplish this task, there are a wide range of low cost sensors that can be used to gather information. The most common sensor is an accelerometer. The setup of an accelerometer was briefly described in Chapter I. The use of accelerometers has been tested in several pavement application studies. Dawkins et al proposed using accelerometers to help predict the IRI of roadways (17).

The BiFi project used probe vehicles, each equipped with a StarFrec Flightrecorder and a reference accelerometer to record vehicular data. The reference accelerometers were attached to the rail below the front seat and collected acceleration data in the X, Y, and Z directions (18). Ndoye et al (7) focused more on the synchronization of pavement data rather than the actual data collection techniques. However, it should be noted that vertical accelerometers were used in the study. The semi-automated distributed network created could log accelerometer data, which are routinely used for stability control and navigation. The accelerometer sensor could record vertical acceleration in the vehicle along a proposed route. Using GPS, a time and location stamp could be placed on each measurement to provide a profile of the road (7). The Pothole Patrol study, developed by the Massachusetts Institute of Technology (MIT) in the Boston area, capitalized on similar concepts. Each probe vehicle, in this case a fleet of Boston taxis, was equipped with three accelerometer sensors. The three accelerometers report acceleration and position.
380 times per second. The signal processing software on the mounted computer then combines this with the vehicle speed and yields a low-rate stream of high probability pothole detections (8).

Other Equipment

Several other sensors found in typical vehicles may also be helpful in assessing the condition of roads. Dawkins et al (17) proposed that measuring steer angle could be used to detect potholes. The report also noted that a linear potentiometer would be able to calculate the IRI directly if one were installed on a production vehicle, but is not available at this time (17). The BiFi project outlined the use of anti-lock braking system information, outdoor temperature, fog light use, and velocity to model road condition, friction, and weather conditions (18).

Condition sensors also need a series of equipment to process and input data. This equipment does not necessarily collect road condition data, but helps to integrate the condition sensors in an applicable manner. The Pothole Patrol probe vehicles were equipped with a Soekris 4801 embedded computer running Linux, a WiFi card, a Sprint EVDO Rev A network card, and an external GPS device. These were used to compliment the three accelerometer sensors (8). The INTRO project in Sweden used PUMA units for data acquisition. Each unit was equipped with a standard SD card and a GPS receiver. The units logged a variety of data, including longitudinal acceleration, wheel speed and angle, yaw rate, location, vehicle speed, and brake application (19). The CarTel software ran on Linux with a 586-class processor, 128 MB of RAM and a giga-byte of flash memory. Each computer is equipped with a WiFi card and a GPS unit. While the CarTel project is currently being utilized for traffic advisory purposes, expansion to include road condition is possible in the future (20).

DEPLOYMENT AND SYSTEM INTEGRATION

Penetration Percentage

One of the key factors in probe vehicle studies is deployment. Once the vehicles have been equipped with the necessary sensors and receivers, a reasonable level of coverage must be obtained on the network. Road coverage and fleet size both factor into deployment. Each probe vehicle must be able to cover a certain amount of road, while the entire fleet should be large enough to obtain sufficient data. Dai et al (21) focused on the optimum probe penetration percentage for data acquisition. While the actual tests were for traffic data collection (as opposed to pavement condition), the principles can still be applied to pavement condition assessment. The emerging concept of using probe vehicles to provide real-time traffic information requires the determination of several unknown variables, including coverage and accuracy. Therefore, a traffic simulation method was used for varying penetration in an attempt to discover the minimum number of probe vehicles required to accurately depict real time traffic information. The traffic parameters used in the simulation include route speed, link travel times, and incident detection (21).

The performance of each penetration ratio was assessed in terms of coverage and accuracy. The coverage of the network was defined as the proportion of links that are traversed by probe vehicles, which should be more than the predefined initial probe vehicle proportion over a given time period. The accuracy of the data collected was a function of the probability that the relative error in travel times is less than the required tolerance (i.e. 5%). The more probe vehicles traversing a given link over a longer period of time will create a better picture of what the road conditions actually are. However, it is impractical in actual deployment to use an extremely high number of probe vehicles, mainly due to the large cost that would be
incurred. Therefore, a heuristic algorithm was developed to determine the ideal minimum probe penetration that will still reliably estimate link speeds and travel times over the network. For example, a probe penetration of 5% will achieve at least 90% accuracy in the simulated network if the traffic volume is greater than 2500 vehicles per hour (21).

**Distributed vs. Centralized Systems**

There are multiple ways to transmit the collect data from probe vehicles to a satellite source for analysis. The main two are distributed and centralized systems. Distributed systems focus on more transmission from vehicle to vehicle. Centralized systems rely on road-side hubs for data transmission from vehicle to hub. There is a lot of speculation as to which system provides more coverage and more accurate data.

Otto et al (22) took a closer look at this debate. With respect to data distribution for traffic applications, two distinct methods are proposed. Both methods yield various pros and cons for the application of both traffic advisory systems and pavement condition information. The use of such models for traffic data collection is believed to improve data coverage, cost of collection, and accuracy of results. Centralized data models, also referred to as infrastructure-based models, rely on road-side equipment for data collection. The equipment collects data from passing probe vehicles and then uploads that data to a centralized location. Distributed data models, in contrast, use vehicle-to-vehicle data exchange to collect data. Information is transmitted directly between nearby probe vehicles. While this method is believed to be able to reduce the cost of data collection, the accuracy of the data is questioned.

**FINDINGS FROM PAST AND ON-GOING STUDIES**

**FHWA Vehicle Infrastructure Integration Proof of Concept**

While the VII Proof of Concept spanned a wide range of ideas, the probe data collection function of the on-board equipment (OBE) in the study is of the most concern for this thesis. The FHWA proposed that an OBE would be equipped with the necessary equipment for pavement condition data collection. Through the DSRC radio system, the data collected would be relayed to an outside terminal for processing. The probe collection works by gathering the vehicle data and position in order to create a snapshot of the current state of the vehicle and roadway. By saving a large amount of snapshots along the route of the vehicle, data and position information can be readily collected. The study recommended that the probe data collected in the POC be analyzed; representative models of probe data user applications should be developed in order to assess the true mathematically relevant requirements on vehicle sampling density and scope of vehicle parameters sampled (6).

**Auburn University Pooled Fund Pavement Applications Study for IntelliDrive**

Research regarding pavement condition data was performed under the umbrella of the initiative formerly known as IntelliDrive\textsuperscript{SM} starting in 2010. Testing was performed at the National Center for Asphalt Technology (NCAT) test track. Vehicles instrumented with accelerometers, gyroscopes, and suspension deflection meters were used to estimate the IRI. The concept relies on the correlation between vehicle vibrations and pavement profile while traveling along a road surface. During testing, the vibrations increased on rough roads and decreased on smooth roads. By taking the root mean square of a signal measurement, the amount of overall vibrations across a given segment was determined. Variables such as speed and vehicle suspension were also taken into account. Figure 2 shows the results of the root mean
square quarter car acceleration model in comparison to the IRI. The resulting data shows the same trend as the known IRI values for the pavement sections, with only a few expected differences in magnitude. The study suggested that since roughness changes slowly over time, an estimation of the IRI will be much more robust and accurate using a higher penetration of measurement vehicles (17).

The detection of potholes using typical vehicle sensors was also explored during the study. The existence of large bumps in the road was identified by spikes in the measured vibration signal. The research team instituted two algorithms (i.e., a sigma threshold and wavelet transform), to correctly detect these spikes in the signal. The threshold established in the data processing was 6 times the standard deviation of the signal. A scaling factor in both methods was adjusted to identify more or less spikes in the signal (23). Figure 3 shows the detected pothole locations using both methods.

![Figure 2 IRI compared to RMS acceleration of quarter car model (22).](image2)

![Figure 3 Pothole locations using a 6σ threshold with (a) Wavelet Transform Method and (b) Sigma Threshold Method (23).](image3)
As a reliable probe vehicle system would involve the wireless transmission of data, tests were conducted at the NCAT test track via dedicated short range communication (DSRC) radios to determine the capabilities of real-time transmission. The preliminary tests concluded that a vehicle operating at highway speeds would travel 500 m before successful data transmission. The size of the data tested was equivalent to one lap around the test track (approximately 2700 m). The effective transmission range was determined to be approximately 700 m without the loss of any data packets. It was recommended that the algorithms for processing data be implemented in the vehicle, so that the actual transmitted data will include a short message. The shorter message transmission will optimize the flow of wireless information for a system operating in real-time (17).

The final report recommended that a pilot program be conducted with one or more states. The most feasible applications for improving pavement maintenance included implementing a root mean square algorithm on accelerometer measurements to estimate the IRI and using a sigma threshold algorithm on accelerometer measurements to detect potholes. The prototype vehicle recommended was a 2007 Infinity G35 sedan equipped with the following: Novatel Propak v3 GPS receiver, Crossbow 440 IMU, and Celesco CLP Linear Potentiometers. These devices are shown in Figure 4 (23).

Figure 4 Hardware used in prototype system (Left) Novatel Propak v3 GPS receiver (Center) Crossbow 440 IMU (Right) Celesco Linear Potentiometer (23).

**Bearing Information through Vehicle Intelligence: BiFi**

The BiFi Project, conducted in Sweden, is an ongoing study that tests the hypothesis that normal vehicles can be used to estimate road stability. The study was created by the need for a better road monitoring system to address problems with the pavement in a timely fashion. The goal of the project is to use vehicle data, field measurements, and CAN-bus data to accurately detect stability reduced sections of pavement. This would avoid unnecessary road closures and keep the Swedish timber transportation operations running smoothly (18). The first test measurements were conducted in February, March, and April of 2010. The results thus far have been positive. Over 240km of road have been measured in Goteborg, Sweden, totaling about 2GB of vehicular data. One distinct finding from the preliminary tests was that different types of road materials used different wavebands from the reference sensors. For roads that were half gravel and half asphalt, the acceleration measurements were inherently different. In addition, lateral acceleration signatures from the instrumented vehicles (using accelerometers) have shown a correlation to specific road conditions. Test results from the Slipper Road Information System also indicate that pavement condition can be directly linked to vehicle acceleration sensors (24).
Massachusetts Institute of Technology Pothole Patrol

The Pothole Patrol is an experimental evaluation which attempted to address road condition issues. It assessed road condition using a mobile sensor system with a fleet of probe vehicles, namely a group of seven Toyota Prius taxis in the Boston area. Accelerometers were installed in the glove boxes of the taxis to maintain consistent readings and remain out of the way of vehicle operators. An on board computer integrated the sensors as the taxis drove their normal routes throughout the day. Using probe vehicles for this type of pavement monitoring creates a dynamic measurement system which covers a large scope of the road network (8).

Several anomalies arose during pothole detection. First, braking, door slams, sudden swerves, etc. all yielded high-energy acceleration signatures. In addition, pothole detections do not always record the same signature, since some of the measurement depends on the dynamics of the probe vehicle. A machine learning approach was implemented to address these issues. Several of the roads were first manually inspected, so the testers could get an idea of where the real discontinuities were and then compare them to the sensor measurements. The event classes that were considered were: crosswalks and expansion joints, potholes, railroad crossings, manholes, hard stops, and turns. Based on peak X and Z accelerations from the inspected incidents, the detector can be trained to report only correct observations. A clustered based filter was also applied to the process, which only reports detections that occurred several times (disposal of outliers). This filter has resulted in a 90% success rate for pothole and other hazard detection. The GPS positioning was reported to be within 3.3 meters on average, which is consistent with typical GPS measurements (8).

Five main filters were applied to the data to help eliminate false positive detections. They are as follows:

1. Ignore low speeds, which eliminates door slams and most curb interactions
2. High pass filters out low frequency signals, accounting for turns, braking, and acceleration
3. Z-Peak filters out minor anomalies that are not significant in the study
4. XZ Ratio filter to eliminate railroad crossings, speed bumps, and expansion joints
5. Speed/Z Ratio, which removes relatively small anomalies at high speeds

Tuning parameters were used to implement these filters. They were based on the training data samples collected before the experiment. It should be noted that since most drivers swerve to avoid large road anomalies such as potholes, the gathered data could be lower than expected. Based on preliminary evaluation, it was determined that the Pothole Patrol process yielded only a 7.6% false positive detection rate. It was also concluded that the success rate for anomaly detection yields is much higher on roads in good condition. A poor conditioned road presents many more unknowns, so the process is more prone to false positive detection. In the controlled experiments, less than 0.2% of the detections were misidentified (8).

CarTel: A Distributed Mobile Sensor Computing System

CarTel is a mobile sensor computing system which collects, processes, delivers, and visualizes heterogeneous data from mobile sensing units, typically attached to automobiles. The nodes in the system gather data and deliver the data to a central portal via opportunistic wireless internet connection (WiFi or Bluetooth). The system takes advantage of new technology which allows for the cheap embedding of computing systems in vehicles. By deploying these outfitted vehicles, a higher scale and accuracy in
traffic data collection can be achieved. Studies have confirmed that this technology and principle can be used in environmental monitoring, civil infrastructure monitoring, geo-imaging, data muling, and automotive diagnostic analysis. CarTel has been utilized in both Boston and Seattle for over a year on six cars. It has aimed to handle large amounts of data, handle opportunistic wireless connectivity, and provide a simple programming interface. Ten CarTel nodes have been installed to date, with an expansion plan in place. While the main application of the system is not related to pavement condition, CarTel still capitalizes on several basic principles that can be applied to pavement condition assessment.

