ASHESI UNIVERSITY COLLEGE

CLASSIFICATION OF ROAD SURFACE QUALITY USING ANDROID SMARTPHONE DEVICES

FRANCIS DELALI VORGBE

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Thesis

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CLASSIFICATION OF ROAD SURFACE QUALITY USING ANDROID SMARTPHONE DEVICES

By

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Declaration

I hereby declare that this dissertation is the result of my own original work and that no part of it has been presented for another degree in this university or elsewhere.

Candidate's Signature:……………………………………………………

Candidate's Name:…………………………………………………………

Date:…………………………..

I hereby declare that the preparation and presentation of the dissertation were supervised in accordance with the guidelines on supervision of dissertation laid down by Ashesi University College.

Supervisor's Signature: ……………………………………………………

Supervisor's Name:…………………………………………………………

Date:……………………………………

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Abstract

The quality of roads in a country contributes greatly to its economic development. In Ghana and elsewhere in Africa, essential goods such as agricultural produce are transported mostly by road. Good roads not only promote economic activity, they contribute positively to the quality of life of their users. In many areas, however, the road infrastructure is not of uniform quality, comprising tarred roads, dirt roads, smooth roads, bumpy roads, and roads that are barely motorable. Roads with poor surface conditions damage vehicles, slow down traffic, lead to accidents, and are uncomfortable to drive on. A possible solution to the problem is system that automatically detects and reports the surface conditions of roads.

This study explores the use of an Android-based mobile application to detect and report the surface quality of roads. We start by collecting hand-labeled training data from vehicles traversing carefully selected roads of differing quality. In addition, we use GPS sensors to reliably match road quality information to specific locations. A logistic regression machine learning algorithm is used to train a road surface classifier based on the accelerometer readings collected. This study aims to detect the surface condition of roads and present that data in a manner that can be easily be embedded into maps online.

We find that we are able to distinguish between good and bad roads with a true positive rate of 92%. We are able to distinguish between good and fair roads with a true positive rate of 83%. The study is however unable to reliably distinguish between fair and bad roads.

To the best of our knowledge this study is the first to attempt the automatic classification of entire sections of road as opposed to the detection of individual road anomalies such as potholes.

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1.0 Introduction and Background

The quality of a road contributes to the quality of life of the people who use the road. Good roads promote economic activity, and generally contribute positively to the quality of life of road users. In Ghana and elsewhere in Africa, essential goods such as agricultural produce are transported mostly by road. In many areas, however, the road infrastructure is not of uniform quality, comprising tarred roads, dirt roads, smooth roads, bumpy roads, and roads that are barely motorable. Roads with poor surface conditions damage vehicles, considerably slow down traffic, lead to accidents and are uncomfortable to drive on. This makes it important for authorities responsible for road maintenance to keep roads in good conditions by quickly repairing damaged roads.

Tools like Google maps and other GPS wayfinding systems are increasingly being used to find directions to unknown places. With the recent advent of smartphones that have the ability to access maps online, many users have gotten access to such services. Though helpful in wayfinding, such systems are unable to provide information on the quality of roads. According to the International Data Corporation (IDC), as of the 4^{th} quarter of 2012, Google's Android operating system was the most used smartphone operating system in the world with 70% of smartphones owned being an Android powered smartphone [1]. The GlobalWebIndex reports that 54% of smartphone users use the Google Maps application, making it the most used smartphone application in the world [2]. These statistics highlight the wide use of location finding applications all over the world. Having established the wide usage of mapping applications, it can be argued that access to road quality information on maps will be beneficial to a large number of people.

All over the world, keeping roads in good condition has proved challenging for institutions responsible for road maintenance. Because road surface quality deteriorates over time due to normal wear and tear from usage, harsh weather conditions, and poor maintenance, it is necessary for the responsible agencies to spend resources monitoring and repairing deteriorating roads. The Ministry of Finance and Economic Planning of Ghana reported in 2012 that the road networks in Ghana suffer from rapid deterioration and poor rural connectivity, with only 41% of roads in good condition [3]. Having reliable and up-to-date information on the state of roads is therefore important to governmental authorities responsible for their maintenance, and also to motorists who ply the roads. Governments can use this data to facilitate quick response to deteriorating roads, while motorists can use readily available road surface quality information to avoid roads with poor surface conditions.

This study explores the use of a smartphone-based tool to address the need for reliable and up-to-date road surface quality information. It aims to explore the reliable classification of road surface quality using accelerometer readings collected from Android powered mobile devices.

To achieve this, an Android application is developed to measure and record acceleration along the x, y, and z axes of the mobile device. In addition to this, the location of the mobile device is recorded frequently via GPS to reliably match road quality information to specific locations. During the training phase of the study, a vehicle equipped with a mobile device running the developed application traverses roads of differing qualities to collect and manually label acceleration and location data. Using a logistic regression machine learning algorithm, the labeled data is used to train a classifier that distinguishes between good, fair and bad roads.

