A DRIVER, VEHICLE AND ROAD SAFETY SYSTEM USING SMARTPHONES

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As vehicle manufacturers continue to increase their emphasis on safety with advanced driver assistance systems (ADAS), I propose a ubiquitous device that is able to analyze and advise on safety conditions. Mobile smartphones are increasing in popularity among younger generations with an estimated 64% of 25-34 year olds already using one in their daily lives. With over 10 million car accidents reported in the United States each year, car manufacturers have shifted their focus of a passive approach (airbags) to more active by adding features associated with ADAS (lane departure warnings). However, vehicles manufactured with these sensors are not economically priced while older vehicles might only have passive safety features. Given its accessibility and portability, I target a mobile smartphone as a device to compliment ADAS that can bring a driver assist to any vehicle without regards for any on-vehicle communication system requirements.

I use the 3-axis accelerometer of multiple Android based smartphone to record and analyze various safety factors which can influence a driver while operating a vehicle. These influences with respect to the driver, vehicle and road are lane change maneuvers, vehicular comfort and road conditions. Each factor could potentially be hazardous to the health of the driver, neighboring public, and automobile and is therefore analyzed thoroughly achieving 85.60% and 89.89% classification accuracy for identifying road anomalies and lane changes, respectively. Effective use of this data can educate a potentially dangerous driver on how to operate a vehicle safely and efficiently. With real time analysis and auditory alerts of these factors, I hope to increase a driver’s overall awareness to maximize safety.
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I would like to dedicate this thesis to my family. To my sister who was always there to talk to and to my brother who taught me my first For Loop. To my mom who has inspired me since day one. Her constant motivation to do the best in anything has led me here with many achievements. I would have never accomplished so much without your unconditional love and support.
# TABLE OF CONTENTS

## ACKNOWLEDGMENTS

## LIST OF TABLES

## LIST OF FIGURES

## CHAPTER 1. INTRODUCTION

1.1. Introduction 1

1.2. Motivation 2

1.3. The Smartphone and Its Sensors 4

1.4. Accelerometer Accuracy 6

1.5. Speed Estimation 10

1.6. Road Map: Overview of Each Chapter Contents 11

## CHAPTER 2. VEHICLE ON-BOARD DIAGNOSTICS

2.1. Introduction 15

2.2. OBD-II 17

2.3. System Architecture 20

2.4. Smartphone Interface 25

2.5. Summary 28

## CHAPTER 3. THE VEHICLE

3.1. Introduction 29

3.2. Related Work 30

3.3. Experimental Setup 31

3.4. Gear Shifting 32

3.5. Vehicular Comfort 35
# LIST OF TABLES

1.1 Significance of triaxial measurements .................................................. 5

2.1 OBD-II signaling protocols and common vehicle manufacturers. .......... 17

2.2 OBD-II PIDs with size and units. ......................................................... 18

3.1 Automobiles used in vehicle comfort analysis. ...................................... 31

3.2 Road characteristics used in assessing comfort of a vehicle. ................. 32

3.3 ISO location weights. ............................................................................. 38

3.4 ISO frequency weighting values. ............................................................ 38

3.5 Vibrational ride index obtained in vehicle comfort analysis. ................. 41

3.6 Sensory pleasantness obtained in audio comfort analysis. .................... 44

4.1 Road anomaly color classification. .......................................................... 62

4.2 Road anomaly classification accuracy. ................................................... 66

5.1 Data access in offline mode simulating online mode ............................ 75

5.2 Smartphones and accelerometer characteristics .................................... 80

5.3 Accuracies obtained for each lane change ............................................ 87
LIST OF FIGURES

1.1 The one mile stretch on I-75 in Gainesville, Florida which caused ten people to lose their lives in multiple crashes. 3

1.2 Nexus One and 3-axis diagram of the accelerometer. It employs a Bosch BMA150 3-axis accelerometer which is capable of detecting movement in any direction. This movement may be the slightest lane change or a disturbance caused by a pothole. 5

1.3 Experimental setup to test the accuracy of the BMA-150 accelerometer sensor embedded in the phone. (a) Phone holder placed on a bicycle wheel (b) Nexus One placed inside the holder to perform centripetal acceleration experiment 6

1.4 Nexus One accelerometer accuracy results. The centripetal acceleration was calculated (experimental) and compared with the data recorded by the phone (measured). 8

1.5 Time domain accelerometer data transformed to the frequency domain. Identifying and removing this low frequency noise here helps in more accurate acceleration measurements that will be analyzed in the time domain. 9

1.6 Fourth order low pass butterworth filter applied to raw data of the accelerometer (x-axis) 10

1.7 Speed estimation using Nexus One BMA150 accelerometer. (a) Raw acceleration in frequency domain (b) High pass filtered acceleration (c) Acceleration in time domain of (a) and (b) (d) Acceleration integration of (c). The raw acceleration data resulted in a maximum speed of 136 mph while the filtered acceleration resulted in a maximum speed of 63.4 mph. Actual maximum speed recorded by the vehicle was 55 mph. 12
1.8 Diagram illustrating the many influences on vehicular safety while driving on the road. This thesis selects a few of these characteristics that contribute to the: driver, vehicle and road, and what influential factors they contain which decreases driver safety.

2.1 Smartphone popularity analysis which shows that 43% of all mobile phone users own a smartphone. Android is also the most popular mobile operating system. These numbers both are estimated to grow substantially over the coming years as embedded technology advances.

2.2 OBD-II message format: target address (TA) and source address (SA).

2.3 Hardware architecture illustrating the connectivity between smartphone, ELM327 and OBD-II interface where it can read ECU data from the vehicle.

2.4 Sensor fusion diagram illustrating the connectivity and sensors used (speed and accelerometer) throughout multiple applications.

2.5 OBD-II port and device. (a) OBD-II connector port with different pin layouts depending on what signaling protocol used by the vehicle (b) OBD-II bluetooth receiver which uses ELM327 hardware to communicate with the OBD-II port in the vehicle.

2.6 The Android and OBD-II software architecture.

2.7 Android application accessing live vehicle data from the OBD-II port. Bluetooth is used as the communication transfer protocol. (a) Resetting the ELM327 OBD-II device (ATZ) (b) Acquiring speed from the vehicle (010D), 64 mph.

2.8 Android application receiving both GPS data and OBD-II data. Speed was obtained from both sources, previewed on the screen and logged to a csv file for further analysis in Matlab.
2.9 Speed obtained from OBD-II and GPS. Both signatures are very similar proving the utility of OBD-II as well as GPS for speed. GPS frequency was 1 Hz while OBD-II frequency fluctuated 4 Hz - 9 Hz.

3.1 Vehicle comfort location positioned on the front of the passenger seat. (a)-(b) 2007 Toyota Yaris (c)-(d) 1992 Chevrolet S-10

3.2 Gear shifts from three vehicles accelerated initially at rest. Each shift is clearly defined by its sharp drop in acceleration experienced by a jerk in the vehicle revealing a gear shift. (a) 1992 S-10 Single Cab (b) 2007 Toyota Yaris (c) 2007 Volvo S-40

3.3 The vibrations on the x, y and z axes were measured using 3-axis accelerometer and audio was recorded using the microphone; both embedded in the smartphone.

3.4 Ride index (RI) calculated containing raw acceleration values, frequency weights, and final output of RI using the calculated VDV measurements for each axis.

3.5 Ride index (RI) calculated for each vehicle over all three road types. The lower value indicates a higher vehicle comfort. Car 2 in this method is classified with the most comfort.

3.6 Averaged ride index for each vehicle calculated for each of the three roads with a lower value conveying a higher vehicular comfort. Car 2 has the best averaged comfort over the three road types.

3.7 Normalized sensory pleasantness values for each vehicle on all three road types. In each case, the Chevrolet S-10 outperformed its competitors pertaining to low noise levels. A higher SP designates greater comfort.

3.8 Averaged median sensory pleasantness of all three road types for each vehicle.
A higher sensory pleasantness designates greater vehicular comfort.

4.1 Rough road sign with patched roads.

4.2 The system utilizes the accelerometer and GPS sensors of the phone to initiate the classification process. The accelerometer data is then sent to a smoothing process in only the x-axis. Anomalies are then classified and synchronized with the time of the GPS data. After an interpolation procedure of the GPS data matching up with the accelerometer data, I can then form the road condition map using Google Earth.

4.3 Vehicle and phone location during road conditions analysis. (a) The vehicle used in this experiment, a 1992 Chevrolet S-10. Suspension is older allowing the accelerometer to feel more raw measurements caused by surface anomalies. (b) Placement of the mobile smartphone used in this experiment. Mobile was located on the floorboard in the passengers seat. The mobile used was an HTC Nexus One equipped with an accelerometer.

4.4 Roads in Denton that were covered in this experiment. Red coloring indicates one side of the road (or right lane) while the green indicates the other side of the lane (left lane). Clockwise and counter-clockwise was an easier way to describe which direction while organizing the condition measurement process.

4.5 Examples of potholes encountered on the road. (a) and (b) both illustrate a formation of a pothole with a large decrease in the z-axis followed by an increase. A threshold is set to detect this pothole in every case.

4.6 Examples of bumps encountered on the road. (a) illustrates the original formation of a bump with an increase in the z-axis followed by a decrease (b) illustrates a secondary process in classifying a bump which incorporates the x-axis. An increase in the x-axis followed by the identifying method of (a)
helps distinguish a pothole from a bump.

4.7 Examples of bumps in time domain (left) and frequency domain (right). We can see a high amplitude in the x-axis around 1 Hz. This along with the combination of high amplitude around 2 Hz in the z-axis, results in a classification of a bump in the frequency domain.

4.8 Examples of potholes in time domain (left) and frequency domain (right). A high amplitude around 2 Hz is common in the z-axis while a low amplitude around 1 Hz in the x-axis. In some cases, this x-axis amplitude was very low almost irrelevant in some cases. These characteristics differ from that of the previous anomaly, bumps.

4.9 Examples of uneven roads. (a) and (b) both illustrate the formation of an uneven road seen significant decrease in the x-axis (blue line). A threshold is set as the horizontal blue line to identify an uneven part of the road.

4.10 Examples of rough roads. (a) and (b) both illustrate the formation of a rough road seen in the z-axis with a higher frequency. (a) clearly seen as rough when viewing its surrounding area. (b) is not as apparent but still distinguishable. Low amplitudes, high frequency and short durations can be seen in both figures. I use all these characteristics to classify rough roads.

4.11 Examples of magnetic road anomalies. (a) illustrates the location in which (b) was recorded. A train track which can be classified as a bump can clearly be distinguished. (c) and (d) illustrate two instances where bridges which contain expansion joints and connectors which can cause classification as bumps.

4.12 Map of road conditions. Visual representation road conditions using GPS coordinates and Google Earth. Intensity levels are designated by colors, signifying either a pothole, bump, uneven, rough, or smooth road type. (a)
one lane (b) two lanes

4.13 Example of pothole location accuracy. On further examination of a pothole location provided by the road condition map, a pothole was found at the exact location.

4.14 Interstate bridge bump. Seen is two bridge connections on an interstate creating multiple bumps as a vehicle enters the bridge and exits the bridge. GPS coordinates were accurate enough to identify the bridge.

5.1 LaneChange system architecture consists of three levels: sensor data, maneuver analysis and safety level.

5.2 LaneChanges software architecture containing two proposed methods of acquiring sensor data in online and offline modes. Online data is acquired in real time through the embedded sensors. Offline is simulated through previously recorded data logs from driving scenarios.

5.3 Application class and method diagram. Online (OnSensorChange) and offline (fromFile) functions below contain the data injection functionality. The other classes Detection, SensorData and LaneChanges (main Activity) make up the application as a whole.

5.4 2008 Pontiac G8 - 3.6L V6 with a 5-speed automatic transmission

5.5 Smartphone axes aligned to that of the motion of the vehicle. Y-axis designates longitudinal acceleration and deceleration while x-axis conveys lateral movement of the vehicle. Placement of the phone was on the center console.

5.6 Measurement locations used for analyzing safe and unsafe driving techniques. A smartphone arm strap holder was used which secured the phone to the center console allowing easy obtainable and hands free data collection.
5.7 Sensor analysis for the Galaxy Nexus utilizing different smoothing rates. Higher smoothing rates have a greater impact on the amplitude of the signal.

5.8 Smoothing distribution for different smartphones which incorporate different accelerometer manufacturers which utilize different frequencies. A higher smoothing rate is necessary to filter out environmental noise which increases as the sampling rate increases.

5.9 Acceleration signature of (a) left lane change and (b) right lane change. These formations are distinguishable in Figures 10(a) and 10(b).

5.10 Lane changes recorded by the x-axis of a smartphone’s accelerometer. A left lane change is formed by a small decrease followed by an increase. A right lane change is formed oppositely. (a) Four safe right lane changes and three safe left lane changes in series (b) Four sudden right and left lane changes performed in series, eight total.

5.11 Stored training templates used for DTW classification for left lane changes.

5.12 DTW matching of an aggressive left lane change: (a) original signals and (b) DTW performance resulting in a match with a DTW distance value of 7.4847. This was tested with an incorrect match on the good training template resulting in a higher DTW distance value of 42.7748. The lower distance value conveys the correct match.
1.1. Introduction

Imagine driving home from work. You get in your car, buckle your seat belt, check your rear-view mirror, roll down the windows for a cool breeze, reverse your vehicle and finally put the gear into drive (D) initiating the accelerator pedal. Maybe you’re thinking about what to have for dinner or what the weekend has in store, but you don’t see that large pothole approaching. Swerving to avoid it, you slam into the side of a neighboring vehicle which results injury to yourself and to your vehicle. In the fast-paced society of today, we are obsessed with arriving at our destination the fastest and getting back home as quickly as possible. Nevertheless, it is this fast-paced lifestyle that can put us in harms way. Ignoring the overwhelming safety concerns while driving, or even unaware of hazardous road conditions can both lead to potential accidents. Such accidents not only damage our vehicle, hurt our driving record, and put our own health at risk, but also endanger many neighboring drivers who are in the same vicinity. Today, it is said that having a mobile phone in your car increases your chance of an accident [1], but what if a mobile phone could ultimately decrease the chance of being involved in or even creating a wreck on the road? In recent years, there has been a tremendous growth in smartphones embedded with numerous wireless sensors such as accelerometers, GPS, magnetometers, multiple microphones, and even cameras [2, 3, 4]. The scope of wireless sensor networks has expanded into many application domains such as Intelligent Transportation Systems that can provide users with new functionalities previously unheard of. Experimental automobiles in the past have included certain sensors to record

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Section 1.1, 1.3 and 1.4 in this chapter are reproduced from M. Fazeen, B. Gozick, R. Dantu, M. Bhukhiya and M.C. González, ”Safe Driving Using Mobile Phones,” IEEE Transactions on Intelligent Transportation Systems, accepted March 2012, with permission from IEEE.
data preceding test crashes [5, 6]. After analysis, crash scenarios are stored and analyzed with real time driving data to recognize a potential crash [7] and try to prevent it [8]. These sensors can add thousands of dollars to the cost of an already expensive luxury automobile. This is not convenient for the average person, who buys an affordable mid-sized vehicle, focused primarily on family safety. Sacrificing luxury for safety accommodations is something all buyers have to endure when shopping for a vehicle that can balance their family’s health with a reasonable price tag. With the economy not flourishing as in the past, we are always looking for cheaper alternatives that provide an efficient means of support without cutting corners. Using a mobile phone as one of these alternatives can provide the critical safety requirements we so vigorously seek at a most affordable price, as this device is already bound to most of our lives. Because these new smartphones are equipped with sensors capable of working together to formulate complex results, I envision a cheap and convenient mobile device that is able to analyze and advise the driver on sudden and harmful situations that arise from vehicle maneuvers and environmental factors. This type of driver assist is only meant to complement the driver but not to take full control of the vehicle. Providing constructive feedback to the driver is crucial in correcting bad driving behaviors. Recently, Ford and BMW have proposed ideas on this type of driver assist where it can be integrated into their telematics system along with hundreds of other vehicles sensors [9]. Given the sensing capability of a single smartphone, I utilize the internal accelerometer, microphone and GPS of the phone in place of the expensive hardware installed that is able to provide feedback to the driver and eventually improve overall awareness as well as performance over time.