**European Intelligent Roads Study (Intro)**

The INTRO program is a European effort to evaluate the use of probe vehicles in road condition data collecting. This study tested several methods of data collection to determine how feasible a large scale deployment of such methods would be. The theory is that inexpensive sensors, some of which are already deployed on production vehicles, can provide nearly constant updated information on road networks without the use of special measuring equipment. Databases already collected using profilometers, skid resistance devices, and user surveys were used for comparison. The task objectives are as follows: Review available sensors, including identification and data collection techniques; Identification of suitable probe vehicles, including cars and buses; Collect data and find relationships (if any) between probe data and databases; Use probe vehicle data to identify areas of poor road condition (includes rutting, cracking, longitudinal roughness, raveling, and potholes).

Tests were conducted in Sweden and the United Kingdom with a variety of probe vehicles and sensors. The units logged an assortment of data, including longitudinal acceleration, wheel speed and angle, yaw rate, location, vehicle speed, and brake application. Testing confirmed the usefulness of these units. Test runs were synchronized using the GPS data. The first aspect analyzed was the repeatability of the probe data. It was found that the level of repeatability relied greatly on the type of road. Researchers found a much higher repeatability with probe vehicles traversing rural roads than those testing on urban roads. This is due to the increased amount of acceleration changes and variability that comes with driving in a heavily populated area. Next, the probe vehicle lateral acceleration was compared to the radius of curvature from the profilometers traveling on the same path. It was hypothesized that there should be some level of agreement between these two data sets. However, since most of the tests in Sweden were conducted on urban roads, it was difficult to establish a relationship between lateral acceleration and the profilometer’s radius of curvature. It became impossible to distinguish irregular driving behavior from actual road defects. The researchers in Sweden suggested that vertical acceleration be added to the PUMA unit’s data collection.

Profilometer data, SCRIM data (skid resistance), and user surveys were the main tools for test comparison to identify pavement defects. The first test involved using steering wheel angle to identify rutting. The theory was that rapid wheel adjustment occurs when the car sinks to the bottom of a rut in the road. The steering wheel angle turned out to be “noisy”, and the presence of ruts was not able to be identified. Therefore, this application was determined to be not practical for probe vehicles. Likewise, the use of ABS and wheel speed data was found to be not practical for identifying areas of low skid resistance. While the data collection occurred with little noise, researchers could not find a correlation that could relate it to skid resistance problem areas. The last theory tested was that lateral acceleration could be used to identify “rough” areas of the pavement. Since drastic changes in lateral acceleration occur during vehicle cornering, these incidents were first isolated. Then, the lateral acceleration data was plotted...
against steering wheel angle. This established relationship allows for the calculation of expected lateral acceleration at any given speed. Therefore, if the data greatly differed from the expected values, it is possible that rough pavement exists at that location. The tests all yielding a fairly high amount of false positives, probably resulting from the several other explanations for a deviation in expected lateral acceleration values. Researchers concluded that while the current process is not practical for utilization, a higher level of filtering could yield better results (19).

In conclusion, the main general findings from the INTRO study were as follows: GPS data gives a relatively accurate vehicle location for practical use; rural roads have much more potential for probe vehicle deployment than urban roads; lateral acceleration correlations with steering angle and speed could potentially identify rough pavement sections with more filtering (19).

LITERATURE REVIEW SUMMARY

Using probe vehicles to collect road infrastructure information is a relatively new concept in the beginning stages of development. Several studies have tested vehicle sensor applications, data collection techniques, processing methods, and overall system feasibility. While the concept will be expanded and refined in the future, it is important to discover the most practical probe vehicle applications at a research level before a network system is integrated. As stated in the objectives section, this thesis hypothesizes that the most promising application involves utilizing accelerometers to detect poor conditioned areas of pavement. The results of previous and on-going studies mentioned in the literature review, along with available technologies at the Virginia Smart Road, led to the direction of this thesis. The key concepts taken from the literature review are summarized below.

- Probe vehicles rely on typical passenger car and truck sensors to collect relevant roadway information (6).
- An integrated system, where condition data would be collected by probe vehicles and transmitted wirelessly, has the potential to reduce asset management data collection costs and improve data robustness.
- Probe vehicle sensors work by collecting data, such as acceleration, and using GPS to pinpoint a specific location that the data applies to (6).
- VTTI Naturalistic Driving Studies has several vehicles outfitted with typical sensors that could prove useful in a probe vehicle system (16).
- Both American (IntelliDrive) and European (Intro) initiatives have concluded that GPS receivers provide acceptable accuracy on rural, straight roadways. Some GPS tests have failed in urban areas, where large buildings interfere with satellites and vehicles experience more constant braking (6, 19).
- A University of Auburn study has shown a distinct relation between the road profile and vertical acceleration, mostly relating their results to the International Roughness Index. The Pothole Patrol Project, performed by MIT in the Boston area, has also successfully used vertical accelerometers to detect large potholes in the road (8, 17, 23).
- Due to the large amount of anomalies that occur while driving, The Pothole Patrol used filters to reduce the amount of false positive pothole detections. This included taking into account quick braking, curb interactions, railroad crossings, speed bumps, and high speed anomalies (8).
- Acceleration and road profiles have been compared using methods such as visual inspection of data, root mean square calculations, Gaussian predictors, coherence function determination, and maximum value identifications (23).

These findings allowed for the development of the experimental plan that can be found in the following chapters.
CHAPTER 3 - EXPERIMENTAL DESIGN AND DATA COLLECTION

OVERVIEW

Based on the findings from the literature review in Chapter II, an experiment was designed to evaluate the ability of probe vehicles to collect relevant pavement condition data. The experiment, described below, was conducted at the Virginia Smart Road, a closed circuit test center located in Blacksburg, Virginia. The experiment first called for preliminary analysis of available data at the VTTI and then proceeded with a more robust data collection process using available instrumented vehicles.

EXPERIMENTAL ENVIRONMENT

The Virginia Smart Road was the location for nearly all experimentation. The facility is built to federal and state specifications with weather-making equipment (rain, snow and fog), variable lighting equipment, a working intersection, and pavement testing capabilities. In addition, the road is paved with 13 different types of pavement, all of which are analyzed and tested for durability and safety (25). The different pavement types allowed for variability during data collection, similar to what may be expected over long stretches of highways and other roads. Figure 5 shows a bird’s eye view of the Smart Road, with labeled sections and areas of interest.

![Figure 5 Virginia Smart Road Layout](image)

The testing area, which begins directly after the Smart Road Bridge (far right of Figure 5) and continues up to the end of Section A, totals over 7,000 feet. Table 1 provides a detailed description of each section, including current surface type and total length. Since all testing was performed traveling uphill in the right hand lane (westbound), the lengths reflect the estimated centerline distance of this lane.
Table 1 Virginia Smart Road Section Layout (Uphill Right Lane)

<table>
<thead>
<tr>
<th>Section</th>
<th>Surface Type</th>
<th>Length (ft)</th>
<th>Aggregate (ft)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Concrete</td>
<td>JRCP and CRCP</td>
<td>3,200</td>
<td>3,200</td>
</tr>
<tr>
<td>L</td>
<td>SMA-12.5</td>
<td>326</td>
<td>3,526</td>
</tr>
<tr>
<td>K</td>
<td>OGFC (SM-9.5D)</td>
<td>302</td>
<td>3,828</td>
</tr>
<tr>
<td>J</td>
<td>SM-9.5D</td>
<td>280</td>
<td>4,108</td>
</tr>
<tr>
<td>I</td>
<td>SM-9.5A</td>
<td>338</td>
<td>4,446</td>
</tr>
<tr>
<td>EFGH</td>
<td>SM-9.5D</td>
<td>1166</td>
<td>5,615</td>
</tr>
<tr>
<td>Bridge</td>
<td>Concrete</td>
<td>315</td>
<td>5,927</td>
</tr>
<tr>
<td>D</td>
<td>SM-9.5A</td>
<td>407</td>
<td>6,334</td>
</tr>
<tr>
<td>C</td>
<td>SM-9.5E</td>
<td>292</td>
<td>6,626</td>
</tr>
<tr>
<td>B</td>
<td>SM-9.5D</td>
<td>289</td>
<td>6,915</td>
</tr>
<tr>
<td>A</td>
<td>SM-12.5D</td>
<td>347</td>
<td>7,262</td>
</tr>
</tbody>
</table>

The test section is almost evenly split between concrete and asphalt pavement, with one small concrete bridge in the middle of the asphalt sections.

PRELIMINARY DATA COLLECTION

In order to first validate the concept behind this thesis, preliminary data that had already been collected at the Virginia Smart Road was obtained. The road profile data came from an inertial-based laser profiler in May of 2010. The data was collected during the annual equipment rodeo at the Smart Road. The acceleration data came from a Brake Assist Study using Naturalistic Driver instrumented vehicles at the Virginia Smart Road (26). The data for both profile and acceleration were collected in the form of uphill runs in the right lane of the Smart Road from the beginning of the first test section to the end of the fifth test section.

For the acceleration profile, measurements were obtained at 2 meter intervals (10 Hz data collection system with vehicle speed of 70 km/h). This frequency slightly varies throughout the test section, which occasionally results in slightly different measurement counts for each run. The total number of measurements for a single test run was typically around 1050 measurements. For the smoothness profile, measurements were obtained at 25 to 150 mm intervals (1 to 6 in.); however, only measurements taken at 2 m intervals were selected to match the acceleration profile. The profile measurements were taken along both wheel paths; these two measurements were averaged to provide one value at each interval. Both sets of distance measurements were converted to feet before being analyzed. Since the acceleration measurements were taken consecutively with no break in data collection, GPS coordinates were used to identify the beginning and end of each test run. Four runs of each data type were used in the analysis.

ROBUST DATA COLLECTION

Once the relationship between acceleration and road profile was validated, further testing was conducted on the Virginia Smart Road. The experiment was designed specifically for vertical acceleration data collection using multiple probe vehicles. This included the collection of acceleration, speed, and supporting vehicular data using two VTTI instrumented vehicles. Road profile data was concurrently collected by a high-speed laser profiler. The objective of this data collection procedure was to provide a
primary source of acceleration data that was robust enough for simulated analysis and specifically tailored towards the goals of this thesis.

**Data Collection System**

The probe vehicles used in testing were instrumented with a Data Acquisition System (DAS). The system developed by VTTI is known as NEXTgen. It is designed for advanced data collection capabilities and is installed in many of VTTI’s vehicles. The NEXTgen system consists of a control box and a head unit. Figure 6 and Figure 7 shows the NEXTgen control box and head unit.

![Figure 6 NEXTgen control box.](image)

![Figure 7 NEXTgen head unit.](image)

In order to record vehicle movements and events during testing, three accelerometers (Model Number AIS326DQ), three gyroscopes (model Number LPY510AL), and a GPS (Fasttrax UP501) were included in the NEXTgen head unit. The head unit was installed near the windshield in all vehicles and is typically found behind the rearview mirror. A computer displayed the collected information from the NEXTgen sensors during testing. The data was stored on a hard drive in the vehicle and later uploaded to the VTTI database for processing. Figure 8 shows a sample of the data display from the NEXTgen computer software.
Figure 8 Sample acceleration and speed data from NEXTgen system.

The NEXTgen system used for the study included the following components:

- 9-40 volt power input
- Real Time H264 Encoding
- Real Time G711 Encoding
- Intelligent Power Control (Battery and Charger in system)
- Ethernet Port
- Serial Port
- USB Port
- 3 CAN Ports
- Wireless Radar
- Cellular Module for Remote Access and System Health Checks
- Continuous Collection of Visual and Vehicle Data
- Lane Tracker and Face Tracker
- Alcohol Sensor
- Sound Level Meter
- Light Meter
- 4 multiplexed video channels providing 10 total video channels
- Record up to 6 channels of continuous video.

Experimental Vehicles and Data Collection System

Three test vehicles were used for data collection. The first vehicle, a Ford Fusion sedan, served as the primary data collection probe vehicle. It was instrumented with the VTTI NEXTgen system. The primary objective of the Ford Fusion was to collect vertical acceleration data. GPS positioning, speed, and distance supplemented the acceleration measurements. The Fusion was used on all three days of testing. In order to expand the study to examine the performance of commercial vehicles, a 1997 Volvo Tractor Trailer was introduced as the second DAS instrumented vehicle. The tractor trailer was only used on the
second day of testing. This vehicle collected the same information as the Ford Fusion. Figure 9 and 10 show the Ford Fusion and tractor trailer prior to testing.

![Figure 9 Sedan probe vehicle.](image)

The third vehicle represented the control of the experiment, a Virginia Department of Transportation (VDOT) high speed laser-profiler. This type of vehicle is the state-of-the-practice for evaluating ride quality. The van measures the pavement profile using two sets of lasers and accelerometers (one in each wheel path), which record the distance from the laser to the pavement. This information is then used to compute the International Roughness Index (IRI), which quantities the smoothness of the road. The profiler was only used on the second day of testing. Figure 11 shows the profiler prior to testing.