2.0 Related Work

Though there is inconclusive data on smartphone ownership in Ghana specifically, a fair idea of the widespread use of such devices can be gleaned from statistics gathered in and around Africa. In 2013, 67 million smartphone were recorded to be in use in the Middle East and Africa. It is expected that this figure will almost double in the year 2014 to 112.2 million [4]. This phenomenon has made applications that run on smartphones accessible to a large number of users. Almost all smartphones manufactured now have inbuilt sensors to track, amongst other variables, the orientation, position and movement of the device. Specifically, smartphones most commonly come fitted with accelerometer sensors, gyroscopes, and GPS to detect device acceleration, tilt, and location respectively.

The approach of automatically determining human and object activity based on readings gathered from sensors embedded in smart phone devices is not a novel one. As sensors have become more readily accessible to the common consumer, so have the number of applications that utilize them. Game developers use readings gathered from inbuilt sensors to influence gameplay on smart phones, by giving players the ability to control game characters and objects by tilting their smart phone device in a specific direction. Researchers have also conducted studies into behavior determination in humans based on sensor readings obtained from smart phones attached to subjects' bodies [5].

In the recent past, many studies have been conducted to correctly determine road surface quality using information gathered from various sensors. This chapter seeks to highlight a number of relevant studies conducted on the subject, discussing the methodology used by various researchers to identify road surface anomalies and thus classify roads based on surface quality.

Eriksson et al. [6] investigated an application of mobile sensing to detect and report the surface conditions of roads in Boston, USA, by gathering data from embedded accelerometers and GPS sensors deployed on 7 taxis. Mohan et al. [7] conducted a similar study in Bangalore, India to monitor road and traffic conditions also by utilizing embedded accelerometers and deploying their system in taxis. Astarita et al. [8], Tai et al. [9] and Mednis et al. [10] further explored the detection of road surface anomalies by recording accelerometer and localization data using mobile phone devices. Astarita et al. [8] and Tai et al. [9] deployed sensing equipment in utilitarian vehicles and motorcycles respectively. A common feature of the work by Eriksson et al. [6] and Mohan et al. [7] was the deployment of the monitoring system using taxis. Both sets of researchers adopted this approach because it was cost effective and achieved a high spatial coverage with a small number of vehicles.

Many similarities can be found in the methods used in related literature to enable the correct determination of road surface quality. Eriksson et al. [6] gathered data from acceleration and GPS sensors, resulting in the following information: <time, location, speed, heading, 3-

axis acceleration>. The first four parameters were recorded using a GPS device and the acceleration vector was recorded using an accelerometer. Various filters were applied to produce pothole detection. The detections were clustered based on location, and a minimum cluster size applied, resulting in the final output of the system [6]. Astarita et al. [8] collected a dataset containing the acceleration values a_x, a_y, and a_z in three axes, the instantaneous speed σ, and position p. We get the intuition from the success of related literature that acceleration data is a good determinant of the surface condition of roads due to the vibrations felt along vehicles axes during encounters with road anomalies.

In related literature, two main categories of sensors have been used to carry out the collection of accelerometer and GPS data. Researchers have used either customized standalone sensing devices or sensors that piggyback on smartphone device. Mohan et al. [7] made use of a Sparkfun WiTilt accelerometer to record acceleration data. This was found to reliably measure acceleration along each axis of the vehicle. In their study to detect potholes in real time using Android smartphones, Mednis et al. [10] tested four different Android smartphones for their ability to accurately collect accelerometer data. The study found that after applying appropriate data processing algorithms to data collected by piggybacked sensors in all four devices, researchers correctly identified road irregularities with a true positive rate of 90%. Mobile devices with piggybacked sensors thus make a good choice for colleting data on the road. As argued by Tai et al. [9], the ubiquitous nature of smart phones enables immediate sharing of road quality information among a large user base. Considering that the intent of this study is to develop a system that ultimately allows road quality data to be crowd sourced, it will be more advantageous to proceed with the use of smartphone piggybacked accelerometer sensors for data collection.

A major concern when collecting accelerometer data by deploying sensors in vehicles is that the placement and orientation of sensors might affect the quality of the signals picked up by the sensor. Mohan et al. [7] point out that a 3-axis accelerometer has a 3 dimensional Cartesian frame of reference with respect to itself. This is usually represented with orthogonal x, y, and z axes. A Cartesian frame of reference with respect to the vehicle hosting the accelerometer can be defined as well. The vehicle's frame of reference can be represented with X, Y and Z axes [5]. Vibrations that manifest along a particular axis of the vehicle will manifest along an axis of the accelerometer, depending on the orientation of the accelerometer. If x,y,z is aligned with X,Y,Z, vibrations occurring along X would manifest along x, and so on. However if the two reference frames are aligned differently, vibrations along X will manifest along another axis of the accelerometer or a combination of them. Mohan et al. [7] refer to the phenomenon of aligned accelerometer and vehicle Cartesian frames as being *well oriented*. Otherwise the accelerometer is *disoriented* [5].