1.2. Motivation

In the early morning of Sunday January 29, 2012 at 3:45am, a tragic accident occurred on Florida’s busy six lane, 75 mile interstate, I-75. The multi-vehicle accident involved two pileups spanning a one mile stretch involving a dozen cars, six tractor-trailers and one motorhome who were all traveling northbound on the three lane wide road. After the burning
metal was put to rest and dense smoke cleared, ten people lost their lives while eleven people survived with injuries, some in critical condition [10]. The cause of the wreck was said to be a combination of poor visibility, hazardous road conditions, and aggressive driving behavior with an initial wreck happening a few hours before with three vehicle collision between a young driver in a sports car, an exhausted truck driver behind the wheel of a semi and a speeding sports utility vehicle (SUV) [11]. An aftermath view of the I-75 accident can be seen in Figure 1.1.

![Figure 1.1. The one mile stretch on I-75 in Gainesville, Florida which caused ten people to lose their lives in multiple crashes.](image)

There are over 10 million car accidents reported in the United States each year [12]. A study conducted in 2009 by the American Automobile Association Foundation for Traffic Safety reported that between the years of 2003 and 2007, 56% of deadly reported involved one or more unsafe driving behaviors [13]. These behaviors exhibit as aggressive to neighboring drivers and are undetectable to most standard transportation equipment. Most car manufacturers have shifted their focus of a passive approach, e.g. airbags, seat belts, and anti-lock brakes, to more active by adding features associated with advanced driver assistance systems (ADAS) [14], e.g. lane departure warning system [15], collision avoidance system
etc. However, vehicles manufactured with these sensors are hard to find in lower priced, economical vehicles as ADAS packages are not cheap add-ons. In addition, older vehicles might only have passive safety features since manufacturers only recently began to introduce an effective driver assist. The best protection against an automobile accident is the ability to prevent it. Prevention will not only save thousands of lives, but also save the time and money that is consistently flushed into the many legal protocols that follow an accident. Vehicle degradation is an inevitable consequence of continuously operating an automobile. A vehicle’s health is always at risk as it is susceptible to external environmental factors, such as the roads and other cars, and also to internal factors, such as aging parts and strenuous driving behaviors. The resources we have available to us to provide a quick fix do not always work and sometimes come too late to even use. By using a device that is already integrated into most of our daily lives to help prevent most automobile catastrophes not only seems logical, but almost revolutionary as a dependence on car manufacturers to provide a safe driving experience is lifted. As smartphones are easily available and widely used, the intuitive functionality presented by a mobile smartphone to detect transportation related safety issues which are influenced by the vehicle, the road, and the driver has an ever expanding practicable design base with limited overhead cost.

1.3. The Smartphone and Its Sensors

The device used was an Android based smartphone, Nexus One. This HTC/Google phone made it relatively easy to acquire data to be analyzed thoroughly. Given its mobility and rise in popularity the past few years, a smartphone-based measuring device makes these findings unique and applicable for future implementations. The phone contains a Bosch BMA150 3-axis accelerometer [18] that is capable of detecting multiple motions triggered by a vehicle. It has a sensitivity range of 2g/4g/8g with a max axial refresh rate of 3300Hz. The limitations of the refresh rate and software integration yield a usable refresh rate around 25-30Hz [19, 20]. Motions captured by the phone can be induced by a number of occurrences. For
example, acceleration, braking, uneven road conditions, or any degree of change in direction performed by the automobile can be numerically distinguishable. Figure 1.2 represents the Nexus One and its relevant axes. If any movement is detected, it is analyzed and expressed numerically in these directions.

![Figure 1.2. Nexus One and 3-axis diagram of the accelerometer. It employs a Bosch BMA150 3-axis accelerometer which is capable of detecting movement in any direction. This movement may be the slightest lane change or a disturbance caused by a pothole.](image)

Table 1.1 refers to each axis of the accelerometer of the phone as well the direction and relevant driving maneuver performed. Examples of possible causes of these axial movements are shown such as movement in the y-axis might signify a sudden change in acceleration or a jerk experienced when shifting gears.

<table>
<thead>
<tr>
<th>Axis</th>
<th>Direction</th>
<th>Typical Driving</th>
</tr>
</thead>
<tbody>
<tr>
<td>x</td>
<td>Left/Right</td>
<td>Turning/Lane Change</td>
</tr>
<tr>
<td>y</td>
<td>Front/Rear</td>
<td>Acceleration/Braking</td>
</tr>
<tr>
<td>z</td>
<td>Up/Down</td>
<td>Vibrations/Road Anomalies</td>
</tr>
</tbody>
</table>

Different driving maneuvers are found and differentiated by using each individual axis of the accelerometer. Table 1.1 refers to each axis of the accelerometer of the phone as well the direction and relevant driving maneuver performed. Examples of possible causes of these axial movements are shown such as movement in the y-axis might signify a sudden change in acceleration or a jerk experienced when shifting gears.
1.4. Accelerometer Accuracy

I test the accuracy of the device by experimental comparison of calculated data and observed data recorded by the phone. For the test, I utilized dynamics equations such as centripetal acceleration and compared that with the measurements recorded by the Nexus One. Do to the availability and budget reasons, I did not use a high end commercial inertial measurement unit (IMU). The IMU would help solidify the accuracy of the accelerometer sensor in the phone; however, I used a different technique to obtain similar results using physical methods explained below. To compare with the ground truth, a series of tests was performed which aimed at testing the accuracy of the Bosch BMA150 accelerometer in the Nexus One. To test the accuracy of the phone, I utilized a bicycle-like wheel that has very good bearings. This provides little friction but is still present as the wheel eventually comes to a complete stop. I attached the phone to the end of the wheel parallel to the rotation of the wheel which is clamped down and immobile. The phone is in the same holster that is used for the comfort testing inside the vehicle, Chapter 3. I spun the wheel and set the phone to record accelerometer values.

![Experimental setup to test the accuracy of the BMA-150 accelerometer sensor embedded in the phone. (a) Phone holder placed on a bicycle wheel (b) Nexus One placed inside the holder to perform centripetal acceleration experiment](image)

The experiment was recorded in which the timings per phone revolution around the
wheel were analyzed. To compare with the accelerometer data from the phone, I calculated the averaged angular acceleration at different revolutions around the wheel in which the phone experienced. Since I used a wheel apparatus, centripetal acceleration or force was calculated in the y-axis and then compared with a calculated value. To describe the experiment, a sensor recording application was started on the phone and placed in the holster which is attached to the outside of the wheel by velcro, seen in Figure 3(a). At the same time, a camcorder began recording the experiment which is later used to obtain the time per phone/wheel revolution. The experimental centripetal acceleration ($ac$) was calculated using the radius of the wheel ($r$), angular velocity ($w$). These are represented below with Equation 1 and Equation 2, respectively.

\begin{align*}
(1) & \quad r = 0.336 \\
(2) & \quad ac = vt^2/r = w^2r
\end{align*}

After the centripetal acceleration was calculated using (1), it was compared against the z-axis data from the phone. Since I had the phone oriented parallel with the wheel and the direction of the centripetal acceleration is always inwards along the radius vector of the circular motion I use the z-axis. I also calculate both the Spearman and Pearson correlation value between the two accelerations. Test 1 resulted in a Pearson correlation of 0.9997 and a Spearman correlation of 1 while Test 2 resulted in a Pearson correlation of 0.9978 and a Spearman correlation of 0.9979. These high correlation values convey that the phone is accurate and therefore a viable device to be used in real world situations such as a vehicle. Comparison results of centripetal acceleration, shown in Figure 1.4, show the accelerometer to be very accurate as well as sensitive at 30 Hz making it a reliable device to be used in these
manners. This experiment was performed multiple times for different time lengths conveying similar results each time.

![Figure 1.4. Nexus One accelerometer accuracy results. The centripetal acceleration was calculated (experimental) and compared with the data recorded by the phone (measured).](image)

Using the accelerometer in the phone for location positioning such as speed estimation and distance calculations can sometimes be difficult using only the raw data from the sensor. With a lower quality sensor manufactured for smartphones which are embedded for simple tasks, using them for other purposes as such can reveal to be an extremely difficult task without proper data analysis. These analyses are usually performed on high quality sensors such as IMU’s used in airplanes and trains which have the functionality to record sensitive movements accurately and display very accurate speed and even distance estimations. I am essentially trying to do the same but with a mobile smartphone equipped with a lower quality sensor. The phone I used here is a HTC Nexus One which is embedded with a Bosch BMA150 typically used in everyday applications such as gaming, pedometer, drop and shock detection, and various small movement applications. The sensor has a listed frequency of 25Hz-1500Hz but only a usable 30 Hz from the given Android API, SensorManager [21]. Though a low
frequency output, the BMA150 still has the capability to sense tilt, motion and shock vibration the cell phone is experiencing. I try to employ this capability for driving behaviors and road condition analysis which both have the possibility to prevent future road accidents and even save lives in the process. However, before these actions can be performed, I have to filter the sensor data coming from the accelerometer so we can get a clear and accurate picture of any real movements that are taking place. Noise and other sensor problems such as drift and random walk can defect the data leading to inaccurate speed calculations.

Noise mainly comes from low level frequency measurements which is a characteristic of the piezoelectric material used in the manufacturing of the sensor. The higher quality of these materials will produce less noise. However, in the BMA150, the noise reveals itself at a very low frequency, less than 1 Hz. Using frequency filtering techniques on certain low frequencies after the measurement process, has led to an advancement in more accurate calculations such as speed and displacement. Figure 1.5 illustrates accelerometer noise.

![Figure 1.5. Time domain accelerometer data transformed to the frequency domain. Identifying and removing this low frequency noise here helps in more accurate acceleration measurements that will be analyzed in the time domain.](image)

To compensate for any initial existing error in the sensor, I have implemented custom
bandpass filter which incorporates a low-pass frequency filter and a high-pass frequency filter, and also a sensor reset mechanism every 20 ms. This combination has proven to be effective for utilizing mobile phone sensors in a vehicle environment. The low pass filter is an adaptable filter which is dependent on the sample rate of the sensor. This makes it scalable for future devices which have more developed hardware such as a higher sensitivity and higher sampling rate. Incorporating the custom high pass filter removed low frequency DC noise which is generated by the sensor. This noise is unwanted and adds to the acceleration output by the sensor.

Figure 1.6 illustrates a 4th order low pass Butterworth’s filter applied to the x-axis of the accelerometer (after custom high pass) which designates the lateral movement of the vehicle. This along with a high pass filter creates a bandpass filter which helps remove additional noise that can be erroneous to when analyzing the data for particular applications.

![Figure 1.6](image)

Figure 1.6. Fourth order low pass butterworth filter applied to raw data of the accelerometer (x-axis)

1.5. Speed Estimation

One particular characteristic of a vehicle is its speed. This tends to fluctuate depending on the driver, type of road, weather conditions, traffic conditions and has great influence on what we want to analyze and how we analyze it. Therefore, an accurate speed estimation
must be obtained which can be synchronized with the accelerometer data obtained from smartphones embedded sensor. The obvious choice to obtain this significant variable is to use the accelerometer directly since I am already utilizing it as a collection device. A test was done accelerating a vehicle from rest and leveling out at a maximum speed of 55 mph. To do this, I first remove the low frequency noise using a high pass filter with a cutoff frequency of 0.25 Hz. We can compare the raw and filtered acceleration in the frequency domain with Figure 7(a) and Figure 7(b), respectively. The data was transformed back into the time domain with the low frequency noise removed. This can be seen in Figure 7(c). The data was then integrated over the 40 second period to obtain a speed estimation of the vehicle. The raw acceleration data resulted in a maximum speed of 136 mph while the filtered acceleration data resulted in a more approximate speed of 63.4 mph. The results are compared with the actual speed of the vehicle in Figure 7(d). The actual speed maximum was 55 mph resulting in a 147.27% and 15.27% error for the raw and filtered acceleration, respectively.

Though this error is significantly reduced, an accurate speed estimation is a significant attribute needed for analyzing vehicle maneuvers. Therefore, the accelerometer proves itself to be unusable when determining speed calculations inside a moving vehicle. The accumulative noise even after a bandpass filter has been applied makes it unreliable when integrating. Integration amplifies this noise which results in an erroneous speed estimations but in time domain, acceleration data without integration can still be very accurate and useful. Since this method is impractical, I look to other vehicle resources that are able to obtain accurate speed estimations, GPS and on-board diagnostics (OBD-II) port.

1.6. Road Map: Overview of Each Chapter Contents

This thesis discusses methods for capturing and analyzing accelerometer sensor data in a vehicular environment. Many different applications can be derived that fully takes advantage of the smartphone advanced hardware. Utilizing its embedded sensors in a practical design, I apply them to extract and distinguish information about the driver, vehicle and road. The
Figure 1.7. Speed estimation using Nexus One BMA150 accelerometer. (a) Raw acceleration in frequency domain (b) High pass filtered acceleration (c) Acceleration in time domain of (a) and (b) (d) Acceleration integration of (c). The raw acceleration data resulted in a maximum speed of 136 mph while the filtered acceleration resulted in a maximum speed of 63.4 mph. Actual maximum speed recorded by the vehicle was 55 mph.

content conveyed in this thesis is organized into 6 chapters.

- Chapter 1 (Introduction): In this chapter, I give an overview of smartphone and its embedded accelerometer. The accelerometer accuracy is demonstrated as well as
utilizing it as a device for speed estimation. I describe advancements in Intelligent Transportation Systems that are already available to the public which contributes to rising retail costs. The motivation of this work is also strongly conveyed with the idea that this work has the ability to save lives.

- **Chapter 2 (On-board Diagnostics):** In this chapter, I give a brief overview of the OBD-II protocol and how it is accessible in a vehicle. I present a hardware architecture as well as a software architecture both used for an Android smartphone integration. Vehicular data was extracted from the vehicle by Bluetooth communications where it was synchronized with the smartphone’s embedded accelerometer.

- **Chapter 3 (The Vehicle):** In this chapter, I present a comfort analysis on five different vehicles which varied in year. I provide an effective comfort analysis utilizing two embedded sensors in the smartphone which are able to assess the basic comfort needs of low vibrations and low noise levels. I applied techniques to each in order to assess vibrational perception as well as acoustical perception. I conclude on the best vehicle for each category.

- **Chapter 4 (The Road):** In this chapter, I analyze road conditions which are classified into five different elements: 1) Potholes 2) Bumps 3) Rough 4) Uneven and 5) Smooth. Each element is defined as a road anomaly and classified using different signal processing techniques. The embedded accelerometer was used for data collection on 40 miles of road in or to distinguish consistent anomaly patterns. Analysis was done offline in Matlab rather than online on the smartphone.

- **Chapter 5 (The Driver):** In this chapter, I analyze lateral movement of the vehicle using the embedded accelerometer. I test multiple smartphones each containing different sensors with different frequency rates. An online and offline technique was used to analyze lane change maneuvers. Lane changes were detected using signal processing techniques and classified using machine learning. All classifications were
done online, on the smartphone. I test this system on multiple drivers to test the consistency of the detection and classification process.

- Chapter 6 (Conclusions): In this chapter, I conclude this thesis by summarizing the contributions, limitations of each system and give an overview of some future work which can be applied to extend some of these systems.