![Figure 10 Tractor trailer probe vehicle.](image)
Experimental Setup and Process

The collection of acceleration and smoothness data took place over three days on the Virginia Smart Road. All test runs were performed strictly uphill in the right lane. The test section began 150 feet before the beginning of Section 1 (just after the bridge) and ended 50 feet after the end of Section 5 (just before the exit ramp). Both start and end locations were marked with a bump strip and cone. In addition, a third bump strip was placed at the beginning of the Section 2 (grooved concrete). For the DAS vehicles, the runs were triggered by a button press at the beginning and ending cone. A special cone was used by the profiler to trigger its runs. Ten runs were made at 50 mph by all vehicles. An additional 2 runs each were made at 40 mph and 65 mph by all vehicles. The Fusion then completed 20 additional runs, all at 50 mph, using the same experimental setup. Figures 12 and 13 show pictures taken from the Ford Fusion during testing.
Data Retrieval

The data was mined from a VTTI database. The relevant information, including acceleration, longitude, latitude, speed, and distance covered were transferred to Microsoft Excel files for each test run. Using the button press triggers, the test sections were identified and cropped. There were 30 total runs processed for the Ford Fusion and 9 runs for the Volvo tractor trailer. The data collected by the laser profiler was also transferred to Microsoft Excel. There were 10 total runs processed for the profiler. Table 2 provides a summary of the test vehicles and data collection.

Table 2 Data Collection Summary

<table>
<thead>
<tr>
<th>Vehicle</th>
<th>Ford Fusion</th>
<th>Tractor Trailer</th>
<th>Laser Profiler</th>
</tr>
</thead>
<tbody>
<tr>
<td>Days Used</td>
<td>3</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Test Runs Completed (50mph)</td>
<td>30</td>
<td>9</td>
<td>10</td>
</tr>
<tr>
<td>Additional Speed Runs?</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Additional Highway Run?</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Primary Data</td>
<td>Acceleration</td>
<td>Acceleration</td>
<td>Road Profile</td>
</tr>
<tr>
<td>Test Trigger</td>
<td>Button Press</td>
<td>Button Press</td>
<td>Specialized Cone</td>
</tr>
</tbody>
</table>
CHAPTER 4 - RESULTS AND ANALYSIS

OVERVIEW

This chapter presents the results from all data analysis conducted for this thesis. The first sections of the chapter show preliminary results from available data at VTTI. Part of these results has been published by the 2012 TRB Conference (12). The subsequent sections show the results from the experiment described in the previous chapter. Following those results are analysis and application examples.

PRELIMINARY RESULTS

In order to validate the experimental design and necessity for the collection of more acceleration data, preliminary analysis was conducted using data available at the Virginia Tech Transportation Institute. The preliminary analysis began with the inspection of four acceleration profiles. The acceleration data was obtained during a Brake Assist Study using a Naturalistic Driver instrumented vehicle at the Virginia Smart Road. While the study aimed to increase optimal braking performance during panic or emergency braking scenarios, a wide range of data, including vertical acceleration, was collected and documented by the vehicles (26). The data was presented as a continuous file, so GPS coordinates were used to identify the beginning and end of each test run. This resulted in the separation of four uphill runs in the right lane of the Virginia Smart Road.

For the acceleration profile, measurements were obtained at roughly 2 meter (6.6 feet) intervals (10 Hz data collection system with vehicle speed of 70 km/h). The distance measurements were converted to feet before being analyzed. The goals of the preliminary analysis were to: plot the acceleration profile for a test run going uphill on the Virginia Smart Road, assess the initial repeatability of acceleration measurements, and compare the acceleration profile to a smoothness profile obtained by a high-speed laser profiler. A plot of the four acceleration profiles, comprised of 1051 individual measurements each, is shown in Figure 14.

![Figure 14 Acceleration measurements on the Virginia Smart Road.](image-url)
**Repeatability of Acceleration Measurements**

Before comparing the acceleration and smoothness profiles, the repeatability of acceleration measurements was analyzed. The four test runs were used in the analysis. All of the measurements were taken by the same NDS instrumented vehicle, traveling uphill in the right lane of the Virginia Smart Road. Since the outfitted accelerometer obtained measurements at slightly different locations and intervals, the measurements were interpolated, using one test run as the reference (Test Run 3, 1051 measurements). The interpolation (spline form) of the measurements was performed using a Matlab script file. Then, cross-correlation was used to align the runs and determine the accuracy of the measurements. This technique has been previously successfully implemented to determine the repeatability and reproducibility of the profiler measurements (27). Cross-correlation is a measure used to verify the similarity of two waveforms. It is defined as follows in Equation 1 (28):

\[
\phi_{xy}(\tau) = E[x(t)y(t+\tau)] = \lim_{L \to \infty} \frac{1}{L} \int_{0}^{L} x(t)y(t+\tau)dt; \quad \tau \geq 0
\]

where,
- \(E[\cdot] = \) expected value
- \(\tau = \) shift factor
- \(x(t), y(t) = \) two waveforms defined in the range of \(t = [0, \infty)\)

Since the acceleration measurements are discrete, the cross-correlation function can be estimated by:

\[
\phi_{xy}(m) = E[x_ny_{n+m}] = \lim_{L \to \infty} \frac{1}{L} \sum_{n=0}^{L-1} x_ny_{n+m}; \quad m \geq 0
\]

where,
- \(m = \) shift between the measurements

Equation 2 can be normalized by dividing it by the standard deviation of the two waveforms. To make the computations more efficient, the waveform measurements can be shifted to have a mean of zero (27). Cross-correlation can then be used to find how much one waveform needs to be shifted to obtain the best match with another waveform. The amount of shifting that provides the highest cross-correlation is selected. After shifting the signal, the integral of the product of both signals is calculated based on Equation 1. The integral is maximized when the signals perfectly match. This procedure can be used to determine the optimum shift to synchronize the measurements. Figure 15 illustrates the operation using a subset of two different test runs of collected acceleration data. It is evident that one data set is shifted slightly to the left. While a visual shift could be applied, the cross-correlation can find the optimum offset that maximizes the correlation between all measurements.

The cross-correlation between the two acceleration measurements is shown in Figure 16 and was calculated using the Matlab cross-correlation function. The peak cross-correlation occurs at a -4 measurement offset. This offset is used to synchronize the measurements. Figure 17 shows the aligned measurements after shifts to the left. This procedure was performed for each of the test runs. The maximum cross-correlation value was then used as a shift factor to match up the data more accurately. A 4 measurement shift (approximately 25 ft) was applied to test runs 1 and 2, while a 2 measurement shift (approximately 12.5 ft) was applied to test run 4.
Figure 15 Acceleration measurements before cross-correlation shift.

Figure 16 Cross-correlation between acceleration test runs 1 and 3.

Figure 17 Acceleration measurements after cross-correlation shift.
After the measurement shift, the repeatability was assessed using the standard deviation of the measurement differences. The process of shifting based on cross correlation results yielded the smallest standard deviation differences in each of the test runs. To evaluate repeatability, the standard deviation of the differences (29) between the reference run (third run) and the other runs was evaluated. These results, along with the variance for each test run, are shown in Table 3. The square root of the average variance describes the total average standard deviation. This was determined to be 0.0225 g. These values were significantly reduced after shifting and can be considered relatively low (ideal repeatability) across the acceleration measurements.

To compare the repeatability of acceleration measurements to road profile measurements (current practice), a signal-to-noise ratio for each measurement type was computed. The signal-to-noise ratio can accurately compare the repeatability of two measurement sets that use different units. The signal-to-noise ratio was found by dividing the average standard deviation of all measurement sets by the total average standard deviation of measurement differences (shown above as 0.0225 for acceleration measurements). The calculated signal-to-noise ratio for the acceleration measurements was 1.21. The calculated signal-to-noise ratio for the profile measurements was 1.16. The higher the signal-to-noise ratio, the more repeatable the measurements are. This shows that the accelerometer measurements are at least as repeatable as the road profile measurements collected by high speed laser profilers.

Validation of the Acceleration and Smoothness Relationship

Smoothness profile data were obtained using an inertial-based laser profiler at the Virginia Smart Road in May of 2010. The profile data collection was performed as part of the annual equipment rodeo at the Virginia Smart Road. For the smoothness profile, measurements are typically obtained at 25 to 150 mm intervals (1 to 6 in.); however, only measurements taken at 2 m intervals were selected to match the acceleration profile. The profile measurements were taken along both wheel paths; these two measurements were averaged to provide one value at each interval. As with the acceleration measurements, the profile distance measurements were converted to feet before being analyzed. The profiler vehicle triggers the start and end of each test run, so the measurements did not need to be cropped or shifted.

A comparison of smoothness profile and acceleration profile measurements performed at the Virginia Smart Road is presented in Figure 18. Similarities between the two profiles can be visually observed. Both profiles comprise three major sections, with section 1 extending roughly from 0 to 1000 ft, section 2 from 1000 to 3050 ft, and section 3 from 3050 ft to the end of the measured sections. Sections 3 is composed of an asphalt pavement while sections 1 and 2 feature a concrete pavement. In section 2, two subsections of roughly 100 ft each comprise an epoxy coated high friction surface start at roughly 2400 ft.

<table>
<thead>
<tr>
<th>Measurement Type</th>
<th>Test Runs Compared</th>
<th>Value (g)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standard Deviation of Differences</td>
<td>Runs 1 and 3</td>
<td>0.0244</td>
</tr>
<tr>
<td>Standard Deviation of Differences</td>
<td>Runs 2 and 3</td>
<td>0.0206</td>
</tr>
<tr>
<td>Standard Deviation of Differences</td>
<td>Runs 4 and 3</td>
<td>0.0224</td>
</tr>
<tr>
<td>Variance of Differences</td>
<td>Runs 1 and 3</td>
<td>0.000540</td>
</tr>
<tr>
<td>Variance of Differences</td>
<td>Runs 2 and 3</td>
<td>0.000422</td>
</tr>
<tr>
<td>Variance of Differences</td>
<td>Runs 4 and 3</td>
<td>0.000503</td>
</tr>
</tbody>
</table>

To compare the repeatability of acceleration measurements to road profile measurements (current practice), a signal-to-noise ratio for each measurement type was computed. The signal-to-noise ratio can accurately compare the repeatability of two measurement sets that use different units. The signal-to-noise ratio was found by dividing the average standard deviation of all measurement sets by the total average standard deviation of measurement differences (shown above as 0.0225 for acceleration measurements). The calculated signal-to-noise ratio for the acceleration measurements was 1.21. The calculated signal-to-noise ratio for the profile measurements was 1.16. The higher the signal-to-noise ratio, the more repeatable the measurements are. This shows that the accelerometer measurements are at least as repeatable as the road profile measurements collected by high speed laser profilers.
These section divisions are denoted in the figure by vertical green lines. Red circles indicate prominent acceleration and profile peaks present that can be observed at the same location in both profiles.

![Figure 18 Reference profile smoothness data and acceleration data from the Virginia Smart Road.](image)

The coherence function between the acceleration and profile signals is shown in Figure 19. This function measures how much one signal is linearly related to the other signal at each frequency or wavelength (30). It is a real function that varies between 0 and 1 and can be viewed as similar to an $R^2$ measure between the two signals at each frequency. It can be seen that between wavelengths of 50 to 300 m, the coherence function is generally higher than 0.50 with relatively strong coherence (mostly above 0.80) for wavelengths between 70 and 200 m. At short wavelengths (high frequency) the coherence is generally relatively low, which may be attributable to the presence of noise at high frequencies. Furthermore, it is possible (though further investigation is needed) that the vehicle suspension works as a low pass filter that diminishes accelerations at wavelengths shorter than 50 m. To obtain a better understanding of the effect of noise and the low pass filtering characteristics of the vehicle suspension, data would need to be collected at a higher frequency rates.

![Figure 19 Coherence between acceleration and profile data.](image)

A relatively simple and quick measure of agreement between the two measurements is Pearson’s correlation coefficient. Pearson’s correlation between the two signals presented was calculated as 0.50.
This value, although not very high, warrants further investigation of the relationship between the two signals.

DETAILED EXPERIMENTAL VERIFICATION

Acceleration Measurement Overview

The following sections present the results of the robust data collection process described in Chapter 3. The two probe vehicles, a sedan and a tractor trailer, collected vertical acceleration measurements using an accelerometer. These measurements were combined with distance measurements to create an acceleration profile along the testing lane of the Virginia Smart Road (similar to that in Figure 18). These vertical acceleration measurement sets (30 with the sedan and 9 with the tractor trailer) are the focus of the analysis. The measurements sets were first assessed for repeatability, an indication of how well each individual set relates to another. Then, vehicle speed and type were analyzed with respect to their effect on acceleration magnitude. Some preliminary highway measurements, taken at the end of the testing process, are also shown.

