Short Papers

Safe Driving Using Mobile Phones

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***Abstract*—As vehicle manufacturers continue to increase their emphasis on safety with advanced driver-assistance systems (ADASs), we propose a device that is not only already in abundance but portable enough as well to be one of the most effective multipurpose devices that are able to analyze and advise on safety conditions. Mobile smartphones today are equipped with numerous sensors that can help to aid in safety enhancements for drivers on the road. In this paper, we use the three-axis accelerometer of an Android-based smartphone to record and analyze various driver behaviors and external road conditions that could potentially be hazardous to the health of the driver, the neighboring public, and the automobile. Effective use of these data can educate a potentially dangerous driver on how to safely and efficiently operate a vehicle. With real-time analysis and auditory alerts of these factors, we can increase a driver's overall awareness to maximize safety.**

***Index Terms*—Accelerometer, mobile phone, road conditions, sensors, vehicle safety.**

I. Introduction

In the fast-paced society of today, we are focused on arriving at our destination as quickly as possible. However, with this lifestyle, we are not always aware of all the dangerous conditions that are experienced while operating an automobile. Factors such as sudden vehicle maneuvers and hazardous road conditions, which often contribute to accidents, are not always apparent to the person behind the wheel. In recent years, there has been tremendous growth in smartphones embedded with numerous sensors such as accelerometers, Global Positioning Systems (GPSs), magnetometers, multiple microphones, and even cameras [1]–[3]. The scope of sensor networks has expanded into many application domains such as intelligent transportation systems that can provide users with new functionalities previously unheard of [4]. Experimental automobiles in the past have included certain sensors to record data preceding test crashes [5], [6]. After analysis, crash scenarios are stored and analyzed with real-time driving data to potentially recognize a future crash [7] and actually prevent it [8]. With more than 10 million car accidents reported in the United States each year [9], car manufacturers have shifted their focus of a passive approach, e.g., airbags, seat belts, and antilock brakes, to more active by adding features associated with advanced driver-assistance systems (ADASs) [10], e.g., lane departure warning system [11] and collision avoidance systems [12], [13]. 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. Since sensors ultimately add onto the cost of a vehicle initially and cannot be affordably upgraded, we target a mobile smartphone as an alternative device for ADASs that can assist the driver and compliment any existing active safety features. Given its accessibility and portability, the smartphone can bring a driver assist to any vehicle without regard for on-vehicle communication system requirements.

With this as our motivation, we 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 [14]. Given the sensing capability of smartphones, we use the internal accelerometer and GPS of the phone in place of the expensive hardware installed in vehicles to assist active features provided in newer ADAS vehicles.

This paper is organized as follows: In Section II, we present the related research. Section III explains the proposed setup of the experiments in which we used a mobile phone as a measuring device to detect vehicle maneuvers and road conditions. In Section IV, we reveal results that were obtained from these experiments that have the potential to aid in driver assist. We demonstrate that both extreme driving behavior and hazardous road anomalies can be identified using a mobile phone rather than expensive motion equipment and can aid existing safety features to increase driver awareness. We conclude the paper in Section V describing our accomplishments.

II. Related Work

Analysis of external sensors data for vehicle performance is a large area of study. Some work has been done in the form of theoretical research and development in a practical design. The main ideas of our work focus on mapping anomalies of a road's surface and classifying different driving behaviors.

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 Global System for Mobile communications radio for traffic localization. Pothole Patrol [15] is another system that monitors road conditions using GPS and an external accelerometer. The system was deployed for testing in taxis using a convenient method to identify fatigued surfaces of a road.

Tracking and analyzing driving behavior is an ongoing ITS study. University of California Berkeley's Mobile Millennium project is a traffic-monitoring system that uses GPS data to obtain individual vehicle location information, process it, and distribute route information back to a mobile phone [4]. Services presented by Wang *et al.* [16] describe an infrastructure that can be used to distribute driver and vehicle information utilizing popular characteristics associated

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with cloud computing. Zhang *et al.* presented a pattern recognition approach to characterize drivers based on their skill level [17]. Skill level was formed as a basic low, medium, or expert level, or a simple 1-to-10 number scale. Using a high-end vehicle simulator, they compare driver behavior such as steering control, lane changes, and traffic levels with an expert driver to help with category resolution. Learning and classification algorithms are then used to predict the driver's overall skill level derived from these conditions. Dai *et al.* [2] focused on a driver's ability to perform on the road. They proposed a technique using a mobile smartphone to detect various driving patterns of an operator mimicking the habits of a drunk driver. When these patterns were in variable sync, it was assumed the driver was intoxicated. Phone implementation showed acceptable results for drunk driver detection and is efficient in energy consumption.