![Diagram illustrating the many influences on vehicular safety while driving on the road. This thesis selects a few of these characteristics that contribute to the: driver, vehicle and road, and what influential factors they contain which decreases driver safety.](image)

Figure 1.8. Diagram illustrating the many influences on vehicular safety while driving on the road. This thesis selects a few of these characteristics that contribute to the: driver, vehicle and road, and what influential factors they contain which decreases driver safety.
2.1. Introduction

The addition of a mobile phones equipped with useful system based sensors has led to many new technological advancements taking advantage of this new hardware. These advancements tackle old traditional problems utilizing new resources presented by a smartphone specifically mobility, the embedded sensors, and the processing power. Some of these topics include but are not limited to localization [22, 23], activity recognition [24], and facial recognition [25, 26]. Since previous attempts on obtaining accurate speed and distance estimation using the accelerometer have not been accomplished, I turn to the source to acquire current speed, the vehicle. Vehicles themselves process enormous amounts of information gathered by hundreds of sensors which are placed throughout the whole vehicle [27]. Tapping into these sensors for Intelligent Transportation Systems has been an interest for many years now [28, 29, 30]. Many works have been done to extract this information, analyze and even send to the cloud [31]. The amount of information that is accessible from the vehicle varies from manufacturer and grade of vehicle. Many sensors that are present in a vehicle can be prompted and sent by the electronic control unit (ECU) which can help aid in safe driving techniques. Nowadays, manufacturers are increasing the number of ECUs which are embedded in the vehicle. There can be more than 50 ECUs installed throughout a modern day vehicle [30], and that number increases greatly with newly developed luxury vehicles which have begun to incorporate more advance driver assistance systems (ADAS). However, seen from previous works, the extra infrastructure costs used to extract, process and send to the cloud does not make this practical for the average driver who might be on a budget. With smartphones increasing popularity among younger generations, I want to incorporate a vehicle collection and monitoring device into an already ubiquitous device. It is estimated that 53%
of 18-24 year olds and 64% of 25-34 year olds own a smartphone which is fully capable of integrating with vehicles on-board diagnostics [32]. We can see in Figure 2.1 by penetrating this market makes sense for practical and applicable reasons.

Figure 2.1. Smartphone popularity analysis which shows that 43% of all mobile phone users own a smartphone. Android is also the most popular mobile operating system. These numbers both are estimated to grow substantially over the coming years as embedded technology advances.

Vehicles today contain two standards, each which contain significant data: (1) OBD-II and (2) CAN-Bus. In this chapter, I give a brief introduction to the OBD-II standard and how it can be integrated with smartphone sensors. I illustrate results which have been developed using the this standard to obtain speed which is a valuable variable when analyzing driver maneuvers. Given the fact that the CAN-Bus is more manufacturer specific when it comes to accessibility, it was not used. However, a system which incorporates the CAN-Bus will exceed that of an OBD-II interface since both speed querying and data availability is significantly greater. Finding another source of vehicular speed is significant given the high power consumption of a GPS inside a smartphone. I seek to find this alternative directly from one of the vehicle’s internal communication systems.
2.2. OBD-II

2.2.1. OBD-II Communication Protocol

On-Board Diagnostics is a generalized term referring to the diagnosis of the many vehicle components such as the engine or braking system. Diagnosing a repair sometimes relies heavily on the OBD-II system which has been installed in most vehicles. For this reason, diagnostic trouble codes have been standardized which can help identify an ineffective component that is located deep inside a vehicle’s chassis. OBD-II is an automotive protocol used for diagnostic tests and determining the state of certain components inside an automobile. However, OBD-II also provides real-time information about the vehicle from multiple sensors. There are five signaling protocols that are permitted with the OBD-II interface. Determining a vehicle’s specific protocol used is based on the manufacturer of the vehicle. For example, General Motors (GM) and Ford use a variation of the SAE J1850 protocol but use different modulation techniques. For American standardization purposes, all vehicles made after 2008 are required to work with the 5th standard shown in Table 2.1.

<table>
<thead>
<tr>
<th>OBD-II Protocol</th>
<th>Manufacturer</th>
</tr>
</thead>
<tbody>
<tr>
<td>SAE J1850 Pulse Width Modulation (PWM)</td>
<td>Ford</td>
</tr>
<tr>
<td>SAE J1850 Variable Pulse Width (VPW)</td>
<td>General Motors</td>
</tr>
<tr>
<td>ISO 9141-2</td>
<td>Chrysler and Asian</td>
</tr>
<tr>
<td>ISO 14230 KWP2000</td>
<td>European and Asian</td>
</tr>
<tr>
<td>ISO 15765 CAN</td>
<td>U.S. Standard for Vehicles (Bosch) 2008+</td>
</tr>
</tbody>
</table>

The Society of Automotive Engineers develops many standardizations that have to do with the transportation fields. SAE J1979 is one standard that outlines the specific method for requesting various vehicle sensor data and describes the available sensors accessible by the employed ECU [33]. SAE J1979 was originally developed to meet the United States OBD requirements set by the government for all vehicles after 1996. To access the sensors that
are available we must directly address them by their defined parameter identification numbers (PID). These PIDs are defined in the SAE J1979. Each PID is encoded in 4-bit hexadecimal number. The resulting response from the ECU would be either a 1 to 4 byte message. Table 2.2 is a list of PIDs that are defined by the SAE J1979 standard.

<table>
<thead>
<tr>
<th>PID</th>
<th>Description</th>
<th>Byte Response</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>05</td>
<td>Engine Coolant Temperature</td>
<td>1 byte</td>
<td>oC</td>
</tr>
<tr>
<td>0A</td>
<td>Fuel Pressure</td>
<td>1 byte</td>
<td>kPa</td>
</tr>
<tr>
<td>0B</td>
<td>Intake Manifold Pressure</td>
<td>1 byte</td>
<td>kPa</td>
</tr>
<tr>
<td>0C</td>
<td>Engine RPM</td>
<td>2 bytes</td>
<td>rpm</td>
</tr>
<tr>
<td><strong>0D</strong></td>
<td><strong>Vehicle speed</strong></td>
<td><strong>1 byte</strong></td>
<td><strong>km/h</strong></td>
</tr>
<tr>
<td>0E</td>
<td>Timing Advance</td>
<td>1 byte</td>
<td>degrees</td>
</tr>
<tr>
<td>0F</td>
<td>Intake Air Temperature</td>
<td>1 byte</td>
<td>oC</td>
</tr>
<tr>
<td>10</td>
<td>MAF Air Flow Rate</td>
<td>2 bytes</td>
<td>g/s</td>
</tr>
<tr>
<td>11</td>
<td>Throttle Position</td>
<td>1 byte</td>
<td>%</td>
</tr>
<tr>
<td>1F</td>
<td>Run Time Since Engine Start</td>
<td>2 bytes</td>
<td>s</td>
</tr>
<tr>
<td>23</td>
<td>Fuel Pressure (diesel)</td>
<td>1 byte</td>
<td>kPa</td>
</tr>
<tr>
<td>2F</td>
<td>Fuel Level Input</td>
<td>1 byte</td>
<td>%</td>
</tr>
<tr>
<td>33</td>
<td>Barometric Pressure</td>
<td>1 byte</td>
<td>kPa</td>
</tr>
<tr>
<td>46</td>
<td>Ambient Air Temperature</td>
<td>1 byte</td>
<td>oC</td>
</tr>
</tbody>
</table>

2.2.2. OBD-II Message Format

The OBD-II communication protocol states different modes in which it directs the message to the appropriate ECU. The list and description of each mode is detailed below.

- Mode $01$: Current vehicle data
- Mode $02$: Freeze frame data
- Mode $03$: Diagnostic trouble codes (DTC)
- Mode $04$: Clear diagnostic trouble codes (DTC)
- Mode $05$: Test results for oxygen sensors (CAN only)
- Mode $06$: Test results for Continuous System Monitoring
• Mode $07$: Cached diagnostic trouble codes (DTC)
• Mode $08$: Special control mode
• Mode $09$: Vehicle information (Enhanced PID)

Mode 1 is used to request data about the vehicle. With this, I can request the vehicle for its current speed, rpm or any of the PIDs listed in Table 2.2. In order to request this data, the OBD-II protocol has a set message format which is also defined in SAE J1979. Figure 2.2 illustrates the message structure which incorporates a header, payload and checksum.

![Figure 2.2. OBD-II message format: target address (TA) and source address (SA).](image)

The three byte header provides details about the priority, the receiver or target address (TA) and the transmitter or source address (SA). The following seven bytes are designated for the data message or what is sent request speed from the vehicle. The remaining byte is the checksum. Like any communication transfer protocol, messages are susceptible to error during the transmission. To detect any errors that may occur, a cyclic redundancy check (CRC) is processed by the OBD-II device. The device then reports back an ERROR response if such a situation takes place [34]. It is in the seven byte data message where I request and retrieve data from the vehicle. Sending and receiving follows the same message format with all messages being in hexadecimal. Below is message format example for requesting and retrieving the speed of a vehicle traveling 17 km/h. The message encompasses the Mode followed by a PID.

To REQUEST current speed from the vehicle, the seven byte message is structured similarly.

• Mode: 01 (01 - current data)
• PID: 0D 00 00 00 00 00 (0D - Speed PID)

To RETRIEVE current speed from the vehicle, each byte must be read appropriately.

• Mode: 41 (4 - response, 1 - current data (mode))

• PID: 0D 31 37 00 00 (0D - Speed PID, 31 - 1 (ASCII), 37 - 7 (ASCII))

2.3. System Architecture

2.3.1. Hardware

The OBD-II interface relies on the older RS-232 serial port connectivity. USB adapters have been made available for OBD-II configurations that can connect to a PC. However, with a smartphone, mobility is one of its key features. With this, I utilize Bluetooth for the connection between OBD-II and smartphone. An OBD-II Bluetooth compatible device is needed to relay messages from the vehicles ECU to the smartphone. For this I utilize an ELM327 OBD-II connector [34]. This connection device is relatively cheap costing only $30 from most vehicle repair shops. Since most smartphones today utilize Bluetooth 2.1 or greater, I exploit this connectivity interface for a vehicle to smartphone data exchange. Figure 2.3 illustrates his hardware involved in obtaining vehicle sensor data using a smartphone and OBD-II interface.

Along with this, I can fuse vehicle data and smartphone sensor data together. Combining these interfaces with a smartphone processing and android platform allows for both data collection and processing on a single device. This idea is shown in Figure 2.4 which incorporates live vehicular data with accelerometer sensor measurements.

2.3.2. Software

Combining an OBD-II interface with the Android platform allows for a sensor fusion idea to be developed. Vehicle data such as speed, rpm, and fuel economy can be correlated with smartphone sensors such as the accelerometer. To accomplish this, I have to establish communications from the mobile to the vehicle. Since smartphones incorporate Bluetooth
as an accessible communications tool, I use this as our transfer protocol. Using a Bluetooth OBD-II transmitter, I can sync an Android smartphone up with this to use sensor data from the vehicle. This transmitter, a PLX Bluetooth ELM327 OBD-II, is shown in Figure 5(b)
where I can see the OBD-II male connector pins. All pins are present in this device which makes it a universal device for all previously listed OBD-II signaling protocols. This device connects directly with the vehicle through a port which is located under the steering wheel shown in Figure 5(a). The ELM327 device acts as a middle man interpreting the data from smartphone and formatting it in a way the vehicle can recognize. With this connection setup, I need software to interface with Bluetooth and parse the incoming OBD-II data.

Figure 2.5. OBD-II port and device. (a) OBD-II connector port with different pin layouts depending on what signaling protocol used by the vehicle (b) OBD-II bluetooth receiver which uses ELM327 hardware to communicate with the OBD-II port in the vehicle.

An Android application was written to send and receive the data using Bluetooth as
the communication protocol. Creating this application centered on programming Bluetooth sockets in Java. Some extra services were also needed such as listening and identifying a Bluetooth host (OBD-II) for initial connectivity. Communication to the ELM327 or OBD-II device relies on query and response system. Meaning that for each message query sent to the vehicle from the smartphone, the OBD-II device will create a response. After a request is sent, the ELM327 is defined a preset time in which it waits for a response from the vehicle. A architectural diagram is illustrated in Figure 2.6 which illustrates the data collection from both the vehicle using the OBD-II interface and smartphone sensor using Android’s SensorManager API. The Android application obtains both data sets using Bluetooth as a medium to interface with the vehicle.

If no response is heard, it sends back a *NO DATA* string to the smartphone. We can alter these preset times using attention terminal (AT) commands. AT commands are often used to control another device remotely. In this case, they are instructions which define the operation parameters in which the ELM327 device can function. These commands are
given first with the prefix AT followed by the actual command. For example, to change the response timeout period, \textit{ATST \textit{xx}} is sent in which \textit{xx} is the time given in milliseconds (ms). By default the timeout is set at 20 ms. I leave this setting to default since increasing the timeout may have a direct impact on the frequency in which the rest of the data is sent. If this timeout period is constantly being exceeded or the response is frequently \textit{NO DATA}, a software reset is needed. Sending the AT Command \textit{ATZ} resets the ELM327 to default settings in which often fixes any delay or malfunctioning receiver. A software reset on the device takes approximately 1 second.

To acquire the speed from the vehicle, two AT Commands were utilized which were essential to the interpretation of the data being received: 1) \textit{ATSP0} and 2) \textit{ATE0}. The Set Protocol (\textit{SPx}) command, \textit{ATSP0}, is given to set the OBD protocol that will be used. The ELM327 device is compatible with a variety of protocols so it can be almost universal when using with different manufacturers. I first set this to default by giving a 0 following the \textit{SP} command. Setting the protocol to default allows for the ELM327 to automatically search for a compatible protocol in which the vehicle is using and format the data accordingly to smartphone and vehicle. By default, message headers are turned off to prevent the user from modifying but can be turned on to specifically define a source and destination (ECU). The Echo (\textit{Ex}) command, \textit{ATE0}, is given which will turn off the ELM327’s function of replaying the message that was originally sent by the smartphone. Since I am using the system as a query and response, echoing is not required for data interpretation and only adds on to the number of bytes parsed and time spent sending. Following these commands, I finally query for the vehicle speed by sending the command \textit{010D}. \textit{01} sets the Mode while \textit{0D} defines the command for vehicle speed. The algorithm implemented in Java for Bluetooth communications over Smartphone and OBD-II is listed in Algorithm 1.
Algorithm 1 OBD-II and smartphone communications using bluetooth.

1: Turn Bluetooth On  
2: Open Socket To OBD-II  
3: Set Protocol to Automatic  
4: Turn OBD-II Echo Off  
5: while Socket is Open do  
6:    Send Speed Command in bytes  
7:    Read OBD-II Response  
8:    while Repose !=" Carrage Return or End Line do  
9:        if Repose starts with 410D then  
10:           Convert Hex to String  
11:           Convert speed - km/h to mph  
12:           Store Speed and Timestamp  
13:        else  
14:           Invalid Response (Error)  
15:        end if  
16:    end while  
17: end while  

2.4. Smartphone Interface

Once Bluetooth socket communications are created, I can freely access sensor data from the vehicles ECU. The hexadecimal response is converted into ASCII where it can be interpreted based on its value: string, integer or double. Figure 7(a) and Figure 7(b) illustrate two scenarios where OBD-II commands were sent and data was retrieved. Figure 7(a) shows an AT Command, ATZ, sent which resets the ELM327 device. A hexadecimal response is received, converted to ASCII to reveal the model and version of the OBD-II device hardware and software. Figure 7(b) shows a speed query using the command 010D. 01 designates a request for live vehicle data while 0D is the speed command. The resulting hexadecimal response is the speed in kilometers per hour. This was converted to ASCII and then into miles per hour.

Successfully integrating vehicle sensor data with smartphone sensor data allows for extreme possibilities enabling a number of applications. For this thesis I utilize this idea to classify aggressive driving behavior. Using Bluetooth as the communication device is resourceful for the smartphone, freeing up its single connectivity port for charging or debug
Figure 2.7. Android application accessing live vehicle data from the OBD-II port. Bluetooth is used as the communication transfer protocol. (a) Resetting the ELM327 OBD-II device (ATZ) (b) Acquiring speed from the vehicle (010D), 64 mph.