Repeatability of Acceleration Measurements

The preliminary analysis concluded that the acceleration measurements demonstrated an acceptable level of repeatability. However, the results warranted further inspection since only four test runs were used in the preliminary analysis. With 30 test runs performed during the instrumented vehicle data collection, a more accurate and statistically relevant representation of repeatability could be realized. The test runs, taken at 50mph, were used in the analysis. All of the measurements were taken by the Ford Fusion, traveling uphill in the right lane of the Virginia Smart Road. A plot of ten of the 30 test runs can be found in Figure 20. From visual inspection, it is evident that the runs are very repeatable, since little deviation from the general trend is evident.

![Figure 20 Acceleration measurements taken by instrumented Ford Fusion.](image)

The same procedure explained in the preliminary repeatability analysis was used for the experimental data. The normalized maximum cross correlation values are shown in Table 4 as percentages. All of the...
runs displayed acceptable correlation with values over 90%, while the majority of the values displayed exceptional correlation with values over 97%.

Table 4 Statistical Comparison of Acceleration Test Measurements

<table>
<thead>
<tr>
<th>Runs Compared</th>
<th>Correlation Value (%)</th>
<th>S.D. of Differences (g)</th>
<th>Var. of Differences (g)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Runs 1 and 10</td>
<td>90.46</td>
<td>0.0199</td>
<td>0.0004</td>
</tr>
<tr>
<td>Runs 2 and 10</td>
<td>97.02</td>
<td>0.0398</td>
<td>0.0016</td>
</tr>
<tr>
<td>Runs 3 and 10</td>
<td>97.75</td>
<td>0.0416</td>
<td>0.0017</td>
</tr>
<tr>
<td>Runs 4 and 10</td>
<td>97.38</td>
<td>0.0444</td>
<td>0.0020</td>
</tr>
<tr>
<td>Runs 5 and 10</td>
<td>97.52</td>
<td>0.0376</td>
<td>0.0014</td>
</tr>
<tr>
<td>Runs 6 and 10</td>
<td>97.33</td>
<td>0.0350</td>
<td>0.0012</td>
</tr>
<tr>
<td>Runs 7 and 10</td>
<td>97.55</td>
<td>0.0101</td>
<td>0.0001</td>
</tr>
<tr>
<td>Runs 8 and 10</td>
<td>90.33</td>
<td>0.0200</td>
<td>0.0004</td>
</tr>
<tr>
<td>Runs 9 and 10</td>
<td>96.55</td>
<td>0.0441</td>
<td>0.0019</td>
</tr>
</tbody>
</table>

To evaluate repeatability, the standard deviation of the differences between the reference run and the other runs was evaluated. These results, along with the variance for each test run, are also shown in Table 4. Only the first ten comparisons are shown below, although each of the 30 runs was used in the calculations. The square root of the average variance describes the total average standard deviation, which was calculated for all thirty test runs. This was determined to be 0.0664. These values can be considered relatively low (ideal repeatability) across the acceleration measurements.

The calculated signal-to-noise ratio for the acceleration measurements was 1.73. The same process was used to evaluate the ten runs performed by the Volvo Tractor Trailer. The results showed promising repeatability, but not to the extent of the Fusion. This could be due to the dynamics of the larger vehicle, which experiences more acceleration variability on the road. The average standard deviation of differences for the truck was calculated to be 0.0712. The signal-to-noise ratio for the truck was determined to be 0.73. The higher the signal-to-noise ratio, the more repeatable the measurements are. This shows that the accelerometer measurements with the sedan are close to the repeatability calculated in the preliminary analysis using the brake study vehicle and high-speed laser profiler. Meanwhile, the repeatability of the tractor trailer measurements may merit further investigation. The script files, which display the equations for all calculated values, can be found in the Appendix.

Effect of Speed on Acceleration Measurements

Unlike laser-based profile measurements, acceleration measurements are sensitive to variations in the probe vehicle being used. The variability of different aspects of acceleration testing was analyzed. First, the effect of speed was tested, since the speed of the vehicle affects the intensity of acceleration measurements. For this analysis, runs at 40, 50, and 65 mph were performed on the Virginia Smart Road. A plot of one run at each speed is shown in Figure 21 below for the Ford Fusion. From visual inspection, it is clear that measurements taken at 65 mph (red) result in higher measured acceleration than those taken at lower speeds. To quantify the difference between speeds, the L1 norm, which is the sum of the absolute values of the acceleration measurements over the entire testing section length, was calculated. The larger the total absolute value, the more acceleration the probe vehicle experiences. One run at each speed was analyzed in this manner. Table 5 summarizes these results.
It does not appear that the increase in magnitude is linear, which is to be expected because vehicle dynamics dictate that acceleration greatly increases at high speeds. The 65 mph measurements experienced a 61% increase in magnitude when compared to the 50 mph measurements. Meanwhile, the 50 mph measurements experienced only a 14% increase in magnitude when compared to the 40 mph measurements. It can be concluded that as speed increases, so does the magnitude of the acceleration. The general ride quality trend still remains intact as each run exhibits similar peaks and rough sections.

The same trend, albeit even more exaggerated, is evident when taking the L1 norm of the truck acceleration measurements. The difference between the absolute value sums are even greater than the sedan probe vehicle measurements, which is expected because the larger truck experiences more acceleration when traversing the road (explored further in the next section). One run at each speed was analyzed in this manner. These results are also summarized in Table 5.

<table>
<thead>
<tr>
<th>Speed</th>
<th>L1 Norm of Sedan Measurements</th>
<th>L1 Norm of Truck Measurements</th>
</tr>
</thead>
<tbody>
<tr>
<td>40 mph</td>
<td>25.97 g</td>
<td>28.00 g</td>
</tr>
<tr>
<td>50 mph</td>
<td>29.73 g</td>
<td>39.98 g</td>
</tr>
<tr>
<td>65 mph</td>
<td>48.04 g</td>
<td>67.99 g</td>
</tr>
</tbody>
</table>

**Effect of Vehicle Type on Acceleration Measurements**

The type of vehicle also has an effect on the magnitude of acceleration measurements. This is due to variations in vehicle parameters, including suspension type and tire size. To illustrate this difference, two probe vehicles were used during testing: a small passenger car and a large tractor trailer. A plot of one run with each vehicle at 50 mph is shown in Figure 22 below.
Figure 22 Acceleration measurements with Ford Fusion and Volvo Tractor Trailer.

From visual inspection, it is clear that acceleration measurements taken with the tractor trailer are higher in magnitude than those taken with the sedan. This is consistent with expectations and reinforces the validity of the collected data. The vehicle dynamics and suspension of the larger, heavier truck cause the vehicle to experience more acceleration as a result of road roughness. To quantify the difference between vehicle types, the L1 norm of the acceleration measurements over the entire testing section length was calculated. One run using each vehicle (50 mph) was analyzed in this manner. Table 6 summarizes these results.

Table 6 Sum of Acceleration Absolute Value for Entire Testing Section by Vehicle

<table>
<thead>
<tr>
<th>Vehicle</th>
<th>L1 norm of Acceleration</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ford Fusion</td>
<td>29.73 g</td>
</tr>
<tr>
<td>Tractor Trailer</td>
<td>40.97 g</td>
</tr>
</tbody>
</table>

Therefore, larger vehicles, operating under the same driving conditions, will experience larger acceleration due to varying vehicle dynamics and suspension. It is likely that the magnitude of acceleration measurements will be different for all vehicles, but that they can be grouped into classes that have similar properties. For a probe vehicle system to be implemented, these groups would have to be determined prior to data collection. Drawing from the previous section, at higher speeds, the dynamics of the vehicle have a much greater impact on the magnitude of acceleration. The experimental results show a nearly 20 g difference in total acceleration between the two probe vehicles when traveling at 65 mph. On the other hand, that difference is less than 3 g when the vehicle speed is 40 mph. Although the proof of concept remains valid because the same general trend is followed for both vehicles, this requires further study since the magnitudes of the acceleration measurements differ.

Preliminary Highway Measurements

To supplement the data collected on the Virginia Smart Road, a test run was also performed with the sedan and tractor trailer on a small stretch of the U.S. Route 460 By-Pass near Blacksburg, Virginia. Acceleration measurements were collected in both the eastbound and westbound directions at 65 mph. The results of the highway data collection are presented in Figures 23 and 24.
Figure 23 Acceleration measurements with Ford Fusion and Tractor Trailer on 460 West.

Figure 24 Acceleration measurements with Ford Fusion and Tractor Trailer on 460 East.

The highway measurements show a relatively “smooth” section of US Route 460. The Fusion probe vehicle registered zero acceleration measurements greater than 0.2 g in the westbound direction and only two acceleration measurements greater than 0.2 g in the eastbound direction. At 65mph, this is nearly twice as smooth as the test section on the Smart Road. There appear to be fewer spikes along the traveled path, indicating smoother transitions between pavement types and acceptable vertical deviations in the roadway. There were no bridge joints across the test sections, which also contributed to the lack of quick increases in acceleration. Table 7 compares some basic statistical measures with those obtained on the Virginia Smart Road. One of the 65mph test runs with the Ford Fusion was used in the analysis. From visual inspection, the highway measurements exhibit the same variation in magnitude between the two probe vehicles as on the Virginia Smart Road.
Table 7 Comparison of Highway and Smart Road Acceleration Measurements

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Smart Road</th>
<th>460 West</th>
<th>460 East</th>
</tr>
</thead>
<tbody>
<tr>
<td>L1 Norm of Acceleration</td>
<td>48.04 g</td>
<td>27.35 g</td>
<td>32.38 g</td>
</tr>
<tr>
<td>Average Absolute Acceleration</td>
<td>0.0478 g</td>
<td>0.0270 g</td>
<td>0.0322 g</td>
</tr>
<tr>
<td>Maximum Absolute Acceleration</td>
<td>0.6965 g</td>
<td>0.1184 g</td>
<td>0.2267 g</td>
</tr>
<tr>
<td>Minimum Absolute Acceleration</td>
<td>0.0000 g</td>
<td>0.0005 g</td>
<td>0.0005 g</td>
</tr>
</tbody>
</table>

EXAMPLE OF POTENTIAL APPLICATIONS

Overview

The results of data collection on the Virginia Smart Road validate the belief that pavement condition can be described using probe vehicle sensing equipment. Vertical acceleration measurements yielded positive preliminary results with respect to ride quality description. Deviations in the pavement profile were identified by vertical acceleration signatures as the probe vehicles traveled along the road. While the acceleration measurements do not directly correlate with the road profile (and therefore the IRI), the same trends can be observed in both data sets. It can even be argued that since vertical acceleration offers a better description of driver perception, it is an acceptable way to define ride quality. Analysis demonstrated an acceptable level of repeatability among various measurement sets. GPS and distance measurements, combined with a cross-correlation procedure, successfully aligned the measurements that were contained in the test section.

This section uses the data collected during testing to simulate what a deployed probe vehicle fleet may be able to provide and then discusses two applications for pavement management. The network level simulation combines measurements recorded by the sedan and the tractor trailer. For the simulation, each measurement set was considered to be a separate probe vehicle. The purpose of this simulation was to model the effect of varying the fleet size (number of probe vehicles) on the average acceleration of the fleet over a given test section (in this case the entire right uphill lane of the Virginia Smart Road). The proposed applications of the acceleration data use the average of multiple test runs to identify areas of low ride quality (high acceleration). Two such applications were explored: splitting the test section into smaller subsections to identify those with high average acceleration and averaging each measurement from multiple probe vehicles to identify locations of high acceleration. The application methods described use only data from the sedan, but the same principles may be applied to any probe vehicle.

Simulation of Real Life Data Collection

Probe vehicle measurements introduce several variables that are otherwise inconsequential to the current state-of-the-practice method for evaluating ride quality. High speed laser profilers measure the actual pavement profile, while accelerometers simply measure the response of the vehicle to the profile. Because of this, unlike road profile measurements, vehicle speed, acceleration, and mechanical characteristics influence the magnitude of the vertical acceleration data. This was demonstrated in the data analysis section. This could result in a large amount of variability in acceleration measurements obtained from a deployed fleet of probe vehicles that have different characteristics and may be traveling at different speeds. For a fleet with a limited number of vehicles, the sensitivity to speed and type may prove to be too great in order to extract useful information from the data. However, two factors help to eliminate this issue: (1) the data will converge towards a specific average vertical acceleration value of a section as
more vehicles are introduced into the system, and (2) acceleration measurements seem to follow the same trend regardless of speed and vehicle characteristics. In order to validate this concept, a very basic network-level simulation was created using the collected data from the Virginia Smart Road.

A Matlab script file was created to simulate a network data collection system comprised of a varying number of probe vehicles. The test section of the Virginia Smart Road severed as the representative pavement section. There were a total of 39 test runs used in the analysis: 30 with the instrumented Ford Fusion (small sedan) and 9 with the instrumented tractor trailer. The use of two different vehicles which have significantly different suspension designs served as a representation of the mixed data that would be collected in an integrated system. Since the acceleration measurements were taken at slightly different distances during test runs, spline interpolation was used to predict acceleration values at the same distances. Then, \( n \) runs were randomly selected with replacement from the 39 runs performed. The file outputted the absolute average vertical acceleration of the \( n \) runs. Calculations were performed ten times for \( n \) equal to 5, 10, 20, 50, and 100. Figure 25 displays the absolute average acceleration for each set of probe vehicle fleet sizes.