Our work reveals roads to be more complex than the identification resolutions presented by both Nericell [1] and Pothole Patrol [15], resulting in a wider array of classifications to reveal a particular road's overall integrity. We identify not only potholes but also bumps and rough, uneven, and smooth roads using multiple axes of the accelerometer. We also utilized a single measuring device rather than expensive external sensors placed in numerous places around the vehicle, which ultimately increases infrastructure costs. Our device, which is a mobile smartphone, contains GPS, microphones, and an accelerometer offering flexibility in methodology and user implementation. Encouraging results in identifying numerous road anomalies and sudden driving maneuvers allow for our system to evaluate an entire road's condition and help advise drivers on unsafe characteristics, respectively, both of which are distinguishable factors that can determine safety on the road.

III. Experimental Setup

Using a mobile phone for these purposes creates numerous variables that must be accounted for as measurements can be misleading in certain situations. Phone location and orientation inside the car should be configured to achieve accurate measurements. Likewise, driving behaviors vary from driver to driver, and performance may be exhibited as unsafe to some while safe for others. Providing quantitative data can help define a baseline in these instances. All data recognized by the mobile is stored on the phone that the user has full control over. Any uploads are kept anonymous and used only for mapping and machine learning techniques. For the driver to recognize these safety factors, we utilize audio feedback. This feature is easily implemented using Android application programming interfaces, with specification options ranging from audio level, speech rate, and language selection. We factor in all of these ideas during our measurement analysis to provide a secure and accurate technique that is most applicable for a wide range of drivers and vehicles on the road.

A. Device Background

The device used was an Android-based smartphone: Nexus One. This HTC/Google phone made it relatively easy to acquire data to be thoroughly analyzed. 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 three-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 3300 Hz. The limitations of the refresh rate and software integration yield a usable refresh rate around 25–30 Hz [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 such as lane changes can be numerically distinguishable. Fig. 1 shows the Nexus One and its relevant axes. If any movement is detected, it is numerically analyzed and expressed in these directions.

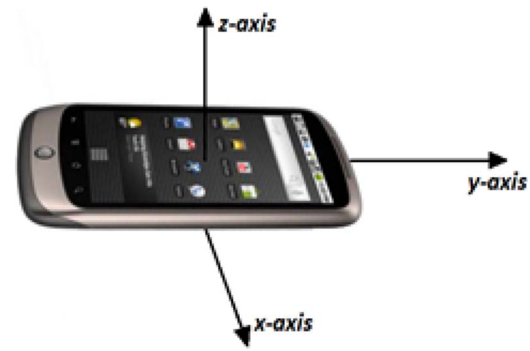


Fig. 1. Nexus One and three-axis diagram of the accelerometer. It employs a Bosch BMA150 3-axis accelerometer, which is capable of detecting movement in any direction. This movement may be the slightest lane change or a disturbance caused by a pothole.

TABLE I
SIGNIFICANCE OF TRIAXIAL MEASUREMENTS

	Measurements Obtained	
Axis	Direction	Typical Driving
x	Left/Right	Turning/Lane Change
y	Front/Rear	Acceleration/Braking
z	Up/Down	Vibrations/Road Anomalies

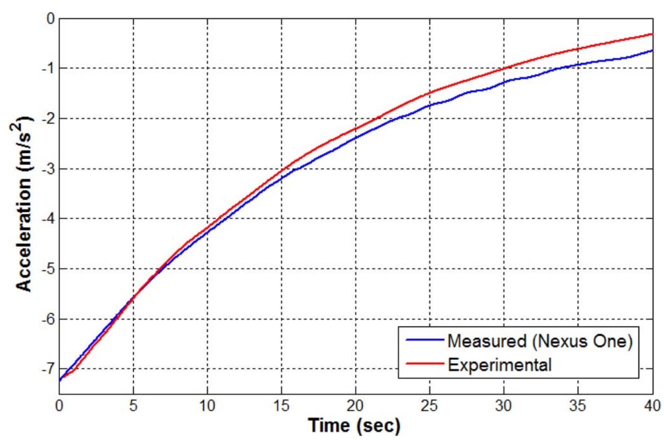
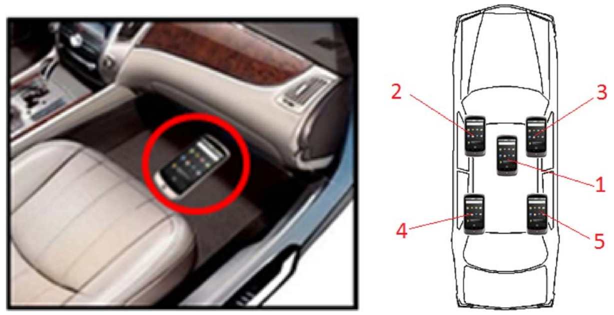


Fig. 2. Nexus One accelerometer accuracy results. The centripetal acceleration was calculated (experimental) and compared with the data recorded by the phone (measured).