Two approaches have been taken to overcome the problem of sensor disorientation. The first solution is to install the accelerometer in a fixed orientation corresponding to the vehicle's orientation; that is, to completely restrict movement of the accelerometer. Eriksson et al. [6] tested fixed installation in three different locations in the cabin of the vehicle: the dashboard, the right side of the windshield, and the embedded PC that was part of the system deployed. It was found that the optimal position for installation was the dashboard, inside the car's glove box because it was an easy location to install sensors, it kept sensors out of the way of passengers, and the signals received were accurate [6]. Using a similar approach, Tai et al. [9] installed the data collecting accelerometers in the storage boxes of the motorcycles used to conduct the study.

The second approach to solving the accelerometer disorientation problem, as used by Mohan et al. [7] and Astarita et al. [8], involves the virtual reorientation of a disoriented accelerometer using Euler angles. Mohan et al. [7] concluded that virtual reorientation of a disoriented accelerometer using Euler angles preserves the essential characteristics of the accelerometer signal. For mobile devices not fixed in a locked position, the problem was presented of how to differentiate between signals recorded as a result of user interaction with the device and signals recorded from vibrations of the vehicle. Mohan et al. [7] concluded that when a user was interacting with a mobile device, the device experienced extraneous acceleration. During such periods it was beneficial to neglect accelerometer readings. To further detect user interaction researchers looked for one or more of the following: key presses, mouse movements and ongoing or recently concluded phone calls [5].

"Location accuracy is important if potholes are to be properly located and multiple detections combined to report a single pothole" [6]. Eriksson et al. [6] and Tai et al. [9] mounted external GPS device on each vehicle involved in their studies to record the location of road anomalies, while Astarita et al. [8] made use of geo-referenced photographs. Eriksson et al. [6] found the accuracy of anomaly location reported by the GPS device to be within 3.3 meters of the true location of the anomaly. Mohan et al. [7] used GSM radios or GPS available in smart phones to determine the location of anomalies. The study employed the use of course-grain GSM radio or fine-grain GPS when necessary by using a method called triggered sensing. This was employed to significantly save energy, as GPS sensing is energy intensive [5]. For a system intended to operate on devices that will be used by the public, energy saving is an issue of great importance.

The methods used to process sensor readings obtained vary across literature. All related studies discussed addressed the problem using supervised machine learning approaches discussed later in greater depth, beginning with the manual collection of a set of training data to obtain ground truth. Eriksson et al. [6] collected training data by repeatedly driving down several known stretches of road and continuously recording accelerometer traces. A passenger in the car labeled each event encountered in real time by pressing a key on a laptop each time the impact of one class of road anomaly was felt. Tai et al. [9] used a different approach to labeling identified anomalies during manual collection of training data. Each motorcycle rider was equipped with a voice recorder, which they could speak into each time a surface anomaly was detected. By speaking the corresponding class of anomaly into the recorder at the time of occurrence, the rider was able to reliably tag road anomaly events. The classes of anomalies developed and used by Eriksson et al. [6] and Tai et al. [9] varied. Eriksson et al. [6] tagged the following event classes: 'Smooth road', 'crosswalks and expansion joints', 'railroad crossing', 'potholes', 'manholes', 'hard stop', and 'turn'. Tai et al. [9] however classified roads using a Roughness Index Function based on the International Roughness Index, which measures roughness based on the measure of vertical deviations on a section of the road [11]. Tai et al. [9] modified the roughness index to mean the number of road anomalies per kilometer, and further defined the following corresponding semantic labels to describe the roughness: 'good', 'fair', 'inferior', and 'dangerous'. Both Eriksson et al. [6] and Tai et al. [9] used labeled data to train the road anomaly detector.

Because road anomalies are reflected in features of acceleration data, a detection algorithm can be developed to filter out various classes of road anomalies [6]. To process acceleration data to extract instances of anomalies, Eriksson et al. [6] used an on board computer to separate the trace into 256 sample windows and then applied a number of filters to the continuous stream of windows. Each filter was designed to reject one or more non-pothole events like sudden stops and door slams, which also yielded high-energy signatures. Eriksson et al. [6] and Astarita et al. [8] used a speed filter to reject any high-energy events occurring at a low speed. This removed events such as door slams. Both studies used a high pass filter to remove low frequency components from the data, which could be introduce by events like acceleration. Astarita et al. [8] and Mednis et al. [10] used peak filters similar to a z-peak filter used by Eriksson et al. [6] and Mohan et al. [7] to reject events for which the peak was lower than a specified threshold. Mohan et al. [7] also used a similar filter to identify road anomalies at low speeds. Eriksson et al. [6] point out that anomaly events reported by the detector are likely to include some false positives. To improve accuracy, the study required possible events to be corroborated to be considered valid. This means a cluster of at least *k* events had to happen in the same location while moving in the same direction [6].