![Average Acceleration Using a Varying Number of Probe Vehicles](image)

**Figure 25 Absolute average acceleration values for varying fleet sizes.**

The graph shows the averages converge to a value close to 0.0338 as more probe vehicles are introduced into the system. There is a drastic difference in the averages between fleets of 5 and 10 vehicles. As the number of vehicles increases, the standard deviation of the calculated average decreases. This confirms that there is less variation in the averages with a larger fleet. Therefore, it is believed that as a network fleet grows in size, the variability introduced with only a few probe vehicle measurements will be minimized. Since the same trend is present in all vertical acceleration measurements, the minimization of the differences created by the presence of speed and vehicle variations is enough to extract useful ride quality information from the data.

**Location of Singularities**

The collected acceleration data could potentially provide a unique support tool for pavement maintenance agencies. Vertical acceleration measurements describe the discomfort experienced by drivers along a roadway. Rough pavement segments are therefore characterized by a series of high vertical acceleration
measurements over a specific length of road. Pavement segments that are relatively rougher than their adjacent segments could indicate aged, deteriorating, or improperly maintained pavement. Rough pavement spot locations are characterized by spikes, or sharp increases in magnitude, by a few measurements or a single measurement. These locations could indicate a pothole, large crack, uneven joint, or other roadway anomaly. By identifying the segments and locations of high vertical acceleration, agencies could identify areas in their road network that are not meeting functional requirements. Furthermore, with a fleet of probe vehicles, this information has the potential to be constantly updated and improved upon. For example, vertical acceleration signatures will increase over time in a specific location if a crack continues to grow or if a bridge joint moves.

By using the data to highlight areas of poor pavement condition, where the pavement smoothness may not be adequate, maintenance agencies can prioritize projects in a more efficient manner. A possible method for this process is establishing an acceleration threshold value. If a specific segment exceeds that acceleration threshold, it could alert maintenance personnel that the pavement is not meeting its functional performance requirements. A threshold value could also be employed to individual acceleration measurements in order to identify spot locations of poor condition. The location threshold value should be greater than the segment threshold value, since the segment threshold value is compared to an average of many measurements. Both strategies were employed with the average of ten experimental runs taken with Ford Fusion using a Matlab script file.

The first script file implemented a segment acceleration threshold value of 0.0342 g. This threshold value represents the third quartile (75th percentile) of acceleration measurements that were observed on the Virginia Smart Road. It can easily be altered for different roadways or to identify more or fewer segments. Any segments that exceeded and average of 0.0342 g were reported. The test section of the Virginia Smart Road was split into segments of 30 data points, each approximately 210 feet. If employed on highways, it may be beneficial to increase the length of each section to tenth-mile or half-mile distances. Figure 26 displays the average absolute acceleration of each of the 33 segments. The red dots indicate average segment values that exceeded the established threshold value (red horizontal line). The segments are then highlighted in a plot of all measurements in Figure 27. The yellow shaded areas indicate the same high acceleration segments as in Figure 26. All measurements were converted to absolute value before analysis.
All 33 segments of the test area are shown in Table 10 with corresponding pavement type and average acceleration. The starred segments correspond to the areas of high acceleration described in Figure 26 and Figure 27.
Table 8 Average acceleration by segment on Virginia Smart Road

<table>
<thead>
<tr>
<th>Segment</th>
<th>Pavement Type (Surface)</th>
<th>Average Acceleration</th>
<th>Percentile</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>JRCP*</td>
<td>0.0359 g</td>
<td>82</td>
</tr>
<tr>
<td>2</td>
<td>JRCP</td>
<td>0.0276 g</td>
<td>62</td>
</tr>
<tr>
<td>3</td>
<td>JRCP</td>
<td>0.0189 g</td>
<td>24</td>
</tr>
<tr>
<td>4</td>
<td>JRCP*</td>
<td>0.0622 g</td>
<td>94</td>
</tr>
<tr>
<td>5</td>
<td>JRCP*</td>
<td>0.0553 g</td>
<td>91</td>
</tr>
<tr>
<td>6</td>
<td>CRCP</td>
<td>0.0255 g</td>
<td>53</td>
</tr>
<tr>
<td>7</td>
<td>CRCP</td>
<td>0.0168 g</td>
<td>21</td>
</tr>
<tr>
<td>8</td>
<td>CRCP</td>
<td>0.0143 g</td>
<td>3</td>
</tr>
<tr>
<td>9</td>
<td>CRCP</td>
<td>0.0165 g</td>
<td>15</td>
</tr>
<tr>
<td>10</td>
<td>CRCP</td>
<td>0.0153 g</td>
<td>6</td>
</tr>
<tr>
<td>11</td>
<td>CRCP</td>
<td>0.0159 g</td>
<td>9</td>
</tr>
<tr>
<td>12</td>
<td>CRCP</td>
<td>0.0199 g</td>
<td>26</td>
</tr>
<tr>
<td>13</td>
<td>CRCP</td>
<td>0.0167 g</td>
<td>18</td>
</tr>
<tr>
<td>14</td>
<td>CRCP</td>
<td>0.0201 g</td>
<td>32</td>
</tr>
<tr>
<td>15</td>
<td>CRCP</td>
<td>0.0160 g</td>
<td>12</td>
</tr>
<tr>
<td>16</td>
<td>SMA-12.5*</td>
<td>0.0351 g</td>
<td>76</td>
</tr>
<tr>
<td>17</td>
<td>SMA-12.5+ OGFC*</td>
<td>0.0349 g</td>
<td>75</td>
</tr>
<tr>
<td>18</td>
<td>OGFC + SM-9.5D</td>
<td>0.0212 g</td>
<td>35</td>
</tr>
<tr>
<td>19</td>
<td>SM-9.5D</td>
<td>0.0199 g</td>
<td>26</td>
</tr>
<tr>
<td>20</td>
<td>SM-9.5D + SM-9.5A</td>
<td>0.0219 g</td>
<td>38</td>
</tr>
<tr>
<td>21</td>
<td>SM-9.5A + SM-9.5D*</td>
<td>0.0386 g</td>
<td>88</td>
</tr>
<tr>
<td>22</td>
<td>SM-9.5D</td>
<td>0.0241 g</td>
<td>44</td>
</tr>
<tr>
<td>23</td>
<td>SM-9.5D</td>
<td>0.0308 g</td>
<td>68</td>
</tr>
<tr>
<td>24</td>
<td>SM-9.5D</td>
<td>0.0255 g</td>
<td>53</td>
</tr>
<tr>
<td>25</td>
<td>SM-9.5D</td>
<td>0.0272 g</td>
<td>59</td>
</tr>
<tr>
<td>26</td>
<td>SM-9.5D</td>
<td>0.0228 g</td>
<td>41</td>
</tr>
<tr>
<td>27</td>
<td>Concrete Bridge*</td>
<td>0.0370 g</td>
<td>85</td>
</tr>
<tr>
<td>28</td>
<td>Concrete Bridge + SM-9.5A*</td>
<td>0.0904 g</td>
<td>97</td>
</tr>
<tr>
<td>29</td>
<td>SM-9.5A*</td>
<td>0.0354 g</td>
<td>79</td>
</tr>
<tr>
<td>30</td>
<td>SM-9.5A + SM-9.5E</td>
<td>0.0246 g</td>
<td>47</td>
</tr>
<tr>
<td>31</td>
<td>SM-9.5E + SM-9.5D</td>
<td>0.0315 g</td>
<td>71</td>
</tr>
<tr>
<td>32</td>
<td>SM-9.5D</td>
<td>0.0294 g</td>
<td>65</td>
</tr>
<tr>
<td>33</td>
<td>SM-12.5D</td>
<td>0.0248 g</td>
<td>50</td>
</tr>
</tbody>
</table>

The joint reinforced concrete pavement (JRCP) at the beginning of the test section creates relatively high acceleration measurements. For this reason, 3 of the 6 segments comprised of this pavement exceeded the threshold value. The next main area of the Smart Road, the continuously reinforced concrete pavement (CRCP) is the smoothest of all pavement types. Of the ten segments of CRCP, none exceed the threshold value. In fact, the segment with the largest average acceleration still only falls in the 53rd percentile of all segments. Around 3,200 feet, the pavement changes from concrete to asphalt. The first two segments,
which are comprised of a combination of SMA-12.5 and OFGC (Open Graded Friction Course), caused high acceleration values that also exceed the threshold. Segment 21, comprised of SM-9.5A and SM-9.5D, yielded the highest acceleration average for strictly asphalt pavement. The final 3 segments that exceeded the threshold value (27-29) were at least partly made up of the small bridge between asphalt sections. This bridge features uneven approaching slabs between the deck and surrounding pavement.

The second script file implemented a single measurement acceleration threshold value of 0.20 g. This threshold value was also chosen arbitrarily, based on the observed acceleration measurements on the Virginia Smart Road. It can easily be altered for different roadways. Any measurement that exceeded 0.20 g was reported. Since the Smart Road is relatively well conditioned, the high acceleration measurements are mostly due to bridge joints. The large spike on the right of the graph is the final joint after a small bridge near the end of the test section. This joint produced the most noticeable discomfort during testing, which is supported by its high acceleration signature. Figure 28 identifies the poor locations of the Virginia Smart Road based on the threshold value established above. The red circles indicate specific measurements that exceeded 0.20 g. All measurements were converted to absolute value before analysis.

![Figure 28 Rough location detection using vertical acceleration measurements.](image-url)
CHAPTER 5 - SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

SUMMARY

Pavement condition assessment is necessary for transportation personnel to properly maintain infrastructure assets (roads, bridges, airports, etc.) in a cost-effective manner. The state-of-the-practice methods for condition assessment often involve expensive equipment outfitted on specialized vehicles, such as high speed laser profilers for ride quality assessment. While new technologies have led to the advancement of such methods, another logical step forward in the data collection and assessment process involves the use of on-board information in normal vehicles. These probe vehicles could provide agencies with a much larger fleet of data collection devices at lower costs and wider coverage. This concept relies on using information taken from typical vehicle sensors and combining the data with global positioning to create a “snapshot” of the road (6).

The U.S. Department of Transportation and Federal Highway Administration have explored the uses of probe vehicles for several years under the initiative now known as Connected Vehicle Research (13). Probe vehicle studies, using various sensors and transmission methods, have also been conducted in other countries. The literature review surrounding such methods led to the belief that measuring ride quality by analysis of vertical acceleration measurements from vehicle accelerometers would provide a practical probe vehicle application. Ride quality, also known as smoothness, describes the amount of vertical deviation in pavement along a traveled path. It has significant influence on the performance of the pavements and is directly linked to the costs assumed by roadway users. Fuel consumption, tire wear, and vehicle durability are all greatly influenced by the smoothness of the road (3). When placed perpendicular to the traveled surface on a vehicle and combined with several transducers, accelerometers create an inertial reference for the vehicle to measure smoothness. Thus, vertical changes in speed measured by an accelerometer indicate deviations in the pavement. Similar concepts had been previously explored by the University of Auburn and Massachusetts Institute of Technology (8, 17).

It was believed that using available resources at the Virginia Tech Transportation Institute, especially the Virginia Smart Road and Naturalistic Driving Studies instrumented vehicles, could provide a robust set of acceleration data and new applications in regards to ride quality. The concept feasibility was first tested using data previously collected by other studies at VTTI. The preliminary analysis included acceleration data mining with respect to a defined test section, comparisons of acceleration measurements to profile measurements, and assessment of acceleration measurement repeatability. It was demonstrated that vertical acceleration measurements exhibit an acceptable level of repeatability and correlation to the road profile. These findings led to the development of a more extensive data collection experiment utilizing two instrumented vehicles on the Virginia Smart Road. Data collection took place over three days, resulting in 30 sets of acceleration data using a small sedan and 10 sets of acceleration data using a tractor trailer.

The collected data was analyzed for repeatability, effect of speed, and effect of vehicle type. In addition, average acceleration signatures in the various pavement sections of the Virginia Smart Road were reported. In order to simulate the methodology for a large scale deployment, varying numbers (5, 10, 20, 50, and 100) of data sets were combined and averaged. These data sets were meant to represent different probe vehicles traveling along the same roadway segment. In addition, two threshold values were
employed to identify rough pavement areas using an average of several test runs. The first threshold value was employed to highlight rough segments of equal length along the entire test section. The second threshold value was employed to highlight rough spot locations along the entire test section. The analysis of the results showed a high level of repeatability among acceleration measurements, determined the change in acceleration magnitude due to speed and vehicle type, displayed the advantage of using a large probe vehicle fleet, and identified rough areas of pavement. These statistical results and applications provide several opportunities to utilize data collected by probe vehicles for transportation agencies.

FINDINGS

✓ Normal production vehicles that are equipped with necessary sensors to collect roadway information are called probe vehicles. These vehicles represent an innovative approach to collecting necessary infrastructure information by essentially becoming the data collection devices themselves. One of the most practical applications of this concept is using vehicle accelerometers to describe road ride quality. A vehicle, or a fleet of vehicles, measuring vertical acceleration and equipped with GPS could provide road agencies with a robust database of ride quality information at low cost.