2.4.1. Speed Analysis

Using the methodology explained in Algorithm 1, a separate Android application was written which used the embedded GPS in the smartphone as well as set up OBD-II communications using Bluetooth. An experiment was performed testing the response of each source of vehicular speed as well as the frequency of each sensor. The vehicle was accelerated through a range of speeds testing accuracy of each sensor. The OBD-II data proved very accurate with its high response rate. However, this sensor frequency was not consistent and varied from 4 Hz to 9 Hz. This rate was still greater than GPS receiving data at 1 Hz. The speed comparison between OBD-II and GPS is shown in Figure 2.9. At some instances, 25 sec and 330 sec, the GPS reported inaccurate speed readings with almost a difference of 5 mph. However, the GPS performed very accurate during a quick acceleration which was performed
around 240 sec. Given the particular application, speed obtained from the GPS could be acceptable incorporating in its delay and slight inaccuracies.

Figure 2.8. Android application receiving both GPS data and OBD-II data. Speed was obtained from both sources, previewed on the screen and logged to a csv file for further analysis in Matlab.

Figure 2.9. Speed obtained from OBD-II and GPS. Both signatures are very similar proving the utility of OBD-II as well as GPS for speed. GPS frequency was 1 Hz while OBD-II frequency fluctuated 4 Hz - 9 Hz.
2.5. Summary

The vehicle is an everlasting resource of data that has yet to be fully exploited for safety applications. Intelligent Transportation Systems has gained interest in the past few years extracting specific sensor data that has need for a particular application. Extracting all the vehicle sensor data is idea which I propose. Utilizing the smartphones 3G/LTE communications to transmit to the cloud and store for future applications is where this work can be progressed. For now, I set up lower level communications between the smartphone and vehicle utilizing Bluetooth technology. The OBD-II interface in the vehicle was exploited to extract data which was originally intended to test for vehicle emissions by the EPA back in the 1970-1980s. The Android platform was used to create multiple Java applications which interpreted the vehicle data. Speed was obtained and stored for future setup and use with vehicle applications such as analyzing driving maneuvers. Sensor analysis was performed comparing GPS and OBD-II speed results. GPS performed significantly well given its lower sampling rate. Nevertheless, given the GPS power hungry system, I found an alternative source for vehicular speed but are still not dependent on a single sensor. GPS can be utilized if OBD-II port is not accessible inside a vehicle conveying overall flexibility of a vehicle and smartphone integrated system.
3.1. Introduction

For a driver to feel completely safe, he or she must have total control over the vehicle they are operating. This idea factors into how the driver feels and reacts on the road. It is essential to secure this relationship for a driver to be fully confident in their abilities on the road. Different types of automobiles, e.g. cars and trucks, perform differently and offer a variety of unique features that can be categorized as personal comforts: rear camera support, side airbags, sound dampening technology, low engine vibration etc. Identifying a comfort level is an initial step to buying a car while also being greatly considered as a safety parameter for potential drivers. The comfort of a vehicle directly reflects the health of the driver and passenger [35]. Gamerio da Silva’s work suggested that certain dynamic factors such as vibration, acceleration, air quality, and noise should be accounted in determining comfort [36]. In order to assess a comfort analysis of a vehicle, I use the accelerometer and microphone in the smartphone to quantify vehicle vibrations and noise levels. These two aspects are very important and very capable of being captured by this embedded device. The device used was an HTC Nexus One which encompasses a Bosch BMA150 accelerometer with a 30 Hz sample rate and an microphone with a 44100 Hz sample rate [18]. During each experiment, the accelerometer and microphone was set to record data simultaneously. The x, y, and z axes of the accelerometer was used to find the total vibrations in each direction present in the passenger seat while the microphone recorded the interior audio levels of the vehicle. I also recorded experiments regarding comfort such as transmission quality.

Section 1.5 and 1.6 in this chapter are reproduced from M. Fazeen and B. Gozick, "Vehicle Comfort," UNT Network Security Lab Internal Report, submitted March, 1 2011, with permission from authors.
Our comfort analysis includes that of industry standards pertaining to both vibrations and noise levels. For vibrations, I implemented the comfort standards presented in International Organization for Standardization (ISO) 2631-1 [35] which describes how human comfort can be calculated pertaining to location and axial vibrations experienced inside the vehicle. I then used sound quality metrics from psychoacoustics related to sensory pleasantness. Sensory pleasantness (SP) involves analyzing the loudness, sharpness, roughness and tonality of noise inside the interior of a vehicle. A combination of these will help distinguish the overall comfort of a vehicle.

3.2. Related Work

Work has been previously done in identifying the comfort of a vehicle. Many different methods have been performed such as signifying comfort level thresholds for passengers as a function of vibration [37, 35, 38] and noise [39, 40]. Experimental setup usually consists of an external accelerometer placed on the passenger seat [41] or expensive microphones placed around the head and torso [42]. Our system integrates both these devices in a compact device which is both mobile and comparable across any vehicle. Results are dependent on both the driver’s abilities and vehicle performance capabilities. Wu et al. [37] identified a vehicle comfort involving the acceleration and braking of a car. Their work studied the effect longitudinal acceleration and deceleration had on a passenger. Resulting techniques provided a comfortable car based deceleration when behind a neighboring car that is also decelerating. This work only provides a comfort analysis while the car is in motion. I focus on the comfort of the car when it is moving and when stationary. I analyze the vibration the vehicle produces whether it is caused by road feedback or engine vibrations. I will identify that vehicle comfort is directly related to the vehicle, road, and driver performance. I also analyze the acoustics seen in the environment inside the car as drivers use the interior sound quality of a vehicle as one of the main assessments for overall vehicle quality [43].
3.3. Experimental Setup

Using a mobile phone for these purposes creates some variables that must be accounted for. Phone location and orientation inside the car should be configured so it will not influence the results. Likewise, driver behavior will reflect in the results therefore a consistent measurement process must be accounted for. Constituting a comfortable ride in a vehicle is a difficult process as the definition of comfort might be different for everyone. The smartphone is only used in this case as a collection device. No data sharing has been implemented to any other system. Data that is collected by the smartphone sensors is then used in an offline technique to analyze the overall vehicle comfort. I try to factor in all of these ideas during our measurement analysis to try and provide an accurate technique that is most applicable for an average driver. A range of vehicles and road types were used in determining both the vibrational comfort and acoustical comfort of the vehicle. I utilize this technique to demonstrate a vehicles performance on different types of roads. This is convenient for drivers who may not drive on highways but mainly remain in city conditions on residential and business roads. The vehicles used in the comfort analysis are listed in Table 3.1 while the road used are listed in Table 3.2.

Table 3.1. Automobiles used in vehicle comfort analysis.

<table>
<thead>
<tr>
<th>Vehicle Code</th>
<th>Year</th>
<th>Manufacturer</th>
<th>Model</th>
<th>Vehicle Type</th>
<th>Engine</th>
</tr>
</thead>
<tbody>
<tr>
<td>Truck 1</td>
<td>1992</td>
<td>Chevrolet</td>
<td>S-10</td>
<td>Single Cab</td>
<td>4.3L V6</td>
</tr>
<tr>
<td>Car 1</td>
<td>1997</td>
<td>Honda</td>
<td>CL3</td>
<td>Coupe</td>
<td>3.0L V6</td>
</tr>
<tr>
<td>Van 1</td>
<td>2000</td>
<td>Toyota</td>
<td>Sienna</td>
<td>Minivan</td>
<td>3.0L V6</td>
</tr>
<tr>
<td>Car 2</td>
<td>2007</td>
<td>Toyota</td>
<td>Yaris</td>
<td>Sedan</td>
<td>1.3L 4-cylinder</td>
</tr>
<tr>
<td>Car 3</td>
<td>2007</td>
<td>Volvo</td>
<td>S40</td>
<td>Sedan</td>
<td>2.4L 5-cylinder</td>
</tr>
</tbody>
</table>
Table 3.2. Road characteristics used in assessing comfort of a vehicle.

<table>
<thead>
<tr>
<th>Road Type</th>
<th>Speed Limit (mph)</th>
<th>Total Distance (mi)</th>
<th>Analysis Duration (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Residential</td>
<td>30</td>
<td>0.5</td>
<td>60</td>
</tr>
<tr>
<td>Business</td>
<td>35</td>
<td>1.4</td>
<td>60</td>
</tr>
<tr>
<td>Highway</td>
<td>60</td>
<td>1.8</td>
<td>60</td>
</tr>
</tbody>
</table>

3.3.1. Phone Location

It was important to create a vehicle comfort measurement setup to make very convenient while providing efficient vibration and audio levels in the front seat. The front seat is where the driver or the main passenger is located so that is the area I focus on. Velcro is used to secure a phone holster, which was provided by HTC as a phone accessory, to the passenger seat. The phone is placed inside the holster where it is close fitting and secure to the seat. Subsequently, the phone does not move around in any direction caused by acceleration, deceleration, bumps and turns while staying fastened to the passenger seat. This results in vibration levels produced inside the vehicle which are experienced similar by the driver. In the case of the Chevrolet truck which contains a bench seat rather than individual bucket seats, it was placed in the middle between driver and passenger. Audio levels are also obtained in the same location at the same time which is also needed to evaluate a vehicle comfort level. The bottom of the holster is open allowing the microphone to be exposed to the car’s interior. Figures 1(a)-1(d) show the position and orientation that was used during the vehicle comfort testing.

3.4. Gear Shifting

Knowing that your vehicle is performing efficiently is always a concern for many drivers. Engine problems can arise at any time, even while accelerating in high speed traffic. Slipping in and out of gears can happen frequently with older transmissions and can be a potential risk while driving on a highway. Using a mobile smartphone, I found it possible to recognize gear shifts. For manual transmissions, sequentially shifting around 2500 RPM is essential to
Figure 3.1. Vehicle comfort location positioned on the front of the passenger seat. (a)-(b) 2007 Toyota Yaris (c)-(d) 1992 Chevrolet S-10

sustain an efficient fuel economy. Recognizing gear slippage in automatic transmissions can be an early warning of low transmission fluid, worn clutch discs or a faulty shift solenoid, which are all essential components responsible for transporting you safely to your next destination. Monitoring gear shifts can have a greater purpose when evaluating vehicle comfort. Today, vehicle manufactures have developed and deployed technology to provide a smoother ride for the driver. Toyota incorporates a continuously variable transmission into some of its cars which provides increased acceleration while producing little discomforting jerks. Lexus has also developed excellent smooth shifting with their automatic Electronically Controlled Transmission with intelligence (ECT-i) which operates the engine efficiently and smooth when manual shifting occurs. I experienced this smooth shifting transmission when testing
The Volvo S40. Figures 2(a), 2(b) and 2(c) represent the Chevrolet S-10, Toyota Yaris and Volvo S40 gear shifting performance of transmission when accelerating to 30 mph then leveling off. When analyzing acceleration data of Volvo, gear shifting became less apparent than compared to the other vehicles that were tested. This feature adds to the overall comfort of the vehicle. This experiment was performed using all the vehicles listed in Table 3.1, each resulting in easily identifiable gear shifts.

Figure 3.2. Gear shifts from three vehicles accelerated initially at rest. Each shift is clearly defined by its sharp drop in acceleration experienced by a jerk in the vehicle revealing a gear shift. (a) 1992 S-10 Single Cab (b) 2007 Toyota Yaris (c) 2007 Volvo S-40

The main purpose of analyzing gear shifts is to obtain analysis of a driver’s behavior which could affect the vehicle’s overall comfort performance. Most manual vehicles provide an indicator which lets the driver know when to shift to the next gear. However, direct vehicle feedback is not always recognized and drivers use audio feedback from the transmission or speed levels to initiate a gear shift. Shifting into the next gear quickly or within a certain
small time frame can put an unwanted strain on the vehicle’s transmission. This strain can accumulate and degrade the transmission over a long period of time which could eventually result in faulty parts. Not only does gear shifts influence vehicle comfort, but by analyzing gear shifts using the accelerometer and future syncing this information with On-Board Diagnostic (OBD-II) interface, I can give a complete analysis of transmission performance. Synchronizing direct vehicle feedback with OBD-II communications explained in Chapter 2 is a role of future work. In this paper, I state that finding gear shifts is possible which could which can directly correlate with vehicle comfort. Section 3.5 explains this influence and uncovers other factors that determine a vehicle’s overall comfort.

3.5. Vehicular Comfort

There has been much work in the comfort testing of vehicles stating that the comfort of a car is affected by various factors, such as vibration, acoustic sound, smell, temperature, visual stimuli, humidity, and seat design. Some of which cannot be measured, especially by a limited device such as a smartphone. Moreover, some are opinionated (smell, temperature, and seat design) and cannot be measured on a confident scale. However, given the convenience of our device which is accessed by many, utilizing a phone to test the comfort is a reasonable for certain significant main factors, noise and vibrations. While there are many opinions on defining comfort, I choose a process that is capable of analyzing with the mobile phone. Some factors that have been covered to assess ride comfort are seat vibrations, steering wheel vibrations, interior noise levels, and vehicle handling quality [42, 44, 45, 46]. Although this area is very extensive and is performed by many commercial companies using the International Organization for Standardization (ISO) standards [35] for measuring total ride comfort, the measuring devices used are abundant in variety. There are no specific devices that are widely accepted to test comfort levels by the majority of the car manufacturing industry or even automobile consumers. Audio levels are also a key comfort factor. Sensory pleasantness is an acoustical method for determining a metric or level of a certain sound
sample. It is a product of numerous techniques incorporating many fundamental acoustical properties which is why it is often used for acoustical experiments. For a consumer, achieving comfort in a car is one of the most important aspects needed before a large purchase and the possibility for a consumer to achieve this on a personal level is significant. It is in this scope in which I am motivated to determine vehicular comfort. The most significant aspects for comfort can be identified as vibration levels and noise levels. Focusing on these two main factors is the start to any comfort experiment and will be the basis for our method. Adding in any additional factors which can be measured by a mobile smartphone in the future can extend this comfort analysis.

A full system diagram of the comfort analysis can be seen in Figure 3.3. Vibration levels along with noise levels are captured inside a vehicle by a mobile phone’s accelerometer and microphone, respectively. After analysis from both, the vehicles which excel in each category can be identified and a conclusion can be made on which vehicle has the greatest comfort.

![Diagram of comfort analysis](image)

Figure 3.3. The vibrations on the x, y and z axes were measured using 3-axis accelerometer and audio was recorded using the microphone; both embedded in the smartphone.

3.5.1. Vibration Dose Value

Identifying comfort of a vehicle can be different when experiencing different types of roads. Performance of each vehicle depends highly on the type of the road as well as the
performance of the driver. To find the appropriate comfort, I selected three types of roads to test each vehicle: 1) Residential 2) Business (Urban) 3) Highway (Interstate). The usage of these roads is based on the area, thus determining the quality of the road while the frequency of the maintenance also differs. The driving speed is also another factor in measuring the comfort level of a vehicle. Therefore, I selected the posted speed limit of the particular road as the traveling speed to obtain readings. To minimize the speed variation, the cruise control was used whenever possible. In short, five vehicles were driven on each road type using its posted speed limit and the right lane was used when encountering a divided highway with two or more lanes. Table 3.1 reflects the five different automobiles that were used to acquire comfort measurements. To obtain a variety of measurements, the vehicles used vary in both type and year. Table 3.2 shows the road types that were used in the vibrational and acoustical comfort experiments along with the speed limit and measurement duration.

For measuring vibration levels, there is no specific device that is widely by the majority of automobile manufacturers; hence, I utilize a mobile phone. I incorporated the International Organization for Standardization (ISO) standards 2631-1 [35] for determining total ride comfort. ISO 2631-1 describes how human comfort can be calculated pertaining to location and axial vibrations experienced inside the vehicle and defines a comfort scale based on the vibration dose value (VDV). VDV uses frequency weights on each axis of vibrational data, for a given frequency range of 0.5-80 Hz and is defined using the weighted axial acceleration values (\(a_i\)) during a time duration (T) with units of m/s\(^{1.75}\).