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

We test the accuracy of the device by experimental comparison of calculated data and observed data recorded by the phone. For the test, we utilized dynamics equations such as centripetal acceleration and compared that with the measurements recorded by the Nexus One. Comparison results, as shown in Fig. 2, show the accelerometer to be very accurate and sensitive at 25 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.



(a) (b)

Fig. 3. Phone placement locations in a vehicle. (a) Vehicle floorboard with the y-axis parallel to the forward motion of the vehicle used for road anomaly identification. (b) Locations in which the phone was tested to measure driving maneuvers. It was determined that loc. 1, which is the center console, gave the best relative data with low engine feedback.

To compensate for any initial existing error in the sensor, we have implemented a high-pass frequency filter and a sensor reset mechanism every 20 ms. This combination has proven to be effective for utilizing mobile phone sensors in a vehicle environment.

B. Phone Orientation and Location

The orientation of the phone is a variable that may be constantly changing with the movement of the vehicle, and so might be arbitrarily placed inside the vehicle when the driver enters. The phone's orientation for each experiment remained the same, with the y-axis pointing toward the front of the vehicle and the screen (z-axis) facing the roof. A holster that was provided with the phone was used along with velcro to secure the phone to the vehicle's surface. To obtain appropriate data, the phone was tested in multiple locations for each experiment before a final decision was declared. These locations are shown in Fig. 3(b) as locations 1–5. The specific surface used was dependent on which experiment was being performed. For the road condition analysis, it was firmly secured to the floorboard of the front passenger section shown in Fig. 3(a). For analyzing driver behavior, the phone was fastened on the center console, i.e., loc. 1 in Fig. 3(b). The driving behavior experiments each had a time duration of less than 2 min, which incorporated multiple maneuvers, whereas road condition measurements varied, lasting for the length of the road being measured.

IV. Results

A. Vehicle Conditions

1) Speed and Shifting: Knowing that your vehicle is properly performing is a concern for many drivers. Engine problems can exist even while accelerating in high-speed traffic. Slipping in and out of gears can frequently happen with older transmissions and can be a potential risk while driving on a highway. Using a mobile smartphone, we found it possible to recognize gear shifts. For manual transmissions, sequentially shifting around 2500 rev/min is essential to sustain 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 safely transporting a passenger. Fig. 4 shows the Toyota Yaris accelerating from rest to approximately 30 mi/h before leveling off. This experiment was performed using all the vehicles listed in Table II for multiple instances, each resulting in easily identifiable gear shifts. Experiments were conducted using normal driving behaviors in and out of traffic conditions.

Fig. 4 was converted to velocity by integrating the curve using the trapezoidal method. With this, we calculated the speed at the moment

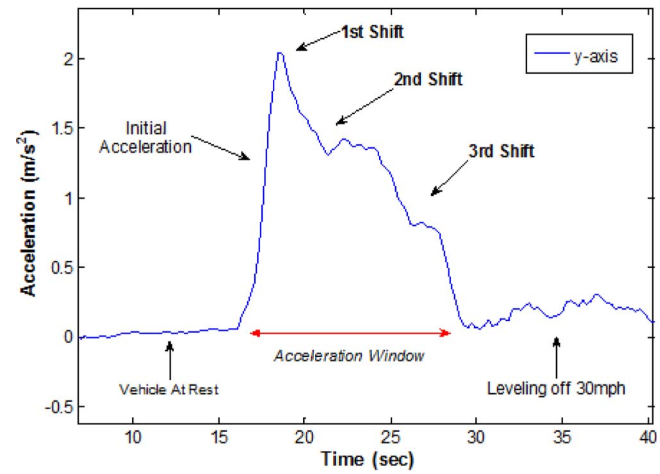


Fig. 4. Engine gear shift analysis of an automobile using the y-axis of an accelerometer. The vehicle begins at rest, followed by an initial acceleration, with each shift illustrated by a small jerk. The speed at each shift was calculated and compared in Table III.