✓ Vertical acceleration measurements follow the same trends as the road smoothness profile, the state-of-the-practice in ride quality. Similarities between the two measurement types can be observed visually and proven statistically with the coherence function. Between wavelengths of 50 to 300 m, the coherence function was generally higher than 0.50 with relatively strong coherence (mostly above 0.80) for wavelengths between 70 and 200 m. At short wavelengths (high frequency) the coherence is generally relatively low; this may be attributable to the presence of noise at high frequencies.

✓ Vertical acceleration measurements conducted under controlled conditions exhibit an acceptable level of repeatability. The repeatability calculations were performed after spline interpolation (align distances) and cross-correlation (align accelerations). All of the runs displayed acceptable correlation with values over 90%, while the majority of the values displayed exceptional correlation with values over 97%. The standard deviation of differences, a method used to quantify repeatability, was determined to be 0.0664 for thirty test runs with the small sedan. The calculated signal-to-noise ratio for the acceleration measurements was 1.73.

✓ The experiment confirmed that probe vehicle speed affects the magnitude of acceleration. To quantify the difference between speeds, the L1 norm, which is the sum of the absolute values of the acceleration measurements over the entire testing section length, was calculated. The 65 mph measurements experienced a 61% increase in magnitude when compared to the 50 mph measurements. Meanwhile, the 50 mph measurements experienced a 14% increase in magnitude when compared to the 40 mph measurements. As speed increases, so does the magnitude of the acceleration, but the general ride quality trend still remains intact.

✓ The results also confirmed that probe vehicle type affects the magnitude of acceleration. This is due to variations in vehicle parameters, including suspension type and tire size. To quantify the difference between vehicles, the L1 norm was calculated. The truck L1 norm was significantly larger than that of the sedan. Larger vehicles, operating under the same driving conditions, will experience larger acceleration due to varying vehicle dynamics and suspension. It is likely that the magnitude of
acceleration measurements will be slightly different for all vehicles, but that they can be grouped into classes that have similar properties.

✓ A network-level simulation was created using the collected data. The use of two different vehicles which greatly vary in size served as a representation of the mixed data that would be collected in an integrated system. Fleet sizes of 5, 10, 20, 50, and 100 were generated. As the fleet size increased, the average (absolute) acceleration converged to around 0.0338 g. The standard deviation of the calculated average among the 10 generated examples decreased with increasing fleet size.

✓ A segment threshold can be established using the average (absolute) acceleration values of equal length segments (in this case, roughly 210 feet) along the test section. This threshold can help to identify segments of high acceleration, displayed as continuous high signatures in a measurement plot. Segments of high acceleration can be a result of distressed, unmaintained, or poorly constructed pavement. Based on the gathered data on the Virginia Smart Road, the segment threshold used was 0.0342 g. However, a higher threshold (or longer segments) may be more applicable on public roadways.

✓ A single point threshold can be established using the original vertical acceleration measurements gathered during data collection. This threshold can help to identify locations of high vertical acceleration, displayed as spikes in a measurement plot. Single locations of high acceleration can be a result of discontinuities, such as large cracks, joints, potholes, and other road anomalies. Based on the data gathered on the Virginia Smart Road, the single point threshold used was 0.2 g. However, a different threshold may be more applicable to public roadways.

CONCLUSIONS

The validation of these concepts under controlled conditions confirms the original hypothesis that probe vehicles, equipped with common vehicular sensors, can be used to evaluate road condition. In particular, vehicle accelerometers can be used to describe the ride quality, or smoothness, of the road. This was confirmed by the validation of the relationship between acceleration and profile measurements, a successful repeatability study, and the demonstration of several application examples.

RECOMMENDATIONS

For future research this thesis proposed to find a new method for measuring pavement smoothness by using probe vehicles instead of typical profilers. However, the range is limited, and further examination into a full scale probe vehicle system is possible. Further development of the system can include, but is not limited to the following:

1) The collection of acceleration data on other roads such as interstate highways and the use of a larger fleet of probe vehicles. Expanding the study could first begin with a fleet of 5-10 instrumented vehicles, traveling on a small network of roads. The pavement condition would be evaluated using acceleration data method developed in the thesis. With each vehicle collecting data on the network, areas of poor pavement condition can be “flagged” and mapped using the GPS coordinates. Any jumps in acceleration values by a large percentage of the fleet vehicles at the same location would indicate a poor conditioned section. If the small fleet proves to be useful in characterizing road
condition, the scope could be expanded to include more roads and more instrumented vehicles. This could be helpful in prioritizing maintenance and rehabilitation projects in the future. The repeatability of acceleration measurements with data collection occurring under regular road conditions would be a vital part of this step in experimentation.

2) Several probe vehicle research projects are considering the use of smart phones to measure the vehicle acceleration. As an additional consideration, we could look into the use of these devices for data collection. This would replace the NDS instruments in the VTTI vehicles. If a strong correlation could be found with the smart phones as well, it may become more cost effective and easier to deploy at a large scale. The same statistical methods that were described above from the NDS vehicles would be used on the data gathered by the smart phones.

3) If the basic concepts are validated, it is feasible to even further expand the instrumented vehicle approach. The implementation of a regular fleet of vehicles to collect data can be integrated and communicated through connected vehicle technology. It is expected that smoothness conditions obtained by this method will be very similar to the results of the Virginia Smart Road tests. In fact, the hypothesis is that as more vehicles collect data on a particular stretch of road, the areas of poor pavement condition will become more evident. With the instrumented vehicles transmitting data in real time, pavement agencies will have a much better idea of which assets need maintenance in a timely fashion.
REFERENCES


APPENDIX

PRELIMINARY ANALYSIS SCRIPT FILE

%% Import data
accx1 = xlsread('accx1.xlsx');
accy1 = xlsread('accy1.xlsx');
accx2 = xlsread('accx2.xlsx');
accy2 = xlsread('accy2.xlsx');
accx3 = xlsread('accx3.xlsx');
accy3 = xlsread('accy3.xlsx');
accx4 = xlsread('accx4.xlsx');
accy4 = xlsread('accy4.xlsx');
profx = xlsread('profx.xlsx');
profy = xlsread('profy.xlsx');

%Make data sets the same length
n = length(accx1);
nplus = n + 1;

for i = 1:n
    res = abs(profx-accx1(i));
    ind = find(res==min(res));
    profx(i) = profx(ind);
    profy(i) = profy(ind);
end

profx(nplus:end) = [];
profy(nplus:end) = [];
Y = sin(2*pi*1/20*accx1);
Y1 = Y.*abs(accy1)-0.05;
Y2 = Y.*abs(profy);

%Plot profile and acceleration data
figure1 = figure;
axes1 = axes('Parent',figure1,'Position',[0.07262 0.6106 0.895 0.3403],...'FontSize',20,...'FontName','Times New Roman');
box('on');
hold('all');
xlim([0,max(profx)]);
ylim([1.05*min(profy),1.05*max(profy)]);
plot(profx,profy,'Parent',axes1);
xlabel('Distance (m)','FontSize',24,'FontName','Times New Roman');
ylabel('Profile (mm)','FontSize',24,'FontName','Times New Roman');

axes2 = axes('Parent',figure1,'Position',[0.07437 0.112 0.8968 0.3702],...'FontSize',20,...'FontName','Times New Roman');
box('on');
hold('all');
xlim([0,max(accx1)]);
ylim([1.05*min(accy1),1.05*max(accy1)]);
plot(accx1,accy1,'Parent',axes2);
xlabel('Distance (m)','FontSize',24,'FontName','Times New Roman');
ylabel('Acceleration','FontSize',24,'FontName','Times New Roman');
%Plot coherence function

m = 256;
figure2 = figure;
[Cxy256,F256] = mscohere(accy1,profy,hamming(m),3*m/4,m,1/mean(diff(accx1)));
[Cxy256,F256] = mscohere(accy2,profy,hamming(m),3*m/4,m,1/mean(diff(accx1)));
axes('Parent',figure2,'XScale','log','XMinorTick','on',...'Position',[0.07262 0.1053 0.895 0.8456],...'FontSize',20,...'FontName','Times New Roman');
box('on');
hold('all');
semilogx(1./F256,Cxy256,1./F128,Cxy128)
xlabel('Distance (m)',...'FontSize',24,...'FontName','Times New Roman');
ylabel('Coherence Cxy',...'FontSize',24,...'FontName','Times New Roman');

corr_acc = zeros(1,7);
for i=1:size(corr_acc,2)
    a = mvaveragec(accy1,i-1);
    corr_acc(i)=corr(a(i:end-(i-1)),profy(i:end-(i-1)));
end

D = profy(1:end-2)-2*profy(2:end-1)+profy(3:end);
Acc = accy1(2:end-1);
PROFX = profx(2:end-1);
ACCX1 = accx1(2:end-1);
Filt_D = mvaveragec(D,3);
Filt_Acc = mvaveragec(Acc,3);
corr(Filt_D(4:end-3),Filt_Acc(4:end-3));

figure4 = figure;
axes1 = axes('Parent',figure4,'Position',[0.07262 0.6106 0.895 0.3403],...'FontSize',20,...'FontName','Times New Roman');
box('on');
hold('all');
xlim([0,max(profx)]);
ylim([1.05*min(Filt_D(4+7:end-3))/2,1.05*max(Filt_D(4+7:end-3))/2]);
plot(profx(5+7:end-4),Filt_D(4+7:end-3)/2,'Parent',axes1);
xlabel('Distance (m)',...'FontSize',24,...'FontName','Times New Roman');
ylabel('Profile Acceleration',...'FontSize',24,...'FontName','Times New Roman');

axes2 = axes('Parent',figure4,'Position',[0.07437 0.112 0.8968 0.3702],...'FontSize',20,...'FontName','Times New Roman');
box('on');
hold('all');
xlim([0,max(accx1)]);
ylim([1.05*min(Filt_D(4+7:end-3))/2,1.05*max(Filt_D(4+7:end-3))/2]);
plot(accx1(5:end-4-7),-mean(Filt_Acc(4:end-3-7))+Filt_Acc(4:end-3-7),...'Parent',axes2);
xlabel('Distance (m)',...'FontSize',24,...'FontName','Times New Roman');
ylabel('Acceleration',...'FontSize',24,...'FontName','Times New Roman');

Corr_Matrix = zeros(200,2);
for i=1:200
    Corr_Matrix(i,1)=corr(Filt_D(4+i:end-3),Filt_Acc(4:end-3-i));
    Corr_Matrix(i,2)=corr(Filt_D(4:end-3-i),Filt_Acc(4+i:end-3));
end
D_Hat = smoothing_spline(D,16);
Acc_Hat = smoothing_spline(Acc,16);
corr(D_Hat,Acc_Hat);
ST=(0:2:2*(length(D_Hat)-1))';
st=(0:2:2*(length(accY)-1))';
figure5 = figure;
axes1 = axes('Parent',figure5,'Position',[0.07262 0.6106 0.895 0.3403],'FontSize',20,'FontName','Times New Roman');
box('on');
hold('all');
xlim([0,max(profX)]);
ylim([-1.05*max(D_Hat)/2,-1.05*min(D_Hat)/2]);
plot(profX(2:end-1),-D_Hat/2,'Parent',axes1);
xlabel('Distance (m)','FontSize',24,'FontName','Times New Roman');
ylabel('Profile Acceleration','FontSize',24,'FontName','Times New Roman');
axes2 = axes('Parent',figure5,'Position',[0.07437 0.112 0.8968 0.3702],'FontSize',20,'FontName','Times New Roman');
box('on');
hold('all');
xlim([0,max(accx1)]);
ylim([1.05*(-mean(Acc_Hat)+min(Acc_Hat)),1.05*(-mean(Acc_Hat)+max(Acc_Hat))]);
plot(accX(2:end-1),-mean(Acc_Hat)+Acc_Hat,'Parent',axes2);
xlabel('Distance (m)','FontSize',24,'FontName','Times New Roman');
ylabel('Acceleration','FontSize',24,'FontName','Times New Roman');

ACCELERATION REPEATABILITY SCRIPT FILE

%Input Ford Fusion Measurements (10 Sets)
accx1 = xlsread('fusionx1.xlsx');
accy1 = xlsread('fusiony1.xlsx');
accx2 = xlsread('fusionx2.xlsx');
accy2 = xlsread('fusiony2.xlsx');
accx3 = xlsread('fusionx3.xlsx');
accy3 = xlsread('fusiony3.xlsx');
accx4 = xlsread('fusionx4.xlsx');
accy4 = xlsread('fusiony4.xlsx');
accx5 = xlsread('fusionx5.xlsx');
accy5 = xlsread('fusiony5.xlsx');
accx6 = xlsread('fusionx6.xlsx');
accy6 = xlsread('fusiony6.xlsx');
accx7 = xlsread('fusionx7.xlsx');
accy7 = xlsread('fusiony7.xlsx');
accx8 = xlsread('fusionx8.xlsx');
accy8 = xlsread('fusiony8.xlsx');
accx9 = xlsread('fusionx9.xlsx');
accy9 = xlsread('fusiony9.xlsx');
accx0 = xlsread('fusionx0.xlsx');
accy0 = xlsread('fusiony0.xlsx');