The analysis starts by utilizing acceleration data gathered by an accelerometer placed in the passenger seat of a vehicle. The raw data from each axis is transformed in a Fourier Series. Each value, given its particular axis, is multiplied by a frequency weight found in Table 3.3. Each axis has a different frequency weight (Wb or Wd) and different weighting values for each frequency range found in Table 3.4. Once the frequency weighted acceleration (\(a_i\)) is obtained in the time domain, I calculate VDV. This is also defined in ISO 2631-
1 using Equation 3 with \( i=x,y,z \). I then calculate a ride index (RI) value found using the VDV axis measurement which conveys a single metric from the three axis acceleration that correlates vibrations inside a vehicle of comfort to human perspective based on frequencies. Ride index can be viewed in Equation 4. Given our sensor limitations and studies showing high comfort correlation between 2-20 Hz [45], I use a frequency range of 2-12.5 Hz. Each road measurement had a time duration of 60 seconds, a fraction of the whole road measurement.

\[
VDV = \int_{t=0}^{t=T} a_i^4(t) \, dt
\]

(3)

\[
RI = \left( \sum VDV^4 \right)^{\frac{1}{4}}
\]

(4)

Table 3.3. ISO location weights.

<table>
<thead>
<tr>
<th>Location</th>
<th>Axis</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Seat</td>
<td>X</td>
<td>( W_d )</td>
</tr>
<tr>
<td></td>
<td>Y</td>
<td>( W_d )</td>
</tr>
<tr>
<td></td>
<td>Z</td>
<td>( W_b )</td>
</tr>
</tbody>
</table>

Table 3.4. ISO frequency weighting values.

<table>
<thead>
<tr>
<th>Weighting</th>
<th>Frequency (Hz)</th>
<th>Weighting Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( W_b )</td>
<td>( 0.5 &lt; f &lt; 2 )</td>
<td>0.4</td>
</tr>
<tr>
<td></td>
<td>( 2 &lt; f &lt; 5 )</td>
<td>( f/5 )</td>
</tr>
<tr>
<td></td>
<td>( 5 &lt; f &lt; 16 )</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>( 16 &lt; f &lt; 80 )</td>
<td>( f )</td>
</tr>
<tr>
<td>( W_d )</td>
<td>( 0.5 &lt; f &lt; 2 )</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>( 2 &lt; f &lt; 80 )</td>
<td>( 2/f )</td>
</tr>
</tbody>
</table>

Figure 3.4 illustrates the vibrational comfort index, ride index, and the process which is used to find the metric. Raw acceleration values from the accelerometer (x, y, and z),
the set frequency weights, and the calculated VDV component. The combination of these variables will lead to a vehicular comfort index, or RI.

![Diagram](image)

**Figure 3.4.** Ride index (RI) calculated containing raw acceleration values, frequency weights, and final output of RI using the calculated VDV measurements for each axis.

3.5.2. Sensory Pleasantness

Noise comfort is defined as a function of sensory pleasantness. Ford has done similar techniques on measuring noise comfort of a vehicle by using some of the same sound quality measurements; for example, loudness, sharpness and fluctuation strength [47]. Nor also performed similar techniques and used the same sound metrics for the basis of their comfort analysis with the addition of roughness [42]. By using this quantitative measurement from psychoacoustics, sensory pleasantness, which contains the sound metrics of loudness, roughness, sharpness and tonality, I am able to create a noise comfort index. I find these variables to be important when evaluating noise levels in a car, and therefore allows for an easy and efficient index when comparing multiple vehicles. Sensory pleasantness is defined in Equation 5 with the value assignments of Roughness (R), Sharpness (S), Tonality (T), and Loudness (N). Each of these metrics is a fundamental of acoustics and each has a criteria it is measuring.

- Roughness: the temporal variation of a sound expressed in amplitude or frequency
• Sharpness: characterizes the perceived high frequency level relative to the overall level
• Tonality: the tonal prominence of a sound
• Loudness: measures the perceived loudness of a sound of a frequency

An arbitrary reference measurement was taken in a vehicle to portray the ideal audio comfort scenario as a comparison the other five vehicles. This reference value was obtained from an initial experiment viewed in Equation 5 as $P_o$, $R_o$, $S_o$ and $N_o$. These values were obtained from a stationary vehicle with no internal noise present inside the vehicle. The reference duration was 60 seconds.

$$\frac{P}{P_o} = e^{-0.7 \frac{R}{R_o} e^{-1.08 \frac{S}{S_o}(1.24 - e^{-2.34 \frac{T}{T_o}}) e^{-0.023 \frac{N}{N_o}}}}$$

By using these values for each vehicle, I can obtain a sound quality metric which can be used as an index for noise vehicle comfort

3.6. Results

Though one of the most intricate challenges is to determine personal human preferences, I distinguish that the most comfortable car would be that exhibiting low noise and subtle vibration levels. Since the driver was in control of the car, I stressed the front seat signifying its importance in these analyses. These measurements evaluate a vehicles comfort level in which can directly impacts the drivers awareness on the road. A more comfortable ride experience implies an increased driver awareness resulting in a decrease for safety concerns that may have existed previously.

3.6.1. Vibration Dose Value

Using the ISO 2631-1 vibration dose value (VDV) methodology, I obtained a ride index (RI) for five vehicles which is comparable between road types. Performance of each vehicle
depends highly on the type of road driven and also driver behavior. Since the RI, measured in $m/s^{1.75}$, depends on VDV axial measurements, I note the dependencies for each axis. The y-axis is greatly affected by driver performance such as acceleration and braking, the z-axis is dependent on the condition of the road such as potholes and bumps, and the x-axis reflects results based on both the driver and the road. Table 3.5 shows the results obtained during the vibrational ride comfort analysis. Each value is a ride index formulated from the vibrations experienced in the x, y, and z axes of the passenger seat using a mobile phone accelerometer. A lower RI value illustrates a greater vehicle comfort. The values were averaged from multiple runs from each road at the same time of day and distance traveled.

Table 3.5. Vibrational ride index obtained in vehicle comfort analysis.

<table>
<thead>
<tr>
<th>Vehicle</th>
<th>Road Types and Ride Index</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Residential (30 mph)</td>
</tr>
<tr>
<td>Truck 1</td>
<td>6.0293</td>
</tr>
<tr>
<td>Car 1</td>
<td>6.1492</td>
</tr>
<tr>
<td>Van 1</td>
<td>5.0851</td>
</tr>
<tr>
<td>Car 2</td>
<td>3.2230</td>
</tr>
<tr>
<td>Car 3</td>
<td>8.3149</td>
</tr>
</tbody>
</table>

From data presented in Table 3.5 and visually in Figure 3.6, I can conclude that Car 2, Toyota Yaris, experienced the greatest comfort pertaining to seat vibration originating from a combination of the driver and the road. Each road has a designated classification which correlates with the speed limit and also the road quality. This road quality can directly reflect on the ride index as some vehicles perform better on certain types of roads which might include potholes and rough roads. In short, vehicles perform differently on different roads. Listed below are the rankings of vehicles in order of overall averaged highest comfort to lowest comfort.

(i) 2007 Toyota Yaris (Car 2)
(ii) 1997 Honda CL3 (Car 1)
Figure 3.5. Ride index (RI) calculated for each vehicle over all three road types. The lower value indicates a higher vehicle comfort. Car 2 in this method is classified with the most comfort.

(iii) 1992 Chevrolet S-10 (Truck 1)
(iv) 2000 Toyota Sienna (Van 1)
(v) 2007 Volvo S40 (Car 3)

This reflects Figure 3.5 illustrating these rankings for all the roads where as Figure 3.6 is an averaged over all the roads. We can see that Truck 1 is ranked third on the residential road but fourth on the highway. In contrast, the ride index can directly reflect the condition of the road but is greatly dependent on the speed [41]. Since drivers usually encounter each road type during a driving duration, I average the ride index for each vehicle over the three road types to gain an idea of the vehicles overall performance or comfort level. This can be seen in Figure 3.6 with Car 2 having the greatest average ride index. This resulting ride index concludes that the Toyota Yaris has the best vehicle comfort in the front part of the vehicle related to vibration.
3.6.2. Sensory Pleasantness

The audio comfort analysis was performed simultaneously as the vibrational comfort analysis. Multiple trials for each road were performed shown in Figure 3.7 and then averaged together to determine the overall sensory pleasantness value shown in Figure 3.8. The sound quality metrics used which formulate a comparable noise comfort are median values of loudness (L), sharpness (S), and roughness (R). Hence, the final sensory pleasantness value obtained is the median relative sensory pleasantness (MRSP). Since tonality can be measured by many different techniques and is purely subjective, I conclude it has little effect on sensory pleasantness and provide it with a constant. This idea is widely used for acoustical analysis utilizing sensory pleasantness. Table 3.6 represents the normalized relative median sensory pleasantness of each road type.

The values are normalized against the highest sensory pleasantness value for each road. It can be seen that the Chevrolet S-10 has the highest MRSP value in each trial for each road. A higher sensory pleasantness value designates a more comfortable audio related experience. Listed below is the overall ranking of vehicles based on an acoustical comfort
Table 3.6. Sensory pleasantness obtained in audio comfort analysis.

<table>
<thead>
<tr>
<th>Vehicle</th>
<th>Road Types and Normalized Sensory Pleasantness</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Residential (30 mph)</td>
</tr>
<tr>
<td>Truck 1</td>
<td>1</td>
</tr>
<tr>
<td>Car 1</td>
<td>0.0506</td>
</tr>
<tr>
<td>Van 1</td>
<td>0.2258</td>
</tr>
<tr>
<td>Car 2</td>
<td>0.1096</td>
</tr>
<tr>
<td>Car 3</td>
<td>0.0087</td>
</tr>
</tbody>
</table>

Figure 3.7. Normalized sensory pleasantness values for each vehicle on all three road types. In each case, the Chevrolet S-10 outperformed its competitors pertaining to low noise levels. A higher SP designates greater comfort.

The method taking into account all the road types.

(i) 1992 Chevrolet S-10 (Truck 1)
(ii) 2000 Toyota Sienna (Van 1)
(iii) 2007 Toyota Yaris (Car 2)
(iv) 1997 Honda CL3 (Car 1)
(v) 2007 Volvo S40 (Car 3)

This order reflects Figure 3.8 illustrating the normalized sensory pleasantness that was av-
eraged for each vehicle type. Truck 1 greatly outperforms the other vehicles in this area. Despite its year, the truck provides a different vehicle build when comparing to the other vehicles. The truck is a single cab vehicle with a lower sound pressure level. The tires are larger along with a bigger suspension height creating a greater distance from cabin position to the physical road. These characteristics all factor in to provide a greater acoustical comfort for the driver.

![Figure 3.8. Averaged median sensory pleasantness of all three road types for each vehicle. A higher sensory pleasantness designates greater vehicular comfort.](image)

3.7. Summary

Using a mobile smartphone, I used two of the embedded sensors, 1) accelerometer and 2) microphone to determine the comfort of a vehicle with respect to human perception. A detailed analysis of a vehicle is done with respect to the comfort of the driver pertaining to vibrational and acoustical comfort. Consistent gear shifts of three vehicles were identified and correlated transmission quality with vibrational comfort. Multiple roads were tested revealing how each road type reflects its quality on the comfort perceived. Utilizing both sensors simultaneously during each trial, I am able to correlate a vehicle’s vibrational comfort with its acoustical comfort. In this respect, the Chevrolet S-10 performed very well in the
audio testings as well as scoring high in the vibration testing. When identifying the most comfortable ride given any of the three types of roads when comparing with the other four vehicles, the truck performed the best. However, given the fact that vibrational comfort is greatly influenced by the driver behavior, road quality and noise levels, seen with Car 2, it is very difficult to determine a methodology that is satisfactory for a mass of drivers. This test however was successful given our consistent and detailed methodology over each trial run testing the vibrations and audio levels to determine vehicular comfort.
CHAPTER 4

THE ROAD

4.1. Introduction

Driving or riding in a vehicle, whether a personal or public transportation, has become the main mean for traveling from point A to point B in the United States. Work, school, shopping and even joyriding all encounter the use of a car, truck or bus to be subsequently traveled on public roads. With this number increasing every day, the strain a road can endure is only temporary before it becomes a hazard for people and their vehicles. "Wear and tear" can be seen on all roads as they begin to break down forming numerous harmful anomalies which may seem random in location to the average driver. However, these anomalies are usually spawned from overused roads or faulty road construction materials. When we begin to question our safety during our daily commute, we turn to a major road identification and improvement system.

Numerous road related accidents are accounted for each year causing both vehicle damage (flat tire, loss of control, damage to undercarriage) and automobile hospitalization accidents. This problem seems unavoidable as each road will eventually break down from overuse or extreme weather conditions, or a combination of them both. A solution is to create a quick temporary patch over the anomaly or choose the time consuming option to re-pave the whole road encumbering drivers commutes. A patch can go a long way if it is established early enough; however, catching these potholes or bumps before they grow in size and begin to affect the integrity of the road is difficult. This process can drastically improve the safety of the drivers on the road while saving the local government thousands of dollars.

Section 1.5 and 1.6 in this chapter are reproduced from M. Fazeen, B. Gozick, R. Dantu, M. Bhukhiya and M.C. González, "Safe Driving Using Mobile Phones," IEEE Transactions on Intelligent Transportation Systems, accepted March 2012, with permission from IEEE.
With the aid of some kind of real time road analysis, we can help alleviate this problem which has plagued hundreds of roads in each city all over the country. This chapter demonstrates a road anomaly classification system utilizing a mobile smartphone’s embedded sensors. An accelerometer is used to capture the performance of each road where it can then be analyzed and identified in sections. The smartphone’s GPS is used for mapping anomaly locations where a map can be created showing the road quality of a particular area. All analysis was done offline using Matlab. The phone in this case was only used as a measurement collection device.

4.2. Related Work

There has been some work in the field of road analysis, specifically, road anomaly detection. Nericell [1] is a system researched and developed by Microsoft that detects traffic honking, bumps, and vehicle braking using external sensors. For detection it uses multiple external sensors such as a microphone, GPS, accelerometer, and GSM radio for traffic localization. Pothole Patrol [48] is another system that monitors the road conditions using GPS and an external accelerometer. The system was deployed for testing in taxis, which
blanketed Boston, MA to identify uneven road surfaces. Pothole Patrol uses an onboard GPS and accelerometer attached to a small embedded PC that is used to collect, store and send data. Data is sent when WiFi connectivity is available to a server where a pothole detection algorithm takes place. The accelerometer was placed on the dashboard to detect road anomalies such as potholes, manholes, expansion joints, and railroad crossings.

Our work reveals roads to be more complex than the identification resolutions presented by both Nericell [1] and Pothole Patrol [48], resulting in wider array of classifications to reveal a particular roads overall integrity. I identify not only potholes but bumps, rough, uneven, and smooth roads. I also utilize a single measuring device rather than external sensors placed in numerous places around the vehicle which ultimately increases infrastructure costs. Our device, a mobile smartphone, contains GPS, microphones and an accelerometer offering flexibility in methodology and user implementation. Encouraging results in identifying numerous road anomalies allow for our system to evaluate an entire roads condition revealing safety concerns.

4.3. Architecture

To get a clear picture of what vehicles endure on the road, I have to first identify each road characteristic for a complete road analysis. There are five main characteristics or anomalies that make up the road. These five anomalies are 1) Pothole 2) Bump 3) Uneven 4) Rough and 5) Smooth. Almost every road today has been degraded or improved consisting of one or a combination of the five characteristics. For initial data collection, I had to first verify the data being obtained. To do this, I incorporated the microphone embedded in the phone, using voice as our verification process. Whenever the vehicle encountered a road surface anomaly, I recorded the anomaly verbally identifying it. The microphone continuously recorded each and every experiment allowing the classification process to be verified so the total anomaly classification accuracy could be acquired. To verify this process, I synch up the timestamps from the accelerometer data and the microphone data to see what anomaly was
presented and what profile it revealed in the z-axis and x-axis. The y-axis was not used in this classification process since the vehicles longitudinal acceleration made it noisy and unusable.