TABLE II
Automobiles Used in Identifying Lane Changes and Road Conditions

Year	Manufacturer	Model	Vehicle Type	Engine
1992	Chevrolet	S-10	Single Cab	4.3L V6
1997	Honda	CL3	Coupe	3.0L V6
2000	Toyota	Sienna	Minivan	3.0L V6
2007	Toyota	Yaris	Sedan	1.3L 4-cylinder
2007	Volvo	S40	Sedan	2.4L 5-cylinder
2008	Pontiac	G8	Sedan	3.6L V6

TABLE III
Speed Percent Error Calculations Measured by Phone

Gear Shift	Time Occurred (s)	Dashboard Speed (mph)	Speed from Integration (mph)	Percent Error
1	18.87	14	13.42	4.14
2	22.13	20	20.13	0.64
3	27.25	31	31.30	0.96

of each shift. Obtaining speed from the accelerometer rather than relying on the GPS helps relieve unnecessary strain on the battery, which is a major concern with smartphones today. Table III shows each gear shift, the time of each occurrence, the reference speed, and the speed calculated from the accelerometer. The reference speed was recorded from the car's dashboard at the time of the experiment using video and is compared with the speed obtained using the trapezoidal method. Percent error is also shown, which reveals the accelerometer to be very accurate at low speeds and short distances. Although patterns were less apparent, we still had great success identifying gear shifts from higher quality automobiles, such as the Volvo S40.

B. Driving Patterns

1) Acceleration and Deceleration: Increasing driver awareness about vehicle behavior is beneficial to everyone on the road. The way a vehicle is maneuvered on the road can influence how other drivers react as they habitually follow previous movements to potentially avoid an unforeseen road hazard. Fig. 5 shows examples of acceleration and deceleration (braking) being safely and suddenly performed.

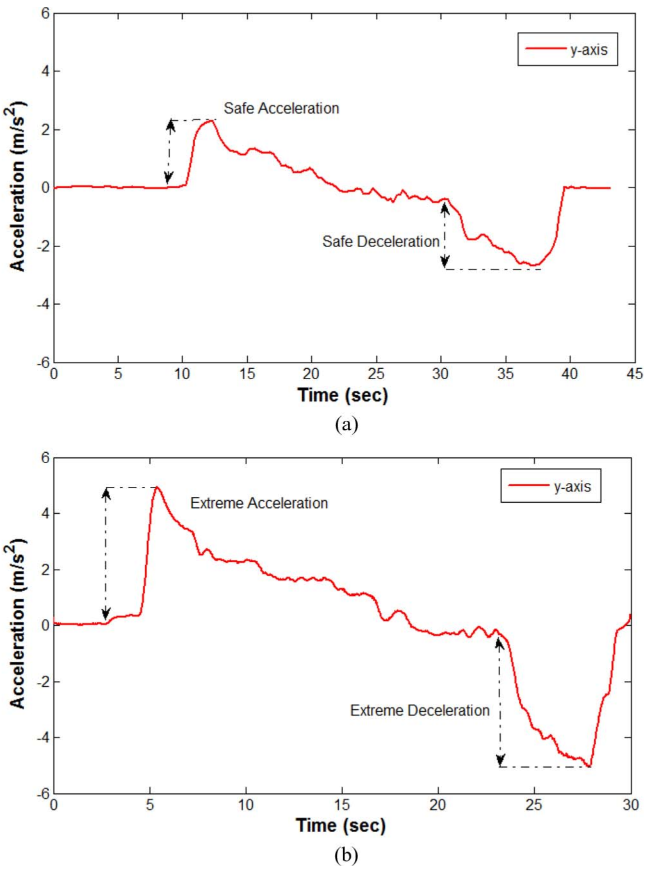


Fig. 5. Acceleration and braking being performed in two different manners. (a) Safe acceleration and deceleration. (b) Sudden acceleration and deceleration. Both are represented by an increase and decrease in the y-axis, respectively.

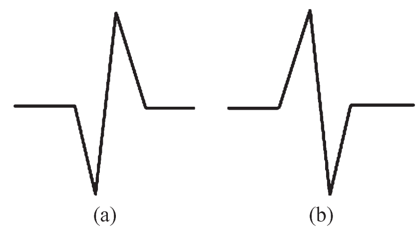


Fig. 6. Acceleration signature of (a) left-lane change and (b) right-lane change. These formations are distinguishable in Fig. 7.