%Input Profiler Measurements (10 Sets)
profX1 = xlsread('profilex1.xlsx');
profY1 = xlsread('profiley1.xlsx');
%Interpolate Distance Measurements for Ford Fusion
y0 = accy0;
y1 = interp1(accx1,accy1,accx0,'spline');
y2 = interp1(accx2,accy2,accx0,'spline');
y3 = interp1(accx3,accy3,accx0,'spline');
y4 = interp1(accx4,accy4,accx0,'spline');
y5 = interp1(accx5,accy5,accx0,'spline');
y6 = interp1(accx6,accy6,accx0,'spline');
y7 = interp1(accx7,accy7,accx0,'spline');
y8 = interp1(accx8,accy8,accx0,'spline');
y9 = interp1(accx9,accy9,accx0,'spline');

%Interpolate Distance Measurements for Profiler
p0 = profy0;
p1 = interp1(profx1,profy1,profx0,'spline');
p2 = interp1(profx2,profy2,profx0,'spline');
p3 = interp1(profx3,profy3,profx0,'spline');
p4 = interp1(profx4,profy4,profx0,'spline');
p5 = interp1(profx5,profy5,profx0,'spline');
p6 = interp1(profx6,profy6,profx0,'spline');
p7 = interp1(profx7,profy7,profx0,'spline');
p8 = interp1(profx8,profy8,profx0,'spline');
p9 = interp1(profx9,profy9,profx0,'spline');

na = length(y0);
np = length(p0);

%Cross Correlation for Ford Fusion
xc1 = xcorr(y1-mean(y1),y0-mean(y0),'coeff');
xc2 = xcorr(y2-mean(y2),y0-mean(y0),'coeff');
xc3 = xcorr(y3-mean(y3),y0-mean(y0),'coeff');
xc4 = xcorr(y4-mean(y4),y0-mean(y0),'coeff');
xc5 = xcorr(y5-mean(y5),y0-mean(y0),'coeff');
xc6 = xcorr(y6-mean(y6),y0-mean(y0),'coeff');
xc7 = xcorr(y7-mean(y7),y0-mean(y0),'coeff');
xc8 = xcorr(y8-mean(y8),y0-mean(y0),'coeff');
xc9 = xcorr(y9-mean(y9),y0-mean(y0),'coeff');
%Standard Deviation for Ford Fusion
sda1 = std(y1-y0);
sda2 = std(y2-y0);
sda3 = std(y3-y0);
sda4 = std(y4-y0);
sda5 = std(y5-y0);
sda6 = std(y6-y0);
sda7 = std(y7-y0);
sda8 = std(y8-y0);
sda9 = std(y9-y0);

%Variance for Ford Fusion
vra1 = var(y1-y0);
vra2 = var(y2-y0);
vra3 = var(y3-y0);
vra4 = var(y4-y0);
vra5 = var(y5-y0);
vra6 = var(y6-y0);
vra7 = var(y7-y0);
vra8 = var(y8-y0);
vra9 = var(y9-y0);

%Standard Deviation for Profiler
sdp1 = std(p1-p0);
sdp2 = std(p2-p0);
sdp3 = std(p3-p0);
sdp4 = std(p4-p0);
sdp5 = std(p5-p0);
sdp6 = std(p6-p0);
sdp7 = std(p7-p0);
sdp8 = std(p8-p0);
sdp9 = std(p9-p0);

%Variance for Profiler
vrp1 = var(p1-p0);
vrp2 = var(p2-p0);
vrp3 = var(p3-p0);
vrp4 = var(p4-p0);
vrp5 = var(p5-p0);
vrp6 = var(p6-p0);
vrp7 = var(p7-p0);
vrp8 = var(p8-p0);
vrp9 = var(p9-p0);

%Average Acceleration and Signal-to-Noise Ratio Calculations
accavg = (y1+y2+y3+y4+y5+y6+y7+y8+y9+y0)/10;
accsnum = std(accavg);
acctotstd = sqrt((vra1+vra2+vra3+vra4+vra5+vra6+vra7+vra8+vra9)/9);
accsden = acctotstd/(2^0.5);
accsnratio = accsnum/accsden;

%Average Profile and Signal-to-Noise Calculations
profavg = (p1+p2+p3+p4+p5+p6+p7+p8+p9+p0)/10;
profsnum = std(profavg);
proftotstd = sqrt((vrp1+vrp2+vrp3+vrp4+vrp5+vrp6+vrp7+vrp8+vrp9)/9);
profsden = proftotstd/(2^0.5);
profsnratio = profsnum/profsden;

NETWORK LEVEL SIMULATION SCRIPT FILE

%Import Ford Fusion Data
cary01 = xlsread('fusiony1.xlsx');
cary02 = xlsread('fusiony2.xlsx');
cary03 = xlsread('fusiony3.xlsx');
cary04 = xlsread('fusiony4.xlsx');
cary05 = xlsread('fusiony5.xlsx');
cary06 = xlsread('fusiony6.xlsx');
cary07 = xlsread('fusiony7.xlsx');
cary08 = xlsread('fusiony8.xlsx');
cary09 = xlsread('fusiony9.xlsx');
cary10 = xlsread('fusiony0.xlsx');
cary11 = xlsread('fusiony11.xlsx');
cary12 = xlsread('fusiony12.xlsx');
cary13 = xlsread('fusiony13.xlsx');
cary14 = xlsread('fusiony14.xlsx');
cary15 = xlsread('fusiony15.xlsx');
cary16 = xlsread('fusiony16.xlsx');
cary17 = xlsread('fusiony17.xlsx');
cary18 = xlsread('fusiony18.xlsx');
cary19 = xlsread('fusiony19.xlsx');
cary20 = xlsread('fusiony20.xlsx');
cary21 = xlsread('fusiony21.xlsx');
cary22 = xlsread('fusiony22.xlsx');
cary23 = xlsread('fusiony23.xlsx');
cary24 = xlsread('fusiony24.xlsx');
cary25 = xlsread('fusiony25.xlsx');
cary26 = xlsread('fusiony26.xlsx');
cary27 = xlsread('fusiony27.xlsx');
cary28 = xlsread('fusiony28.xlsx');
cary29 = xlsread('fusiony29.xlsx');
cary30 = xlsread('fusiony30.xlsx');
carx01 = xlsread('fusionx1.xlsx');
carx02 = xlsread('fusionx2.xlsx');
carx03 = xlsread('fusionx3.xlsx');
carx04 = xlsread('fusionx4.xlsx');
carx05 = xlsread('fusionx5.xlsx');
carx06 = xlsread('fusionx6.xlsx');
carx07 = xlsread('fusionx7.xlsx');
carx08 = xlsread('fusionx8.xlsx');
carx09 = xlsread('fusionx9.xlsx');
carx10 = xlsread('fusionx0.xlsx');
carx11 = xlsread('fusionx11.xlsx');
carx12 = xlsread('fusionx12.xlsx');
carx13 = xlsread('fusionx13.xlsx');
carx14 = xlsread('fusionx14.xlsx');
carx15 = xlsread('fusionx15.xlsx');
carx16 = xlsread('fusionx16.xlsx');
carx17 = xlsread('fusionx17.xlsx');
carx18 = xlsread('fusionx18.xlsx');
carx19 = xlsread('fusionx19.xlsx');
carx20 = xlsread('fusionx20.xlsx');
carx21 = xlsread('fusionx21.xlsx');
carx22 = xlsread('fusionx22.xlsx');
carx23 = xlsread('fusionx23.xlsx');
carx24 = xlsread('fusionx24.xlsx');
carx25 = xlsread('fusionx25.xlsx');
carx26 = xlsread('fusionx26.xlsx');
carx27 = xlsread('fusionx27.xlsx');
carx28 = xlsread('fusionx28.xlsx');
carx29 = xlsread('fusionx29.xlsx');
carx30 = xlsread('fusionx30.xlsx');

%Import Truck Data
trucky01 = xlsread('trucky1.xlsx');
trucky02 = xlsread('trucky2.xlsx');
trucky03 = xlsread('trucky3.xlsx');
trucky04 = xlsread('trucky4.xlsx');
trucky05 = xlsread('trucky5.xlsx');
trucky06 = xlsread('trucky6.xlsx');
trucky07 = xlsread('trucky7.xlsx');
trucky08 = xlsread('trucky8.xlsx');
trucky09 = xlsread('trucky9.xlsx');
truckx01 = xlsread('truckx1.xlsx');
truckx02 = xlsread('truckx2.xlsx');
truckx03 = xlsread('truckx3.xlsx');
truckx04 = xlsread('truckx4.xlsx');
truckx05 = xlsread('truckx5.xlsx');
truckx06 = xlsread('truckx6.xlsx');
truckx07 = xlsread('truckx7.xlsx');
truckx08 = xlsread('truckx8.xlsx');
truckx09 = xlsread('truckx9.xlsx');

%Interpolate Ford Fusion Distance Measurements
car01 = cary01;
car02 = interp1(carx02,cary02,carx01,'spline');
car03 = interp1(carx03,cary03,carx01,'spline');
car04 = interp1(carx04,cary04,carx01,'spline');
car05 = interp1(carx05,cary05,carx01,'spline');
car06 = interp1(carx06,cary06,carx01,'spline');
car07 = interp1(carx07,cary07,carx01,'spline');
car08 = interp1(carx08,cary08,carx01,'spline');
car09 = interp1(carx09,cary09,carx01,'spline');
car10 = interp1(carx10,cary10,carx01,'spline');
car11 = interp1(carx11,cary11,carx01,'spline');
car12 = interp1(carx12,cary12,carx01,'spline');
car13 = interp1(carx13,cary13,carx01,'spline');
car14 = interp1(carx14,cary14,carx01,'spline');
car15 = interp1(carx15,cary15,carx01,'spline');
car16 = interp1(carx16,cary16,carx01,'spline');
car17 = interp1(carx17,cary17,carx01,'spline');
car18 = interp1(carx18,cary18,carx01,'spline');
car19 = interp1(carx19,cary19,carx01,'spline');
car20 = interp1(carx20,cary20,carx01,'spline');
car21 = interp1(carx21,cary21,carx01,'spline');
car22 = interp1(carx22,cary22,carx01,'spline');
car23 = interp1(carx23,cary23,carx01,'spline');
car24 = interp1(carx24,cary24,carx01,'spline');
car25 = interp1(carx25,cary25,carx01,'spline');
car26 = interp1(carx26,cary26,carx01,'spline');
car27 = interp1(carx27,cary27,carx01,'spline');
car28 = interp1(carx28,cary28,carx01,'spline');
car29 = interp1(carx29,cary29,carx01,'spline');
car30 = interp1(carx30,cary30,carx01,'spline');

%Interpolate Truck Distance Measurements
truck01 = interp1(truckx01,trucky01,carx01,'spline');
truck02 = interp1(truckx02,trucky02,carx01,'spline');
truck03 = interp1(truckx03,trucky03,carx01,'spline');
truck04 = interp1(truckx04,trucky04,carx01,'spline');
truck05 = interp1(truckx05,trucky05,carx01,'spline');
truck06 = interp1(truckx06,trucky06,carx01,'spline');
truck07 = interp1(truckx07,trucky07,carx01,'spline');
truck08 = interp1(truckx08,trucky08,carx01,'spline');
truck09 = interp1(truckx09,trucky09,carx01,'spline');

%Create Matrix of all Acceleration Measurement Sets (Fusion and Truck)
probe = [car01,car02,car03,car04,car05,car06,car07,car08,car09,car10,car11,car12,car13,car14,car15,car16,car17,car18,car19,car20,car21,car22,car23,car24,car25,car26,car27,car28,car29,car30,truck01,truck02,truck03,truck04,truck05,truck06,truck07,truck08,truck09];

%Generate Set of Random Numbers
%Used 5, 10, 20, 50, and 100 in this analysis.
r = randi(39,1,100);