After acquiring data from the accelerometer and matching that with the audio analysis for a correct detailed explanation of what was being experienced in the vehicle, I focused on extracting patterns for each anomaly which can subsequently be seen throughout the whole experiment. I focus on using the z-axis to recognize road conditions with the phone mounted face up on the floorboard. Accelerometer data was filtered due to the noisy environment caused by the vehicle. Each anomaly had a unique identification methodology. 1) The z-axis was used to identify potholes. Along with a threshold, the z-axis formation was used to identify small and large potholes. 2) The x-axis was incorporated into the classification process to help distinguish potholes from bumps. 3) For uneven roads, I do a smoothing process on the x-axis and set a threshold. If the x-axis surpasses this line as well as a z-axis threshold, an uneven road was classified. The architecture of which was the basis of this classification process is illustrated in Figure 4.2. It shows the phone retrieving information from its sensors, the accelerometer and GPS. The accelerometer data is then acquired for each direction. The identification process begins by classifying each characteristic. Using the timestamp when each anomaly occurred, I perform a synchronization process on the GPS data. Since the accelerometer samples around 30 Hz and the GPS only at 1 Hz, I interpolate the GPS longitude and latitude data to try and compensate for the lost distance as the vehicle moves. After the time synchronization process is set up, I acquired the exact location where each anomaly occurred on the road. The mapping function can then be carried out using Google Earth [49], which provided an easy way of illustrating road conditions while having great potential use for future drivers using smartphones.

4.4. Experimental Setup

Our road classification looks at the road integrity as a whole and tries to identify each part of the road. I present more details of the road including potholes, bumps, rough
Figure 4.2. The system utilizes the accelerometer and GPS sensors of the phone to initiate the classification process. The accelerometer data is then sent to a smoothing process in only the x-axis. Anomalies are then classified and synchronized with the time of the GPS data. After an interpolation procedure of the GPS data matching up with the accelerometer data, I can then form the road condition map using Google Earth.

roads, uneven roads and smooth roads. Classifying these anomalies on each road can help a city identify the overall condition for each road so they can focus on roads that become an extended hazard or unsafe for travel. The device used to collect road anomalies was an HTC Nexus One which utilized a Bosch BMA150 accelerometer recording at 30 Hz [18] and a GPS recording at 1 Hz. The microphone on the phone was also used to describe the road during all road condition experiments. This audio provided a basis in which each anomaly can be identified and trained for future classifications. This verification process is also used to calculate an accuracy of the road classification technique. The smartphone was attached to the floorboard of the vehicle obtaining the vibrations experienced by the vehicle induced by different conditions of the road. Figure 3(a) illustrates the truck used for the road anomaly classification, a 1992 Chevrolet S-10, and Figure 3(b) shows the phone location during the measurement process.
Figure 4.3. Vehicle and phone location during road conditions analysis. (a) The vehicle used in this experiment, a 1992 Chevrolet S-10. Suspension is older allowing the accelerometer to feel more raw measurements caused by surface anomalies. (b) Placement of the mobile smartphone used in this experiment. Mobile was located on the floorboard in the passengers seat. The mobile used was an HTC Nexus One equipped with an accelerometer.

4.4.1. Targeted Roads

All the roads in Figure 4.4 are located in the Denton, Texas in and around the University of North Texas campus. Each road was chosen specifically because they are the most traveled roads in Denton. Since these roads are the most traveled, they propose that they are also the first roads to start to degrade. Also, since these are the main means of getting around town and also around campus daily, these roads need to be up to date when considering road integrity and road safety for all travelers of the road. These roads are all shown in Figure 4.4 which is color coded with either green or red to designate a direction or left/right lane. Some roads and locations in the map are identified, e.g. UNT campus and Interstate-35, but a full listing of each road covered is given below along with the mileage. The mileage is calculated for one direction then multiplied by two since both lanes are of equal length revealing the total distance traveled for all roads, 38.6 miles.

- Interstate 35: 10 miles
- University Drive: 4.6 miles
• Bonnie Brae: 6.2 miles
• Carroll Blvd: 4.6 miles
• Oak Street: 2.8 miles
• Hickory Street: 2.8 miles
• Bernard Street: 2.2 miles
• Avenue C: 3.4 miles
• Eagle Drive: 2.0 miles

• Total Mileage: 38.6 miles

4.5. Anomaly Classification

There are five main characteristics that make up the road: 1) Pothole 2) Bump 3) Uneven 4) Rough and 5) Smooth. The smartphone was fastened to the floorboard of the vehicle. Audio verification was used during the experiments to correctly identify each road anomaly. After acquiring data from the accelerometer and matching that with the audio analysis for a correct detailing what anomaly feature was being recorded, I focused on extracting patterns for each anomaly. Poor road conditions can lead to re-pavement methods that can cause in increase in both traffic congestion and travel time. A bad road can also increase the chance of an accident. Road conditions can be analyzed using an accelerometer that is capable of detecting subtle and extreme vibrations experienced inside the vehicle.

4.5.1. Potholes and Bumps

When a vehicle encounters a pothole, the tire of the vehicle experiences a fast drop into the pothole. The tire then hits the edge of a pothole as it rolls out. This combination causes a jerking sensation which is captured by the phone. In some cases, there is a slight increase in the z-axis right before the large decrease caused maybe by a small formation of a bump directly on the rim of a pothole. Two examples of these are shown below in Figure 5(a) and Figure 5(b).
Figure 4.4. Roads in Denton that were covered in this experiment. Red coloring indicates one side of the road (or right lane) while the green indicates the other side of the lane (left lane). Clockwise and counter-clockwise was an easier way to describe which direction while organizing the condition measurement process.

Distinguishing bumps from potholes proposes a few challenges. The data often looks similar in when seen by the naked eye but at closer observation they formulate differently. Bumps are formed by the increase in the z-axis followed by a decrease as the vehicle expe-
Figure 4.5. Examples of potholes encountered on the road. (a) and (b) both illustrate a formation of a pothole with a large decrease in the z-axis followed by an increase. A threshold is set to detect this pothole in every case.
A vehicle can be traveling at high speeds for a given type of road. Therefore, at high speeds, only a small time frame is experienced for a particular part of the road. To analyze this part, the more amount of data obtained leads to a more accurate result. For this, I decided on around 70 samples per area is sufficient since smaller sample sizes were not accurate using fast fourier transform (FFT). Seventy samples translates to around 2.5 seconds of data. When performing the frequency transformation on the accelerometer data, we can see an increase or high amplitude in both of the pothole and bump anomalies for the frequencies less than 2 Hz. This high amplitude in the z-axis at this frequency is a characteristic of a pothole and bump and is not existent for smooth roads. For the x-axis, I look for the same increase below the 2 Hz frequency. However, for potholes it does not conform the same as bumps. For bumps, there is an x-axis greater increase in amplitude while potholes relatively form with a low amplitude. Given bumps, depending on how high the amplitude is, I can grade the severity of the bump and a bigger bump creates a greater disturbance in the x-axis increasing the amplitude of the frequency. Figures 7(a), 7(c) and 7(e) illustrate bumps in
the time domain (left) and Figures 7(b), 7(d) and 7(f) represent frequency domain (right). Figures 8(a) - 8(f) portray potholes in the same manner. When comparing the two data sets, we can see the difference lies in the amplitude of the x-axis of the frequency domain figures. I use a z-axis threshold in time domain as well as a x-axis threshold in frequency domain to classify potholes and bumps, respectively.

4.5.2. Uneven

Uneven roads are also difficult at some times to differentiate from a pothole or bump. In some cases, a very uneven road causes the vehicle to dip on one side of the vehicle rather than the other. This dip can also result of a bump if a vehicle is traveling at a very low speed. These features mimic that of a pothole or bump so to be able to distinguish correctly is important. To try and alleviate this, I analyze the features of an uneven surface that can be captured by the smartphone. The frequency of the z-axis data is lower than that of a pothole and bump. I looked for this feature but it was still difficult to find. However, finding cases where it is very uneven is improved when using the x-axis. A road with an uneven feature causes a significant decrease in the x-axis in which I can set a threshold to find. This method is similar to that of finding bumps in the time domain. For example, when a vehicle drives over an uneven surface, the phone not only has displacement in the z-axis but also significantly decreases in the x-axis.

Figure 9(a) and 9(b) below illustrates this process. The threshold line can be seen in both figures as a horizontal line around $-0.5m/s^2$. When the x-axis penetrates this line, it is classified as uneven. It is imperative that the x-axis be used since the uneven characteristics are too close to that of a bump formation. There have been a significant decrease in false positives when identifying uneven roads using this method but there have been a few instances where the uneven segment did not cross the threshold mark resulting in a misclassification as a bump. This happens more often at lower speeds mainly situations 25 mph or under.
Figure 4.7. Examples of bumps in time domain (left) and frequency domain (right). We can see a high amplitude in the x-axis around 1 Hz. This along with the combination of high amplitude around 2 Hz in the z-axis, results in a classification of a bump in the frequency domain.
Figure 4.8. Examples of potholes in time domain (left) and frequency domain (right). A high amplitude around 2 Hz is common in the z-axis while a low amplitude around 1 Hz in the x-axis. In some cases, this x-axis amplitude was very low almost irrelevant in some cases. These characteristics differ from that of the previous anomaly, bumps.
Figure 4.9. Examples of uneven roads. (a) and (b) both illustrate the formation of an uneven road seen significant decrease in the x-axis (blue line). A threshold is set as the horizontal blue line to identify an uneven part of the road.

4.5.3. Rough Road

To define a rough road, I look at the z-axis data. I define a rough road as data that presents itself in a short period, 0.5 s to 1.0 s, and has a high frequency. Neither a pothole, bump or uneven road presents itself in this manner. The amplitude of most rough roads are also very small revealing itself opposite to that of a pothole or bump. It is difficult at some times to differentiate a minimally rough road from a smooth-like road creating false negatives. Figure 10(a) and 10(b) below illustrates two examples of a rough road. Figure 10(a) shows a pothole formation followed by a rough road formation. The rough road can be easily distinguished from the other parts of the road as it has a higher frequency in the z-axis. It also shares the low amplitude characteristic I defined earlier. Figure 10(b) is more difficult to see and might be classified as a smooth-like road if the frequency was like that of its surroundings. However, the high frequency is apparent in two locations, on both sides of a pothole. It can also be easily seen rough-like as a z-axis is producing very frequency in short bursts.
Figure 4.10. Examples of rough roads. (a) and (b) both illustrate the formation of a rough road seen in the z-axis with a higher frequency. (a) clearly seen as rough when viewing its surrounding area. (b) is not as apparent but still distinguishable. Low amplitudes, high frequency and short durations can be seen in both figures. I use all these characteristics to classify rough roads.

4.5.4. Smooth Road

To find the smooth road, I filter the data to smooth out any sudden peaks or noise. Reducing these peaks filters any false positives that might be classified as a pothole or rough road. By default, if no anomaly was classified in a certain area, that region was defined as a smooth road. A smooth road means that no acceleration discomfort is featured on a particular road section. To make sure no anomaly is passed up, each is checked before a smooth road is declared. If it was not defined as one of the other characteristics, then it would be identified as a smooth road, represented in the map with green. Using this method leaves no area of a map unclassified. The next section illustrates the mapping process illustrating each anomaly.

4.5.5. Road Abnormalities

Classifying road anomalies is a difficult task. Misclassifications can occur due to many situations such as objects in the road, train tracks and even bridge formations. This was one challenge presented by the authors in [48]. They tested their system in a city environment which incorporated many bridges and train tracks. False positives were minimized but still
occurred to to their system limitations. Using a mobile smartphone, multiple sensors are available for use. Utilizing an embedded magnetometer which detects ambient magnetic fields I can minimize these false positives. Since train tracks and bridges are both made of iron or steel structures, a magnetometer can detect them. This was tested and successfully identified a magnetic abnormality in the road. Figures 11(b) - 11(d) illustrate some road abnormalities and their correlation to a high magnetic field. Using this extra sensor, I am able to minimize false positives when classifying road anomalies.

4.5.6. The Map

Using these road classifications, I formulated a map using Google Earth [49]. GPS data was interpolated with the acceleration data (acceleration and time) which provided an accurate location for each anomaly. Anomalies were then verified using audio recordings which proved the maps accuracy. A conversion script from an excel file to KML Google Earth file was written to written which worked easily with Google Earth. I present these surface conditions on a road condition map using Google Earth which can be viewed on desktop computers and mobile phones. A color code was given to each anomaly shown in Table 4.1. Figure 12(a) and 12(b). As seen, GPS coordinates easily distinguish left and right lane where anomalies can be differentiated by color.

<table>
<thead>
<tr>
<th>Anomaly</th>
<th>Bump</th>
<th>Pothole</th>
<th>Rough</th>
<th>Smooth</th>
<th>Uneven</th>
</tr>
</thead>
<tbody>
<tr>
<td>Color</td>
<td>Purple</td>
<td>Red</td>
<td>Orange</td>
<td>Green</td>
<td>Blue</td>
</tr>
</tbody>
</table>

4.6. Classification Accuracy

I classify each element or area of the road as smooth, rough, bump, pothole or uneven. After interpolation of the GPS coordinates, localizing each element can be accomplished on the road accurate to within 3 meters [50]. For example, Figure 4.13 below is an example of the accuracy of the GPS coordinates obtained after mapping the road. Using Google Earth
Figure 4.11. Examples of magnetic road anomalies. (a) illustrates the location in which (b) was recorded. A train track which can be classified as a bump can clearly be distinguished. (c) and (d) illustrate two instances where bridges which contain expansion joints and connectors which can cause classification as bumps.
Figure 4.12. Map of road conditions. Visual representation road conditions using GPS coordinates and Google Earth. Intensity levels are designated by colors, signifying either a pothole, bump, uneven, rough, or smooth road type. (a) one lane (b) two lanes
and physically viewing the obtained GPS coordinate location, I witnessed a pothole in the area and found it to be within 3 meters, accurately categorizing that part of the road.

![Figure 4.13. Example of pothole location accuracy. On further examination of a pothole location provided by the road condition map, a pothole was found at the exact location.](image)

Another example would be when identifying bumps. The interpolated GPS coordinates also were very accurate as seen in Figure 4.14 which illustrates a bridge of an interstate. Two bump formations can be seen which precedes and ends on the formation of a bridge. I present this data which was classified prior to incorporating the magnetic field sensor. Demonstrating this bump/bridge formation reveals a feasibility in location accuracy. This bump is formed from the unleveled connection of the road to a bridge which degrades over a period of time forming a rise (bump) or sometimes a small drop off, which also portrays the feeling of a bump.

The road anomaly classification system was tested and illustrated in Table 4.2. This table can be correlated with the data presented in Figure 12(a). This confusion matrix
Figure 4.14. Interstate bridge bump. Seen is two bridge connections on an interstate creating multiple bumps as a vehicle enters the bridge and exits the bridge. GPS coordinates were accurate enough to identify the bridge.

represents the accuracy of detecting each road anomaly. Smooth roads presented the easiest to classify as no ambiguous data was found in the z-axis. When classifying potholes, four false positives (as bumps) occurred. In each of these cases, the pothole was not big enough to impact the threshold parameters I initially set. Using the x-axis and z-axis to classify bumps increased the classification accuracy greatly from an initial 71% to 81.5% seen in Table 4.2. This resultantly had a positive impact on the pothole accuracy as well. I obtained an 85.6% accuracy for the overall road anomaly classification system.

Table 4.2. Road anomaly classification accuracy.