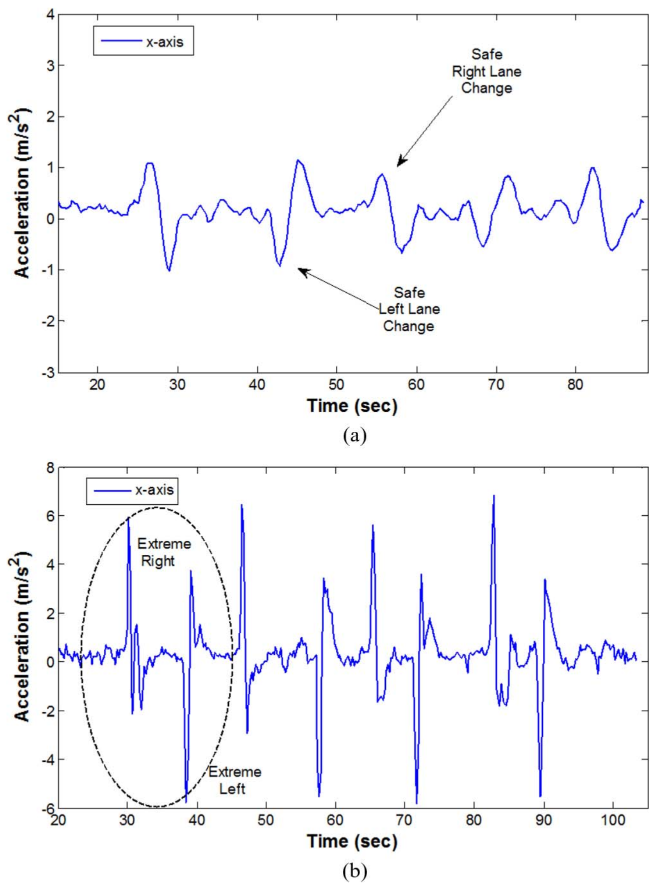


Fig. 7. Lane changes recorded by the x-axis of a smartphone's accelerometer. A left-lane change is formed by a small decrease, followed by an increase. A right-lane change is formed oppositely. (a) Four safe right-lane changes and three safe left-lane changes in series. (b) Four sudden right and left-lane changes performed in series, totaling eight lane changes.

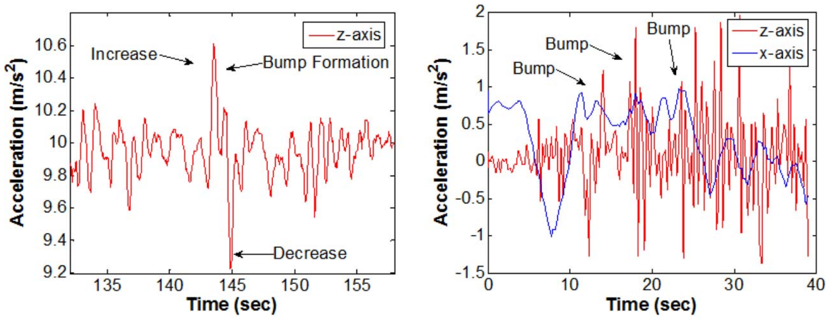
We utilized the x-axis and y-axis data from the accelerometer to measure the driver's direct control of the vehicle as they steer, accelerate, and apply the brakes. With the phone located on the center console, we recorded driving behaviors of acceleration and deceleration under safe and extreme conditions from all the vehicles listed in Table II. Safe acceleration and deceleration are shown in Fig. 5(a) as gradual increase and decrease in the acceleration, respectively. For all our results, safe acceleration or deceleration never reach a g-force of more than ± 0.3 g (approximately 3 m/s^2). We set a slope and a maximum g-force threshold, as well as time comparison, and compare with more extreme scenarios [3]. Fig. 5(b) shows a situation in which the driver quickly accelerates from rest and decelerates to a stop. Both are represented with a steep slope and short time frame and are clearly distinguishable from safe maneuvers as these sudden maneuvers approach ± 0.5 g (approximately 5 m/s^2). With this comparison, it is easy to quantify the difference between safe and sudden longitudinal maneuvers.

2) Changing Lanes: To detect lateral movements or lane changes performed by the driver, we look at the x-axis of the accelerometer. Using the previous phone orientation from the acceleration/deceleration patterns, it is possible to recognize lateral movements created by an automobile and differentiate a left-lane change from a right-lane change. Fig. 6 shows the formation of each maneuver.

Fig. 7 shows safe and sudden lane changes initiated by the driver. A left-lane change is portrayed by a decrease in x-axis, followed by an immediate increase, whereas a right-lane change is formed oppositely. These opposing patterns can be viewed in Fig. 7(a) as the driver completes three safe right-lane changes and two safe left-lane changes. These lane changes are a gradual movement into a neighboring lane and reveal an average g-force of less than ± 0.1 g (approximately 1 m/s^2). An improper technique can be seen in Fig. 7(b) as a driver generates four sudden lane changes by swerving the vehicle into the left lane and back again into the right. Using these data, we can identify not only the number of lane changes that occur and at what time but also the ability to classify safe and sudden lane changes [3]. These unsafe lane changes produce a g-force well over ± 0.5 g. It was observed that an average time to complete a safe lane change was 75% longer than a sudden lane change. These values are set as parameters to analyze future sudden lateral movements such as unintended lane deviations and the act of swerving in and out of high-speed traffic.

C. Road Conditions

1) Road Anomaly Detection: Poor road conditions can lead to repavement methods that can cause an increase in both traffic congestion and travel time. A distressed road can also increase the chance of



(a) (b)

Fig. 8. Bumps recorded using the mobile phone accelerometer. (a) Formation of a bump with an increase in the z-axis, followed by a decrease. (b) Secondary process in classifying a bump that incorporates the x-axis. An increase in the x-axis, followed by the identification method in (a), helps distinguish a pothole from a bump.