%Assign Random Numbers to Specific Column in Acceleration Matrix
probe01 = abs(probe(:,r(1)));
probe02 = abs(probe(:,r(2)));
probe03 = abs(probe(:,r(3)));
probe04 = abs(probe(:,r(4)));
probe05 = abs(probe(:,r(5)));
probe06 = abs(probe(:,r(6)));
probe07 = abs(probe(:,r(7)));
probe08 = abs(probe(:,r(8)));
probe09 = abs(probe(:,r(9)));
probe10 = abs(probe(:,r(10)));
probe11 = abs(probe(:,r(11)));
probe12 = abs(probe(:,r(12)));
probe13 = abs(probe(:,r(13)));
probe14 = abs(probe(:,r(14)));
probe15 = abs(probe(:,r(15)));
probe16 = abs(probe(:,r(16)));
probe17 = abs(probe(:,r(17)));
probe18 = abs(probe(:,r(18)));
probe19 = abs(probe(:,r(19)));
probe20 = abs(probe(:,r(20)));
probe21 = abs(probe(:,r(21)));
probe22 = abs(probe(:,r(22)));
probe23 = abs(probe(:,r(23)));
probe24 = abs(probe(:,r(24)));
probe25 = abs(probe(:,r(25)));
probe26 = abs(probe(:,r(26)));
probe27 = abs(probe(:,r(27))):
probe28 = abs(probe(:,r(28))); 
probe29 = abs(probe(:,r(29))); 
probe30 = abs(probe(:,r(30))); 
probe31 = abs(probe(:,r(31))); 
probe32 = abs(probe(:,r(32))); 
probe33 = abs(probe(:,r(33))); 
probe34 = abs(probe(:,r(34))); 
probe35 = abs(probe(:,r(35))); 
probe36 = abs(probe(:,r(36))); 
probe37 = abs(probe(:,r(37))); 
probe38 = abs(probe(:,r(38))); 
probe39 = abs(probe(:,r(39))); 
probe40 = abs(probe(:,r(40))); 
probe41 = abs(probe(:,r(41))); 
probe42 = abs(probe(:,r(42))); 
probe43 = abs(probe(:,r(43))); 
probe44 = abs(probe(:,r(44))); 
probe45 = abs(probe(:,r(45))); 
probe46 = abs(probe(:,r(46))); 
probe47 = abs(probe(:,r(47))); 
probe48 = abs(probe(:,r(48))); 
probe49 = abs(probe(:,r(49))); 
probe50 = abs(probe(:,r(50))); 
probe51 = abs(probe(:,r(51))); 
probe52 = abs(probe(:,r(52))); 
probe53 = abs(probe(:,r(53))); 
probe54 = abs(probe(:,r(54))); 
probe55 = abs(probe(:,r(55))); 
probe56 = abs(probe(:,r(56))); 
probe57 = abs(probe(:,r(57))); 
probe58 = abs(probe(:,r(58))); 
probe59 = abs(probe(:,r(59))); 
probe60 = abs(probe(:,r(60))); 
probe61 = abs(probe(:,r(61))); 
probe62 = abs(probe(:,r(62))); 
probe63 = abs(probe(:,r(63))); 
probe64 = abs(probe(:,r(64))); 
probe65 = abs(probe(:,r(65))); 
probe66 = abs(probe(:,r(66))); 
probe67 = abs(probe(:,r(67))); 
probe68 = abs(probe(:,r(68))); 
probe69 = abs(probe(:,r(69))); 
probe70 = abs(probe(:,r(70))); 
probe71 = abs(probe(:,r(71))); 
probe72 = abs(probe(:,r(72))); 
probe73 = abs(probe(:,r(73))); 
probe74 = abs(probe(:,r(74))); 
probe75 = abs(probe(:,r(75))); 
probe76 = abs(probe(:,r(76))); 
probe77 = abs(probe(:,r(77))); 
probe78 = abs(probe(:,r(78))); 
probe79 = abs(probe(:,r(79))); 
probe80 = abs(probe(:,r(80))); 
probe81 = abs(probe(:,r(81))); 
probe82 = abs(probe(:,r(82))); 
probe83 = abs(probe(:,r(83))); 
probe84 = abs(probe(:,r(84)));
```matlab
probe85 = abs(probe(:,r(85)));探针85 = abs(probe(:,r(85)));
probe86 = abs(probe(:,r(86)));探针86 = abs(probe(:,r(86)));
probe87 = abs(probe(:,r(87)));探针87 = abs(probe(:,r(87)));
probe88 = abs(probe(:,r(88)));探针88 = abs(probe(:,r(88)));
probe89 = abs(probe(:,r(89)));探针89 = abs(probe(:,r(89)));
probe90 = abs(probe(:,r(90)));探针90 = abs(probe(:,r(90)));
probe91 = abs(probe(:,r(91)));探针91 = abs(probe(:,r(91)));
probe92 = abs(probe(:,r(92)));探针92 = abs(probe(:,r(92)));
probe93 = abs(probe(:,r(93)));探针93 = abs(probe(:,r(93)));
probe94 = abs(probe(:,r(94)));探针94 = abs(probe(:,r(94)));
probe95 = abs(probe(:,r(95)));探针95 = abs(probe(:,r(95)));
probe96 = abs(probe(:,r(96)));探针96 = abs(probe(:,r(96)));
probe97 = abs(probe(:,r(97)));探针97 = abs(probe(:,r(97)));
probe98 = abs(probe(:,r(98)));探针98 = abs(probe(:,r(98)));
probe99 = abs(probe(:,r(99)));探针99 = abs(probe(:,r(99)));
probe100 = abs(probe(:,r(100)));探针100 = abs(probe(:,r(100)));

% Calculate the Average Acceleration of Each Column
mean01 = mean(probe01);探针01的平均加速度
mean02 = mean(probe02);探针02的平均加速度
mean03 = mean(probe03);探针03的平均加速度
mean04 = mean(probe04);探针04的平均加速度
mean05 = mean(probe05);探针05的平均加速度
mean06 = mean(probe06);探针06的平均加速度
mean07 = mean(probe07);探针07的平均加速度
mean08 = mean(probe08);探针08的平均加速度
mean09 = mean(probe09);探针09的平均加速度
mean10 = mean(probe10);探针10的平均加速度
mean11 = mean(probe11);探针11的平均加速度
mean12 = mean(probe12);探针12的平均加速度
mean13 = mean(probe13);探针13的平均加速度
mean14 = mean(probe14);探针14的平均加速度
mean15 = mean(probe15);探针15的平均加速度
mean16 = mean(probe16);探针16的平均加速度
mean17 = mean(probe17);探针17的平均加速度
mean18 = mean(probe18);探针18的平均加速度
mean19 = mean(probe19);探针19的平均加速度
mean20 = mean(probe20);探针20的平均加速度
mean21 = mean(probe21);探针21的平均加速度
mean22 = mean(probe22);探针22的平均加速度
mean23 = mean(probe23);探针23的平均加速度
mean24 = mean(probe24);探针24的平均加速度
mean25 = mean(probe25);探针25的平均加速度
mean26 = mean(probe26);探针26的平均加速度
mean27 = mean(probe27);探针27的平均加速度
mean28 = mean(probe28);探针28的平均加速度
mean29 = mean(probe29);探针29的平均加速度
mean30 = mean(probe30);探针30的平均加速度
mean31 = mean(probe31);探针31的平均加速度
mean32 = mean(probe32);探针32的平均加速度
mean33 = mean(probe33);探针33的平均加速度
mean34 = mean(probe34);探针34的平均加速度
mean35 = mean(probe35);探针35的平均加速度
mean36 = mean(probe36);探针36的平均加速度
mean37 = mean(probe37);探针37的平均加速度
mean38 = mean(probe38);探针38的平均加速度
mean39 = mean(probe39);探针39的平均加速度
```
mean40 = mean(probe40);
mean41 = mean(probe41);
mean42 = mean(probe42);
mean43 = mean(probe43);
mean44 = mean(probe44);
mean45 = mean(probe45);
mean46 = mean(probe46);
mean47 = mean(probe47);
mean48 = mean(probe48);
mean49 = mean(probe49);
mean50 = mean(probe50);
mean51 = mean(probe51);
mean52 = mean(probe52);
mean53 = mean(probe53);
mean54 = mean(probe54);
mean55 = mean(probe55);
mean56 = mean(probe56);
mean57 = mean(probe57);
mean58 = mean(probe58);
mean59 = mean(probe59);
mean60 = mean(probe60);
mean61 = mean(probe61);
mean62 = mean(probe62);
mean63 = mean(probe63);
mean64 = mean(probe64);
mean65 = mean(probe65);
mean66 = mean(probe66);
mean67 = mean(probe67);
mean68 = mean(probe68);
mean69 = mean(probe69);
mean70 = mean(probe70);
mean71 = mean(probe71);
mean72 = mean(probe72);
mean73 = mean(probe73);
mean74 = mean(probe74);
mean75 = mean(probe75);
mean76 = mean(probe76);
mean77 = mean(probe77);
mean78 = mean(probe78);
mean79 = mean(probe79);
mean80 = mean(probe80);
mean81 = mean(probe81);
mean82 = mean(probe82);
mean83 = mean(probe83);
mean84 = mean(probe84);
mean85 = mean(probe85);
mean86 = mean(probe86);
mean87 = mean(probe87);
mean88 = mean(probe88);
mean89 = mean(probe89);
mean90 = mean(probe90);
mean91 = mean(probe91);
mean92 = mean(probe92);
mean93 = mean(probe93);
mean94 = mean(probe94);
mean95 = mean(probe95);
mean96 = mean(probe96);
mean97 = mean(probe97);
mean98 = mean(probe98);
mean99 = mean(probe99);
mean100 = mean(probe100);

%Calculate the Overall Average to the Fleet Network (Sizes of 5, 10, 20, 50 %, and 100)
avg1 = (mean01+mean02+mean03+mean04+mean05)/5
avg2 = (mean01+mean02+mean03+mean04+mean05+mean06+mean07+mean08+mean09+mean10)/10;
avg3 = (mean01+mean02+mean03+mean04+mean05+mean06+mean07+mean08+mean09+mean10+mean11 +mean12+mean13+mean14+mean15+mean16+mean17+mean18+mean19+mean20)/20;
avg4 = (mean01+mean02+mean03+mean04+mean05+mean06+mean07+mean08+mean09+mean10+mean11 +mean12+mean13+mean14+mean15+mean16+mean17+mean18+mean19+mean20+mean21+mean22 +mean23+mean24+mean25+mean26+mean27+mean28+mean29+mean30+mean31+mean32+mean33 +mean34+mean35+mean36+mean37+mean38+mean39+mean40+mean41+mean42+mean43+mean44 +mean45+mean46+mean47+mean48+mean49+mean50)/50;
avg5 = (mean01+mean02+mean03+mean04+mean05+mean06+mean07+mean08+mean09+mean10+mean11 +mean12+mean13+mean14+mean15+mean16+mean17+mean18+mean19+mean20+mean21+mean22 +mean23+mean24+mean25+mean26+mean27+mean28+mean29+mean30+mean31+mean32+mean33 +mean34+mean35+mean36+mean37+mean38+mean39+mean40+mean41+mean42+mean43+mean44 +mean45+mean46+mean47+mean48+mean49+mean50+mean51+mean52+mean53+mean54+mean55 +mean56+mean57+mean58+mean59+mean60+mean61+mean62+mean63+mean64+mean65+mean66 +mean67+mean68+mean69+mean70+mean71+mean72+mean73+mean74+mean75+mean76+mean77 +mean78+mean79+mean80+mean81+mean82+mean83+mean84+mean85+mean86+mean87+mean88 +mean89+mean90+mean91+mean92+mean93+mean94+mean95+mean96+mean97+mean98+mean99 +mean100)/100;

ACCELERATION THRESHOLD SCRIPT FILE

%Input Ford Fusion Measurements (10 Sets)
accx1 = xlsread('fusionx1.xlsx');
accy1 = xlsread('fusiony1.xlsx');
accx2 = xlsread('fusionx2.xlsx');
accy2 = xlsread('fusiony2.xlsx');
accx3 = xlsread('fusionx3.xlsx');
accy3 = xlsread('fusiony3.xlsx');
accx4 = xlsread('fusionx4.xlsx');
accy4 = xlsread('fusiony4.xlsx');
accx5 = xlsread('fusionx5.xlsx');
accy5 = xlsread('fusiony5.xlsx');
accx6 = xlsread('fusionx6.xlsx');
accy6 = xlsread('fusiony6.xlsx');
accx7 = xlsread('fusionx7.xlsx');
accy7 = xlsread('fusiony7.xlsx');
accx8 = xlsread('fusionx8.xlsx');
accy8 = xlsread('fusiony8.xlsx');
accx9 = xlsread('fusionx9.xlsx');
accy9 = xlsread('fusiony9.xlsx');
accx0 = xlsread('fusionx0.xlsx');
accy0 = xlsread('fusiony0.xlsx');

%Interpolate Distance Measurements for Ford Fusion
y0 = accy0;
y1 = interp1(accx1,accy1,accx0,'spline');
y2 = interp1(accx2,accy2,accx0,'spline');
y3 = interp1(accx3,accy3,accx0,'spline');
y4 = interp1(accx4,accy4,accx0,'spline');
y5 = interp1(accx5,accy5,accx0,'spline');
y6 = interp1(accx6,accy6,accx0,'spline');
y7 = interp1(accx7,accy7,accx0,'spline');
y8 = interp1(accx8,accy8,accx0,'spline');
y9 = interp1(accx9,accy9,accx0,'spline');

%Acceleration Section Calculations
accavg = (y1+y2+y3+y4+y5+y6+y7+y8+y9+y0)/10;
for i = 1:30:length(accavg)-30
    section(i) = mean(abs(accavg(i:i+29)));
end
section(section==0) = [];

%Section and Location Threshold Calculations
%Thresholds may be altered based on needs.
%Poor = sections of high average acceleration.
%Spikes = locations of high average acceleration.
accabs = abs(accavg);
avgthreshold = 0.0348;
totthreshold = 0.20;
poor = find(section > avgthreshold);
spikes = find(accabs > totthreshold);