<table>
<thead>
<tr>
<th></th>
<th>Bump</th>
<th>Pothole</th>
<th>Rough</th>
<th>Smooth</th>
<th>Uneven</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bump</td>
<td>31</td>
<td>6</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>81.5%</td>
</tr>
<tr>
<td>Pothole</td>
<td>4</td>
<td>13</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>72.2%</td>
</tr>
<tr>
<td>Rough</td>
<td>2</td>
<td>0</td>
<td>6</td>
<td>0</td>
<td>0</td>
<td>75%</td>
</tr>
<tr>
<td>Smooth</td>
<td>3</td>
<td>0</td>
<td>1</td>
<td>54</td>
<td>1</td>
<td>91.5%</td>
</tr>
<tr>
<td>Uneven</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>2</td>
<td>34</td>
<td>89.4%</td>
</tr>
</tbody>
</table>
4.7. Summary

In a decade where mobile smartphones have almost surpassed the amount of personal computers sold in a year, conveys the idea that we are a mobile society; and as such, we take comfort in our travels expecting to arrive at our destination without harm. Linking these two assumptions, a mobile phone and a vehicle, can create an interesting if not innovative combination when applying towards analyzing road conditions. With smartphones containing sensors such as a microphone, accelerometer, GPS and magnetometer, I was able to create a system for classifying road surface conditions. Obtaining a map of the road surface, which we drive on each day, can save money by avoiding vehicle repair costs, provide comfortable commutes as for taking the smoothest path to a destination, and also lead to the overall improvement of the road as city workers become aware of such hazardous anomalies present on the road.

Much time was spent to collect data for the proposed classification system and then to analyze each anomaly and determine is pattern. This pattern existed in most cases only the z-axis while some were a combination of the x-axis and z-axis in the frequency domain. Integrating the x-axis in allowed for a greater accuracy of correct matches and less false positives and false negatives. Integrating Google Earth allowed for more flexibility to be implemented in different platforms. The obtained accuracy for each road and total system illustrated that the identification methods proposed do work but can still be improved. Rough Roads are the most difficult to find and differentiate from smooth-like roads. Smooth roads resulted in the highest accuracy percentage while potholes revealed to be the lowest. This is due to misclassifications as bumps with potholes also increasing in the x-axis. This classification process produced overall accuracy of 85.6% revealing a potential in such a ubiquitous collection device. Mobile smartphones are both convenient and affordable as most of the public already owns one. This attribute provides a reliable source for obtaining future public road data. If each person operates their phone as a data collector, we as a society can create a network of
road analysis devices creating a robust database of anomalies. This is a form of crowdsourcing. With the more data collected and analyzed, future erroneous anomaly classifications such as potholes, bumps, uneven roads, and rough roads can be reduced significantly. Real-time road updates can keep our roads running smoothly while providing the most comfortable ride possible, increasing the safety of the driver.
CHAPTER 5

THE DRIVER

5.1. Introduction

Drivers have a tendency to formulate their own driving techniques and even imitating behaviors seen visually while on the road. This act may be performed without their knowledge or subconsciously, and therefore are not aware they are performing techniques that may be unsafe to their health and the health of neighboring drivers. To help with drivers unsafe behaviors, we can use an everyday tool which is in abundance and utilized everyday by the public, a smartphone. Equipped with an accelerometer, we can use these small embedded sensor in the phone to analyze and even predict the techniques a driver has and will perform on the road. The maneuver I identify and classify in this chapter is a lateral movement defined as lane changes. A lane change occurs when a driver leaves the current lane and enters an adjacent lane. This act usually consists of the steering wheel being turned a certain degree subsequently changing the direction of the front tires. If this degree of change is too great in a small period of time, the acceleration experienced could have a significant impact. These actions have the ability to have great influence and inhibit other drivers behaviors on the road that could lead to a potential deadly accident. Capturing these maneuvers and intelligently informing the driver can increase driver awareness and even correct for a more safe traveling experience.

Advanced driving assistance systems (ADAS) are progressively advancing with today’s vehicle manufacturers. This new proposed smartphone technology could be used to compliment expensive ADAS systems. The U.S. Department of Transportation reported that unsafe lane changes are one of the leading causes of vehicular accidents and that number increases as speed increases. Distracted driving accounts for approximately 20% of vehicle accidents [51]. Given that cell phones are one of the main cause of distracted driving, the National
Transportation Safety Board has moved to ban all electronic devices while operating a moving vehicle [52]. This movement increases the willingness for improving driving behavior and puts use to an unusable, powerful platform in the vehicle. Minimizing these distractions and educating a driver after a lane change can help prevent and improve this staggering statistic. This area also has great potential for insurance companies who can offer special incentives to drivers who have demonstrated safe driving behaviors. With this, this chapter demonstrates identifying lane changes, classifying them as aggressive and providing feedback on the lateral movement. Real-time alerts using the smartphone are given to the driver where it can possibly benefit to improve unsafe behavior. Driver feedback is one important contribution that I convey in this chapter.

5.2. Related Work

This chapter discusses the first two sensors in detail on how I used them in combination to help identify driving maneuvers, both safe and unsafe. It is first appropriate to present some work that has been done using a smartphone’s camera and mobile vehicles such as detecting lane changes, vehicles, and estimating safe stopping timings. iOnRoad is an Android application which utilizes the camera of the smartphone with machine vision algorithms to provide an ongoing and objective skill feedback for better driving decisions [53]. Particularly, iOnRoad calculates the time gap and collision potential with other vehicles and warns of high risk events. Day or night features are not impacted on the results from iOnRoad as it compensates internally for these different events. When a driver approaches a vehicle from behind at a speed that produces a high risk or potentially threatening to the driver, iOnRoad acknowledges the driver with a time need to stop successfully without causing a collision. Different colors are used to help distinguish safe, aggressive and unsafe time frame. With the distance decreasing between vehicles at high speeds, an unsafe acknowledgment will be revealed to the driver. Audio along with colorful visual warnings are used to help increase driver alertness of the current application’s status. iOnRoad also detects the lane the vehicle
is in while distinguishing a different lane if the vehicle should change. Previewing a demo of this software, a high accuracy in detecting a lane change is presented. An augmented driving technique has also been presented in the form of an iPhone application called Augmented Driving (AD). AD exploits the use of a camera, embedded processor, and augmented reality which has increased in popularity in the advanced theoretical gaming community. The mobile is mounted near the windshield lying horizontally with the camera facing the window and road. A distance estimation of obstacles is estimated using image processing, nearby vehicles are detected, as well as lane detection and a lane change warning. The white and yellow lines on the road distinguish individual lanes and are detected as a change when a vehicle begins to transition left or right into a different lane.

Both of these applications are subject to visual specification and straight road segments. In other words, it is dependent on lane markings to base its location on the road. If these markings are faded or not present at all, it will not detect lane changes and can affect distance estimations and neighboring in-lane vehicle detections. Long straight roads are also required meaning that these applications cannot be used in short residential areas. Interstates and country roads are the only ideal environment. With these clear limitations, I focus on creating a system which is not camera dependent but utilizes other sensors in the mobile smartphone and can function at any speed, and in any road environment at any time of the day. The smartphone has a 3-axis accelerometer which is not characterized by any of these limitations. It is with this I detect and classify unsafe lane departures.

5.3. System Architecture

Determining safety based on driving maneuvers constitutes a variety of behaviors. Speed, acceleration, deceleration, lane changes etc. are all contributing influential factors for road safety. For this chapter, I analyze direct lateral movement of the vehicle, lane changes. This maneuver is very difficult to some especially at high speeds where road conditions and neighboring drivers can define out this maneuver is carried out. I present an architecture to
a proposed driving behavior system in Figure 5.1 which incorporates three levels: 1) Sensors Data 2) Maneuver Analysis and 3) Safety Level. Lane changes are detected and classified in level 2 in which I utilize the accelerometer and speed data from either GPS or OBD-II in level 1. Using sensor processing, I was able to tangibly determine if the lateral maneuver consisted of a safe or unsafe lane changes. Direct audio feedback is given to the driver in real-time in the safety level, level 3. All alerts are given to the driver in real time using the smartphone’s Android platform.

![Diagram of proposed driving behavior system](image)

Figure 5.1. LaneChange system architecture consists of three levels: sensor data, maneuver analysis and safety level.

5.3.1. Hardware

Smartphones have been utilized for various tasks such as phone calls, texting and web browsing. Lately in research, smartphones have been exploited for navigation [22, 23], traffic estimation [4] and transportation modes [19]. I utilize the quickly advancing smartphone to quantify vehicle movements. Lateral movements with a vehicle can be deadly at times and knowing whether the correct maneuvers are safe is critical. To capture these signals, I utilized
four different phones: 1) HTC Nexus One 2) Samsung Nexus S 3) Motorola Droid Razr and 4)
Samsung Galaxy Nexus. Each contains an embedded accelerometer which records at different
sensitivities and frequency rates. Obtaining signatures from each sensor is significant. Noise
will increase with a higher frequency but sensitivity is greater also. By obtaining lane change
signatures and performing sensor analysis from each phone, a universal software application
applicable to a number of phones can be created that can detect real time lane changes.

5.3.2. Software

Analyzing driver behavior is a real time process. To accomplish this on a smartphone, I create an application (LaneChanges) on the phone that works with Android OS utilizing its embedded hardware (processing power, memory, and sensors). Successfully optimizing the integration of code type and system utilization (functions/tasks) is necessary in order to create a highly functional and optimized system; Android application in this case. However, given this is a real time process, limitations occur during development phases which require rigorous pivoting between code development and testing. In order to excel this process, a catalyst is needed. Recognizing this handicap, I introduce an simulating functionality into the LaneChanges application which analyzes stored driver behavior previously obtained by the sensors (e.g. Accelerometer, GPS, Magnetometer etc.) in a file on the smartphone. This simulating functionality allows quick feedback to become accessible offline. Along with this, the I can easily change a piece of code, run new changes on a selected data set to see impact on statistical driver results almost immediately. Integrating this functionality into the smartphone app allows easy switching between real time and simulator modes. This benefits the development process as a whole where changes can be quickly made and quickly simulated to see the apparent impact. Figure 5.2 illustrates the LaneChanges application containing online and offline functionality for obtaining sensor data.

Android Modules. An online (real-time) and offline (from file) methods were implemented to obtain data for testing the lane change application. There is an option for choosing which
method to launch before the application is started. For online mode, the sensor data is acquired using Android’s SensorManager API where the accelerometer can be polled for new data. For offline, the data can be easily acquired stored from a file. I will explain the setup from here on the offline simulation implementation.

Since reading times are always faster than writing times, delay will be minimized therefore wont impact the performance of simulating the data very quickly. Reading from a file and injecting the appropriate accelerometer can easily be accomplished but synchronizing this data injection of accelerometer with other sensors such as the GPS provides a challenge. Synchronizing the data is the most significant factor for appropriately analyzing the data in a simulation (offline) mode. For this, two Threads are used one for each sensor: 1) accelerometer and 2) GPS. I utilize threads in this case so I can implement a delay or sleep timer which simulates something that of a real time implementation. The simulator can run in real time but can also be scaled down to run faster, e.x. 1 s = 1 ms. Using this ratio, offline mode can finish in a fraction amount of the time that is used for the online real time mode. The
table below is an example of a file containing raw accelerometer data. Column one contains the time stamp while column two contains the accelerometer x-axis data. To implement the delay for simulation, I take the first timestamp as \( t_0 \), update the application with the x-axis value, and also read in the second timestamp, \( t_1 \). A calculation is needed for the delay which shown in Eq. 6. Using this continuous delay found in Eq. 6, the time needed to sleep the thread is known which impacts reading from the next value upon wake-up. An example of this sequence is given below in Table 5.1.

(6) \[ \text{Delay} = t_1 - t_0 \]

Table 5.1. Data access in offline mode simulating online mode

<table>
<thead>
<tr>
<th>TimeStamps (ms)</th>
<th>Acceleration (m/s²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( t_0 ) 0</td>
<td>0.153229</td>
</tr>
<tr>
<td>( t_1 ) 08</td>
<td>0.229843</td>
</tr>
<tr>
<td>28</td>
<td>0.229843</td>
</tr>
<tr>
<td>38</td>
<td>0.383072</td>
</tr>
<tr>
<td>49</td>
<td>0.536301</td>
</tr>
<tr>
<td>67</td>
<td>0.612916</td>
</tr>
<tr>
<td>89</td>
<td>0.536301</td>
</tr>
</tbody>
</table>

ex. Delay = 08 - 0 = 8 ms

I implement the detection and classification using Android threads called, asynchronous tasks using the AsyncTask API from Android which was introduced in Android version 1.1 [21]. Asynchronous Tasks work similar to that of Threads which a process can be multitasked and even run in the background. The organization surrounding the AsyncTask makes it better to use than Threads given that Threads can crash with the use of synchronization locks. AsyncTask comes with five built in functions in order of sequence (their names are self-explanatory):

- onPreExecute() - Setup Online (SensorManager) or Offline Modes
• doInBackGround() - Inject Data from Online or Offline Mode - Run Detection Method - Run Classification Method
• onProgressUpdate() - update Android UI Thread
• onPostExecute() - Unregister Sensors (online) or close data files (offline)
• publishProgress() - used to call onProgressUpdate() method to update the UI Thread Interface, inside doInBackgound() 

Figure 5.3 demonstrates the LaneChanges Class and Method diagram. It shows the main activity, LaneChanges, the SensorData class which utilizes the AsyncTask API. SensorData initiates the online or offline modes which begins the data injection for the Detection class. The classification process is then carried out in the LaneChange method here. The SplashScreen class is a pre-application functionality which uses the SensorManager API to determine the frequency of the sensor. This is an important method since many things are dependent on the frequency of the sensor.

5.4. Methodology

5.4.1. Vehicle

For testing lane changes, I used a sedan that is fairly new which differs from the previous road condition experiment using an older single-cab truck of the 1990s. The 2008 Pontiac G8 offers a 3.6L V6 engine with a 5 speed automatic transmission equipped with continuously variable valve timing (CVVT) which allows for smoother shifting. Figure 5.4 illustrates the vehicle used for the initial tests for capturing lane change maneuvers. Though I used one vehicle initially, after validating the classification system, it was implemented in 5 other vehicles each with different drivers successfully.

5.4.2. Phone Placement

To make this experiment convenient for the driver, I want to incorporate a device that is portable but yet securable to the vehicle. A mobile phone fits this description along with a
Figure 5.3. Application class and method diagram. Online (OnSensorChange) and offline (fromFile) functions below contain the data injection functionality. The other classes Detection, SensorData and LaneChanges (main Activity) make up the application as a whole.

Figure 5.4. 2008 Pontiac G8 - 3.6L V6 with a 5-speed automatic transmission

sports armband which is sized/fitted for a smartphone. I use a Samsung Nexus S along with a generic smartphone sports armband, adjustable and securable using velcro. This device allows for not only the measurement device to be portable, but also the measurement location as well allowing for a number of places to be tested. The phone was oriented parallel to the
Knowing how accelerometer relates to the smartphone and vehicle is important since I can control the incoming data and how to subsequently analyze it. I employ the sports armband fitted for a smartphone and strap that to the center console of the vehicle. This console has a latch in which I wrap it around it and secure the armband with velcro. Figure 6(a) represents the sports armband with a velcro strap to secure it to almost any type of surface. This armband encloses a smartphone enough to where there is no slippage which would result in erroneous data. The smartphone can then be inserted through the bottom of the armband which allows for the microphone to be exposed to future purposes, Figure 6(b) and 6(c). With this setup, the driver can access the smartphone interface through the clear plastic window of the armband while having it secured to the vehicle allowing for easy functionality and accurate measurements in x-axis direction, Figure 6(d).

5.4.3. Location

A simple straight road was used initially as the location for lane change testing. Once confident enough in the classification system, I tested different road types including: residential, business and interstate. Different speeds were also tested.
Figure 5.6. Measurement locations used for analyzing safe and unsafe driving techniques. A smartphone arm strap holder was used which secured the phone to the center console allowing easy obtainable and hands free data collection.