TABLE IV
SIZE OF SPEED BUMP RELATED TO SPEED AND z-AXIS DISPLACEMENT (MIN AND MAX)

Speed (mph)	Accelerometer Min (m/s^2)	Accelerometer Max (m/s^2)	Calculated Speed Bump Size (cm)
7.5	9.3	10.81	1.5
10	7.09	11.49	4.3
15	6.93	12.37	5.4
20	9.38	12.47	6.06

Actual height of the speed bump was measured to be 6 cm making it very accurate around 20 mph.

an accident. By expanding on work presented in [1] and [15], we extended road anomaly detection using a mobile phone's accelerometer. The embedded accelerometer is capable of detecting subtle or extreme vibrations experienced inside the vehicle. For example, vibrations experienced as jerks can be caused by potholes or a rugged/damaged road from a rough road. Speed bumps and potholes are two nuisances that plague drivers on the road every day. Using a smartphone, we look for these road characteristics using a combination of the x-axis and z-axis of the accelerometer. When a vehicle experiences a bump, it ascends onto the bump, resulting in a quick rise or spike in the value of the z-axis. This also results in a subsequent increase in the x-axis, depending on the bump formation. At high speeds, the spike in the value of the z-axis is very prominent. However, for low speeds, this rise is not as obvious but still leaves an apparent impact. To detect bumps at low speeds, we compensate with the x-axis and a dynamic threshold based on speed. If the difference between two consecutive acceleration values of the z-axis exceeds the threshold, as well as an x-axis threshold, a bump can be assumed [15]. Differentiating a pothole from a bump can be a difficult task using only a z-axis threshold, as seen in [15], but both are distinguishable using this method. We visually illustrate this method with Fig. 8. Fig. 8(a) shows a bump formation in the z-axis with gravity, whereas Fig. 8(b) shows the secondary technique without gravity using the x-axis to help differentiate a bump from a pothole.

2) Bump Height: We are able to calculate the height of the bump by using simple physics equations dealing with acceleration, time, and displacement. This is shown in Table IV, along with the related speed and accelerometer values. Different speeds however present different results. Knowing the dynamics of a vehicle suspension, we compensate for this incorrect height using a dynamic weight based on speed. Using this idea, we can better estimate the exact height of a speed bump. We implemented this method for a vehicle traveling over multiple speed bumps at different speeds. At 20 mi/h, this technique proved to be very accurate without compensation, presenting a calculated displacement of 6.06 cm and a measured speed bump height of 6 cm.

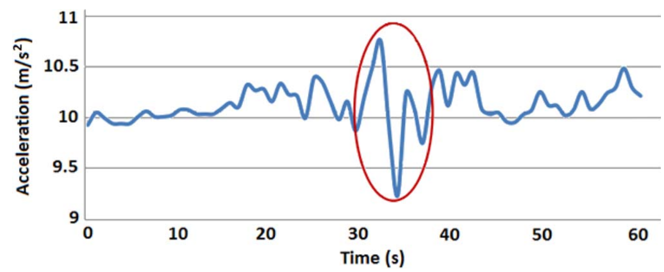
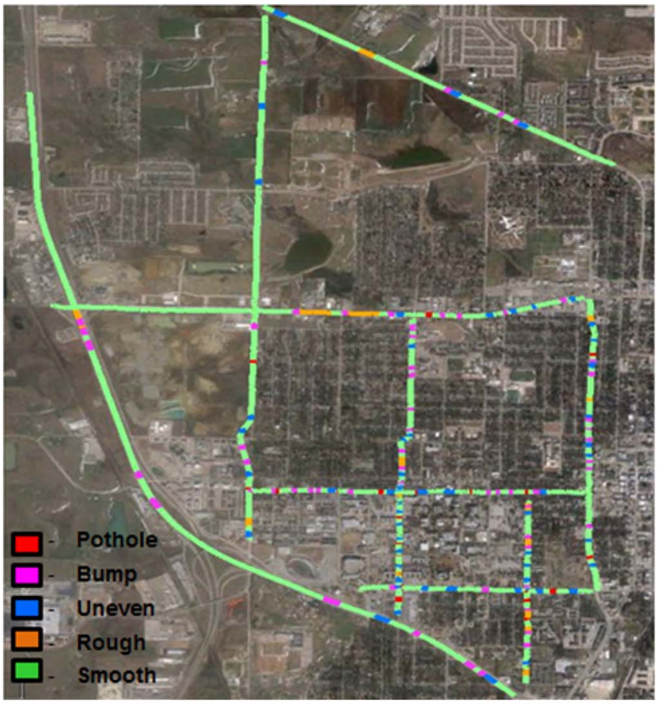


Fig. 9. Speed bump recorded using the z-axis of the accelerometer at a speed of 7.5 mi/h. This figure correlates with Table IV data, with an originating speed bump height measured at 6 cm.

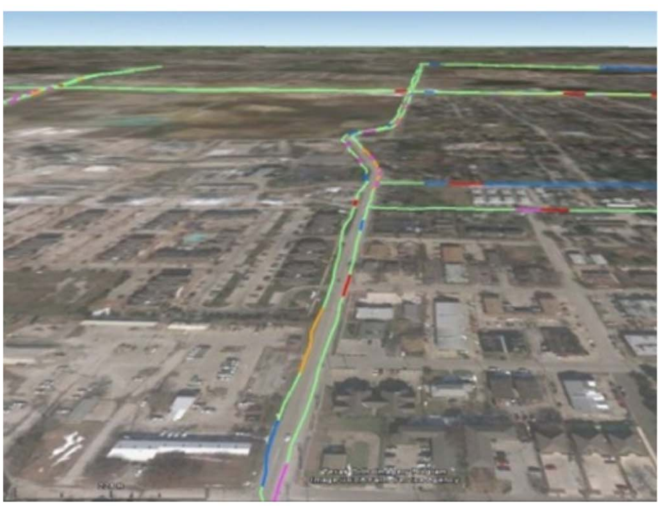
Fig. 9 shows a recording of the accelerometer as a vehicle traveled over a bump at a speed of 7.5 mi/h, which was taken from Table IV. Although a bumplike motion is clearly visible in Fig. 9, at low speeds, the height calculations became unreliable as the car experienced a more comfortable smooth movement rather than the jerk at higher speeds. The results were heavily influenced by how the vehicle approached the bump and the velocity of the car. This process can also be utilized to calculate the depth of potholes to further help in identifying damaged roads.

3) Road Condition Mapping: In addition to the accelerometer readings, we recorded GPS coordinates at the time when road anomalies occurred. These anomalies are defined as a pothole, bump, uneven road, or rough road. We take the accelerometer value for a single GPS value and denote the accelerometer value as a segment of a particular area. In case of multiple accelerometer values, we use interpolation and assign that value to the particular segment. Each segment receives a corresponding value that designates the degree of the road: smooth road, pothole, bump, uneven road, or rough road. A dynamic classification method was used based on the vehicle speed obtained from the GPS. A color code technique is used and assigned to certain interpolated values for segments. Fig. 10 shows a map of road conditions that was derived from measurements taken around Denton, TX. From this, we can now visually see the conditions of the road before having to unwittingly experience them. Fig. 10(a) shows one lane of the road, in a single direction, which covers many of the heavily traveled roads around the city. A total of 45 mi was recorded, with road types ranging from residential and business, to highway and interstate.

Fig. 10(a) is an overview of the city spanning an 8-mi^2 area with only one lane or direction displayed. Red illustrates a pothole, purple designates a bump, blue is an uneven road, orange signifies a rough road, and green represents a smooth surface under ideal driving conditions. Fig. 10(b) is a map of two-lane traffic, i.e., two directions, which



(a)



(b)

Fig. 10. Map of road conditions. Visual representation of road conditions using GPS coordinates and Google Earth. Intensity levels are designated by colors, signifying a pothole, bump, uneven road, rough road, or smooth road. (a) One lane. (b) Two lanes.

can easily be distinguished from one another, proving the resolution of the GPS. Google Earth was used to create both of these maps using GPS coordinates and XML scripts. This classification system was tested and illustrated in Table V. This table can be correlated with the data shown in Fig. 10(a). This confusion matrix represents the accuracy of detecting each road anomaly. Smooth roads presented the easiest to classify as no ambiguous data were 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 that we initially set. Using the x-axis and z-axis to classify bumps greatly increased the classification accuracy from an initial 71% to 81.5% seen in Table V. This resultantly had a positive impact on the pothole accuracy as well. We obtained an 85.6% accuracy for the overall road anomaly classification system.

TABLE V
ROAD ANOMALY CLASSIFICATION ACCURACY

	Bump	Pothole	Rough	Smooth	Uneven	Total
Bump	31	6	0	0	1	81.5%
Pothole	4	13	0	1	0	72.2%
Rough	2	0	6	0	0	75%
Smooth	3	0	1	54	1	91.5%
Uneven	1	1	0	2	34	89.4%