5.4.4. Sensor Analysis

Different phones today use different embedded sensors. These sensors are often manufactured by different companies and therefore contain difference sensing characteristics. Sampling rate, or frequency, resolution, sensitivity are a few characteristics I have identified. To create a system that can be a solution for many different phones, I have to find a technique that will filter environmental noise but not degrade the signal which can help distinguish it from other lateral movements such as turns, u-turns, swerves, wandering and drifting. For example, Figure 5.7 illustrates raw lateral movement of the accelerometer as well as smoothing lateral movement. We can see that the amplitude of the signal begins to
dissipate as the smoothing increases. Therefore, I need to identify a smoothing technique that is primarily based on the sampling rate of the sensor. Table 5.2 identifies four phones that were used in the lane change classification system and its sensor characteristics. It also identifies the smoothing rate that was proposed for each sensor frequency.

![Figure 5.7. Sensor analysis for the Galaxy Nexus utilizing different smoothing rates. Higher smoothing rates have a greater impact on the amplitude of the signal.](image)

Table 5.2. Smartphones and accelerometer characteristics

<table>
<thead>
<tr>
<th>Smartphone</th>
<th>Accelerometer</th>
<th>Resolution (m/s²)</th>
<th>Frequency</th>
<th>Smoothing Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>HTC Nexus One</td>
<td>Bosch BMA150</td>
<td>0.15328126</td>
<td>30 Hz</td>
<td>11</td>
</tr>
<tr>
<td>Samsung Nexus S</td>
<td>STMicroelectronics KR3DM</td>
<td>0.01915361</td>
<td>50 Hz</td>
<td>20</td>
</tr>
<tr>
<td>Motorola Droid Razr</td>
<td>STMicroelectronics LIS3DH</td>
<td>0.0047900393</td>
<td>99 Hz</td>
<td>30</td>
</tr>
<tr>
<td>Samsung Galaxy Nexus</td>
<td>Invensense MPL</td>
<td>0.038344003</td>
<td>128 Hz</td>
<td>45</td>
</tr>
</tbody>
</table>

A quadratic curve fitting technique was used to determine an equation that would give a dynamic smoothing rate based on sensor frequency. Equation 7 represents the dynamic smoothing technique where $S(n)$ is the smoothing rate of a phone and $f$ is the frequency of the phone. This technique is needed due to the fact that sensor manufacturers are utilizing a lower power sleeping mode where the sensor registers at a low sample if the phone is not being moving. I have seen this when analyzing the Motorola Droid Razr.

\[
S(n) = 0.001623f^2 + 0.073648f + 9.1076
\]
I visually plot Eq. 7 to see how the smoothing rate increases as the sampling rate of the sensor increases. I have used this technique in the real-time lane change classification system.

![Graph showing smoothing rate vs. frequency](image)

**Figure 5.8.** Smoothing distribution for different smartphones which incorporate different accelerometer manufacturers which utilize different frequencies. A higher smoothing rate is necessary to filter out environmental noise which increases as the sampling rate increases.

5.5. Detection

Detection and classification are two different methods. Detection is the act of finding any lateral movement by the vehicle. Classifying is the act of labeling the lane change’s aggressiveness. Detection is crucial in order to classify it. Therefore, I utilize characteristics of a lane change signal in order to determine if the vehicle did in fact change to an adjacent lane. Figures 9(a) and 9(b) illustrate the formations of a left lane change and right lane change, respectively. To detect a lane change event, I use a peak detection algorithm that factors in amplitude and the time duration. I set thresholds for each characteristic and compare signal data. If the signal satisfies these conditions, a lane change event is said to be detected. Using the basic formation of the signal, I am able to distinguish a left lane change from a right lane change. Figures 10(a) and 10(b) illustrate these signals as performed safely.
and aggressively.

![Figure 5.9. Acceleration signature of (a) left lane change and (b) right lane change. These formations are distinguishable in Figures 10(a) and 10(b).](image)

5.6. Classification System

5.6.1. Dynamic Time Warping

In this section, I transition to the application domain and explain what classification technique was used where it could be implemented in real time on the measurements. I start with the dynamic time warping (DTW) algorithm and its applicability to classify lateral movement of a vehicle after the detection has occurred.

The technique in DTW is to compress or stretch the time axis of one or both sequences to achieve a better alignment. These two sequences are labeled as a stored training template and a test template. It was originally used for handwriting analysis to identify the origins of a signature to a specific individual. In general, consider two signatures, \( T = \{ t_1, t_2, \ldots, t_A \} \) and \( S = \{ s_1, s_2, \ldots, s_B \} \) of different lengths. The goal is to find the best match between the two signatures by some alignment \( w \), the optimal warping path. The warping path is given by \( w = w(1), w(2), \ldots, w(n) \), where \( w(n) = [i(n), j(n)] \) is the set of matched samples, where \( i \) and \( j \) corresponding to the time axes of two sequences respectively. The objective of the warping function is to minimize the overall cost function given by

\[
D = \sum_{n=1}^{N} \delta(w(n))
\]
Figure 5.10. Lane changes recorded by the x-axis of a smartphone’s accelerometer. A left lane change is formed by a small decrease followed by an increase. A right lane change is formed oppositely. (a) Four safe right lane changes and three safe left lane changes in series (b) Four sudden right and left lane changes performed in series, eight total.
where $\delta(w(n))$ is the squared distance between the sample points given by

\[ (9) \quad \delta(w(n)) = (i(n) - j(n))^2 \]

The warping path must satisfy the following constraints:

- **Monotonicity:** The warping path must progress in the forward direction, i.e $i(n) \geq i(n-1)$ and $j(n) \geq j(n-1)$, where $w(n-1) = [i(n-1), j(n-1)]$ and $w(n) = [i(n), j(n)]$.
- **Boundary:** The function must always start at $w(1) = (1, 1)$ and end at $w(n) = (A, B)$
- **The function must not skip any points, i.e $i(n) - i(n-1) \leq 1$ and $j(n) - j(n-1) \leq 1$**

To generate a warping path, a cost matrix is constructed. This matrix represents the minimum cost required to reach a particular point $(i, j)$ from $(1, 1)$. This minimization problem is usually solved using the dynamic programming approach, whereby a cumulative or accumulated distance $\gamma(i,j)$ is computed as the sum of $\delta(w(n))$, the distance obtained from the current set of points and the minimum of the cumulative distances of the adjacent elements or neighbors. This is given by

\[ (10) \quad \gamma(i,j) = \delta(w(n)) + \min[\gamma(i - 1, j) \quad , \gamma(i - 1, j - 1) \quad , \gamma(i, j - 1)] \]

After performing the time warping, the closest match is obtained by the lowest cumulative distance between the signatures. This identifies the similarities between the two signatures and classifies it a match or not.
5.6.2. DTW Performance

The Test signature is that obtained from real time accelerometer data and a Training is a stored signature, one for each grade of lane change: good, aggressive and bad. I performed DTW between a test signature and stored signatures. This classification process was called each time a lane change detection occurred. Using the simulation mode of the LaneChanges application, I tested DTW on multiple data sets that collected over a period of three months. Each set contained good, aggressive and bad lane changes. These lane changes were performed in real time, no simulation methods were used to generate them.

To use DTW, I obtained three stored training templates that were used to correctly match the lane changes during detection. Figure 5.11 illustrates the stored template for left lane changes. These signatures are used to test against live accelerometer data.

![Stored training templates used for DTW classification for left lane changes.](image)

During our accuracy tests, I obtained very good results. The DTW algorithm correctly matches good lane changes even when compared with a similarly forming signature e.g. aggressive lane change. I illustrate a correct match of an aggressive lane changes and compare that with a distance value of an incorrect matche to help distinguish DTW’s effectiveness. Each resulting DTW classification reveals a distance value. The lower the distance value out of the three templates tested is defined as a match. This match is then quantified as a classification in the system.
Figures 12(a) and 12(b) illustrate a correct match with a DTW distance value of 7.4847. The aggressive test signature was tested against a good training template which resulted in a higher DTW distance value of 42.7748. In this case, DTW performed accurately, correctly matching the aggressive lane change with the correct stored training template.

Figure 5.12. DTW matching of an aggressive left lane change: (a) original signals and (b) DTW performance resulting in a match with a DTW distance value of 7.4847. This was tested with an incorrect match on the good training template resulting in a higher DTW distance value of 42.7748. The lower distance value conveys the correct match.

The accuracies obtained from DTW classification process are listed in Table 5.3. The total number of DTW classifications were performed on a totaled 188 (Total) lane changes. The classification accuracy was calculated as

\[
A = \frac{\#Correct\text{matches}}{Total}
\]

Out of the total 188 lane change maneuvers collected there were a total of 19 misclassifications. Since I was able to distinguish a left lane change from a right lane change using the detection algorithm, no misclassifications were labeled as a different direction. In each case, a misclassification occurred a level higher or lower. No good lane changes were classified as bad and vice versa. Aggressive lane changes were however misclassified as both good and bad. Good lane changes given easier to carry out were more abundant in number. The misclassifications that occurred in this section were labeled as aggressive lane changes.
### Table 5.3. Accuracies obtained for each lane change

<table>
<thead>
<tr>
<th>Vehicle Maneuver</th>
<th>Total Number of Maneuvers</th>
<th>Maneuver Accuracy</th>
<th>Level Accuracy(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Good Left</td>
<td>64</td>
<td>93.75</td>
<td>88.52</td>
</tr>
<tr>
<td>Good Right</td>
<td>58</td>
<td>82.76</td>
<td></td>
</tr>
<tr>
<td>Aggressive Left</td>
<td>30</td>
<td>93.33</td>
<td>90.90</td>
</tr>
<tr>
<td>Aggressive Right</td>
<td>25</td>
<td>88</td>
<td></td>
</tr>
<tr>
<td>Bad Left</td>
<td>6</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>Bad Right</td>
<td>5</td>
<td>100</td>
<td></td>
</tr>
<tr>
<td><strong>Total Accuracy</strong></td>
<td></td>
<td><strong>89.89</strong></td>
<td></td>
</tr>
</tbody>
</table>

This was due to a higher maximum acceleration which was borderline or very close to that of the aggressive lane change stored training template. The misclassified aggressive lane changes as stated earlier were labeled at times good and bad. After analysis, this was because of the same reason as good lane change misclassifications. The tested signatures were either very low or very high in acceleration, bordering a good or bad lane change. In these situations, DTW had a lower distance value outcome matching with an incorrect template rather than a correct template. These situations however were minimum. As we can see with the accuracies in Table 5.3. No misclassifications were obtained for bad lane changes. This is most likely because the maximum acceleration is much greater than that of a good and aggressive lane change. Overall, the DTW classification system performed very well for classifying lateral movement of a vehicle obtaining a 89.89% total system accuracy.

### 5.7. Summary

Using a mobile smartphone inside a vehicle to analyze driving patterns has been tested and has revealed itself to be a viable option for future use. We can clearly see different driving techniques such as lane changes and classify them based their level of performance. Classifying these patterns as safe and unsafe is the main contribution of this chapter and as focusing on it, I have achieved a high accuracy. Using the online and offline simulation setup I explained, it was easily possible to capture various lane changes on the road and analyze them.
offline as it would be in real–time. This maximized efficiency and minimized total downtime spent on the road while not sacrificing any safety concerns. All detection and classifications were done on the mobile smartphone. Multiple drivers were used to test its robustness. Using the Android platform, I was able to detect left and right lane change maneuvers, classify them as good, aggressive or bad, and give real-time feedback to the driver using audio. With this, I can finally educate driver’s on their performance which has real world applications for young teen drivers and elderly, who might be driving alone.
CHAPTER 6

CONCLUSIONS

This thesis focused on transportation related topics such as vehicle maneuvers, vehicle comfort and analyzing road conditions. I utilized mobile smartphones as a collection and processing unit which has multiple sensors embedded inside. To efficiently utilize the mobile phone, I built applications which worked with data obtained by multiple sensors. Not only were the smartphone sensors useful, but I synchronized data collection with the vehicle as well utilizing onboard sensors from the vehicle. The main merit is focused Chapter 5 which detects and classifies lateral movement of vehicles. An exhaustive data collection along with statistical analysis provided unique signatures which was then compared with using an innovative technique used to distinguish hand writing schemes. All the topics concluded inside the vehicle or in a vehicular environment which defines the core contribution of this thesis.

6.1. Summary of Contributions

- **Chapter 1 (Introduction):** In this chapter, I elaborate on the background of why such driver assist systems are needed and how it impacts our society. I present sensor analysis on the accelerometer sensor and identify the impractical use of it as a speed estimation device.

- **Chapter 2 (On-board Diagnostics):** In this chapter, I set up vehicle and smartphone communications in order to extract vehicle sensor data. A hardware and software architecture is given and an Android application was developed. Speed was extracted and compared with GPS for validate which is a significant attribute for road and vehicle analysis.

- **Chapter 3 (The Vehicle):** In this chapter, I present a unique comfort analysis on five different vehicles. I utilized only the sensors in the smartphone to obtain a comfort analysis which incorporate both vibrations and audio levels. A detailed vibrational
and acoustical comfort analysis was given for each vehicle.

- Chapter 4 (The Road): In this chapter, I present a road condition analysis system that utilized the embedded accelerometer in the phone. Signal processing was used to close define the road as one of five anomalies. Forty miles of road was used to obtain these results.

- Chapter 5 (The Driver): In this chapter, I present a unique technique to detect and classify lateral movement of a vehicle. Lane changes were performed by multiple drivers in multiple vehicles to find a consistent characteristics to grade the maneuvers. A unique classification technique was used which was incorporated into a real-time Android application which grades each lane change (good, aggressive or bad). An audio feedback method was used to educate the driver, increasing awareness and performance.

To conclude, this thesis covered questionable transportation related influences consisting of the driver, the vehicle and the road. It has progressively evolved from interdisciplinary research involving data mining, machine learning, mobile computing, software engineering, signal processing, sensor fusion techniques, and applying basic physics of motion in the real world.

6.2. Challenges and Limitations

Not all systems were performed online on the phone. The comfort and road condition analysis were both performed offline. In this case, the smartphone was used as a collection device and techniques were derived offline. The comfort analysis given its extent in detail, was computationally heavily and at the time, the smartphone’s hardware was not as advanced as it was today. Comfort is susceptible to human perception and as such, varies from person to person. A mobile smartphone may not be capable enough to distinguish comfort on a personal level but in our experiments, I was able to generalize the comfort of a vehicle. To further expand this, a subjective viewpoint could be used to correlate our comfort results
with a subjects feedback. This would enhance and validate our findings. Only one vehicle was used to analyze and classify road conditions. Given the availability and beating vehicles take from road anomalies such as bumps and potholes, I only used my personal vehicle. The consistent profiles I presented for each anomaly may not apply to newer vehicles with better suspensions. Absorption might be present, hiding some anomalies such as rough roads or small potholes. Lane Changes formations were consistent however classification technique would differ when using a very low frequency phone. Only high sampling rates were tested (50 Hz+) to work with the selected training templates. Using low sampled test data with a high sampled training data set would result in misclassifications. Higher frequency phones generate a higher sensitivity and therefore low sampled test data would not necessarily match correctly. New training templates would have to be generated upon the splash screen analysis of obtaining the initial frequency of the sensor. This would solve the limitation.

6.3. Future Work

All analyses for road condition anomaly detection and classification were done offline in Matlab. A further relate road condition with quality, the International Roughness Index (RI) can be used which grades a segment of a road. This standard is used in the United States as well as internationally in Europe. RI is closely related to vibrational experienced inside a vehicle and as such, it is therefore closely related to vehicular comfort. A future expanding of Chapter 4 and 5 can relate road anomalies, vehicular comfort and road grade which can help us further define an overall quality of roads. The comfort performance can also be expanded to relate how it performs on different types of roads. More vehicles can be tested to analyze road conditions to find consistent patterns which can be utilizes or compensated from vehicle to vehicle. To expand the hastiness of the lane change application, I can use crowdsourcing which is a technique used gain a variety of data with the help of the public. It gives a particular task to a crowd of people such as filling out a survey or donating funds to an organization. Given the popularity of mobile phones today and the accessible application
based markets available on each, distributing our application to the masses could easily be achieved. This would help minimize false positives as well as improving the overall system interface and design.
REFERENCES