V. CONCLUSION

Using a mobile smartphone, we have demonstrated some innovative applications that are integrated inside an automobile to evaluate a vehicle's condition, such as gear shifts and overall road conditions, including bumps, potholes, rough road, uneven road, and smooth road. Our road classification system resulted in high accuracy, making it possible to conclude on the state of a particular road. Along with these findings, an analysis of a driver behavior for safe and sudden maneuvers, such as vehicle accelerations and lane changes, has been identified, which can advise drivers who are unaware of the risks they are potentially creating for themselves and neighboring vehicles. The direction of lane change, as well as safe acceleration, compared with sudden acceleration, was easily distinguishable. Using a multiple-axis classification method for bumps increased the bump and pothole classification accuracy, resulting in a better road anomaly detection system. Being fueled by demand, future advancements in embedded hardware will yield the smartphone and its sensors to be more powerful devices in terms of processing, sensitivity, and accuracy, paving the way for many more innovative applications. Unlocking its potential in intelligent transportation systems seems only logical as there are conceivably numerous of applications that can help reduce safety concerns on the road.

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Drivers' Adaptation to Adaptive Cruise Control: Examination of Automatic and Manual Braking

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***Abstract*—Drivers may adapt to the automatic braking control feature available on adaptive cruise control (ACC) in ways unintended by designers. This study examines drivers' adaptation using a conceptual model of adaptive behavior developed and examined quantitatively using logistic regression techniques. Data for this model come from a field operational test on the use of an advanced collision avoidance system, which integrated forward collision warning and ACC functions. A sample of "closing" events was extracted from a subset of these ACC data. The logistic regression model predicted the drivers' likelihood to intervene (i.e., manually brake) whenever ACC began braking or slowing down the vehicle. The results indicate that several factors influence drivers' response, including the environment, selected gap setting, speed, and drivers' age. Safety consequences and the design of future ACC systems based on drivers' adaptation to these factors are discussed.**

***Index Terms*—Adaptive cruise control (ACC), driver behavior.**

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I. Introduction

A. Background

Adaptive cruise control (ACC) is an enhanced version of conventional cruise control, which can detect a lead vehicle and allows a driver to follow it at a preset time headway and speed by controlling the engine and braking capability [1], [2]. It automates two components of the driving task, namely, operational control of longitudinal time headway and speed, such that ACC can regulate the speed of a vehicle when a slower lead vehicle is present [3], [4].

Manufacturers typically market ACC systems as convenience systems rather than safety systems. However, ACC has been also incorporated into collision avoidance and brake assist systems as part of integrated advanced safety systems. Some of the benefits of ACC described in the literature have included better distance keeping [5], with thresholds typically ranging from 0.9 to 2.5 s [6], and reduced necessity to monitor the external surroundings or manually accelerate or brake [7]. The reduction in required mental and physical resources makes driving less effortful and reduces driver stress and human errors [8], [9]. However, if the reduction gets too high, it may actually affect the ability of the driver to maintain awareness of situations. ACC systems do have maximum deceleration rates and do not regulate speeds based on stationary vehicles or objects [10]. Furthermore, spacing and velocity errors can occur as shown by Gao and Xiao [11].

ACC cannot properly function when a lead vehicle enters a curved road [12]. That is, the ACC radar will not detect a lead vehicle with high road curvature even when in close proximity to the lead vehicle. Hence, the ACC vehicle will accelerate back to the original cruise speed. When these limitations are coupled with a low level of situation awareness, potential hazards may increase rather than decrease. This was also observed by Rudin-Brown and Parker [12], who found that drivers' response time to a hazard detection task increased with ACC.

Many studies on ACC have typically focused on the potential innovations of the system such as full start–stop control [10], [13] or the overall effect it may have on traffic systems [6], [14]. Both the human driver and the ACC system control the driving task. Hence, driver intervention can always override the ACC control by activating the brake or the accelerator or switching ACC on or off [15], [16]. The gap with the lead vehicle may also decrease whenever the driver deactivates ACC by pressing on the brake, as shown by Pauwelussen and Feenstra [17]. Therefore, additional studies on the safety implications and human interaction with ACC are needed. Because the likelihood of a collision is rare within a study period, a potential surrogate measure (or proxy) for safety, with respect to ACC, is a "closing" event. A "closing" event is defined as the moment that the ACC's automatic braking control is activated until any braking (or deceleration) ceases, regardless of whether a driver intervenes or not. The braking (or deceleration) could be based on either automatic braking from ACC (no driver's intervention) or the driver depressing the brake (driver intervenes). This study focuses on drivers' adaptive responses to ACC during these "closing" events.

Studies have shown that adaptation can greatly influence a driver's response to safety-based systems, and this adaptation may result in unintended safety consequences. For example, Evans and Gerrish [18] showed that antilock braking systems significantly reduced front impacts but increased the number of rear impacts. Similarly, ACC may not be appropriate for dense driving conditions where driver assistance is most needed. Additionally, drivers who become dependent on the feedback provided by ACC may actually become complacent and less aware of their surroundings, resulting in a negative impact on safety.