Using their methodology, Astarita et al. [8] found the true positive detection rate of recorded bumps and potholes to be 90% and 65% respectively on some sites. Eriksson et al. [6] found the performance of their anomaly detector to be 92.4% accurate. It did however report a false positive rate of 0.15%. Of particular interest is the study conducted by Mohan et al. [7], as it was carried out using only smartphone devices, as is the aim of this study. Mohan et al. [7] found that it was able to reliably determine road surface conditions using virtually reoriented smartphone devices to collect acceleration data.

In all, the studies discussed in this chapter reveal in their findings that road surface quality can be reliably determined using acceleration data processed using machine learning algorithms to reveal road surface anomalies.

2.1 Contributions of this thesis

Whereas previous studies have predominantly sought to identify individual road anomalies that are few and far between, this study seeks to reliably classify the surface quality of entire segments of roads. This is relevant in areas where road anomalies occur with such frequency that it will be infeasible to identify each anomaly as a means of classifying a road. Examples of such roads occur frequently in many parts of rural West Africa where dirt roads connect neighboring towns and villages.

Figure 2.1: A road along which surface anomalies occur with a high frequency

3.0 Methodology

This chapter describes the design and implementation of hardware and software components that constitute the mobile sensing system used by this study to automatically classify road surface quality. It describes the architecture and various components that constitute the system. This includes sensors used to capture data, the specific data segments collected, and the method used to train the classifier.

A vehicle that drives over a road anomaly experiences a heightened amount of vibration along its frame. By capturing and recognizing abnormal vibrations, a system can potentially be developed to reliably classify roads based on their surface conditions. The architecture of the system that seeks to achieve such results is described. The vehicle used in the study is fitted with a mobile smartphone device running the Android operating system. The smartphone device is equipped with an inbuilt tri-axial accelerometer sensor, which is used to collect acceleration data along the X,Y, and Z axes of the vehicle at a frequency of 4Hz (four times per second). The smartphone is affixed to the dashboard of the vehicle to completely restrict the movement of the device. This causes the smartphone to mirror the movement of the vehicle, allowing it to record the acceleration of the vehicle. The GPS location of the smartphone device is recorded continuously to attach location information to each segment of accelerometer data. Once collected, the gathered data is processed to extract the required features. A portion of the processed data is then used to train a classifier, using a logistic regression algorithm. The remaining data is used to test the classifier.

3.1 Data Collection

Data collection for this study was done using a Google Nexus One smartphone equipped with an accelerometer and GPS sensor and running an app that we created to collect data. This phone was fixed to the dashboard of a front-wheel-drive Nissan Versa, which was driven on roads of varying quality. The data collection app records accelerometer readings at a frequency of 4Hz (four times per second) and GPS coordinates recorded at a frequency of 1Hz. A timestamp was recorded with each data segment. The following is the resulting data segment:

<timestamp, x-axial acceleration, y-axial acceleration, z- axial acceleration, latitude, longitude>

The timestamp is recorded using the system date/time of the smartphone, the acceleration along three axes is recorded using the smartphone's inbuilt tri-axial accelerometer, and the latitude and longitude using the in-built GPS sensor. Each data segment is recorded and written to a text file stored in the smartphone device's memory.

3.2 Device Placement and Orientation

The proper placement and orientation of the smartphone device used to collect accelerometer data throughout the experiment is of utmost importance. The device must be placed in a position that keeps it stable throughout the data collection process. This is to avoid the recording of acceleration values that are not attributed to the movement of the vehicle. To achieve this, the smartphone was affixed to the dashboard of the vehicle with an adhesive material. It was positioned within arms length of the passenger responsible for manually labeling the data. This was done to facilitate smooth and unhindered labeling of acceleration data.

Acceleration recorded by the smartphone is done along its x, y, and z-axes. Because the smartphone is affixed to the vehicle in the upright position, the axes of the vehicle and the smartphone become misaligned. As can be seen in can be seen in Figure 3.1 and Figure 3.2, while oriented upright, the smartphone's y-axis is aligned with the car's Z-axis. It becomes necessary to perform a transform of the axial orientation of the smartphone to match the orientation of the vehicle. To achieve this, the axial transform seen in Table3.1 is performed.

Table 3.1: Smartphone Axial Transform

Smartphone axis	Transform to match vehicle axis
x	y
y	z
z	x

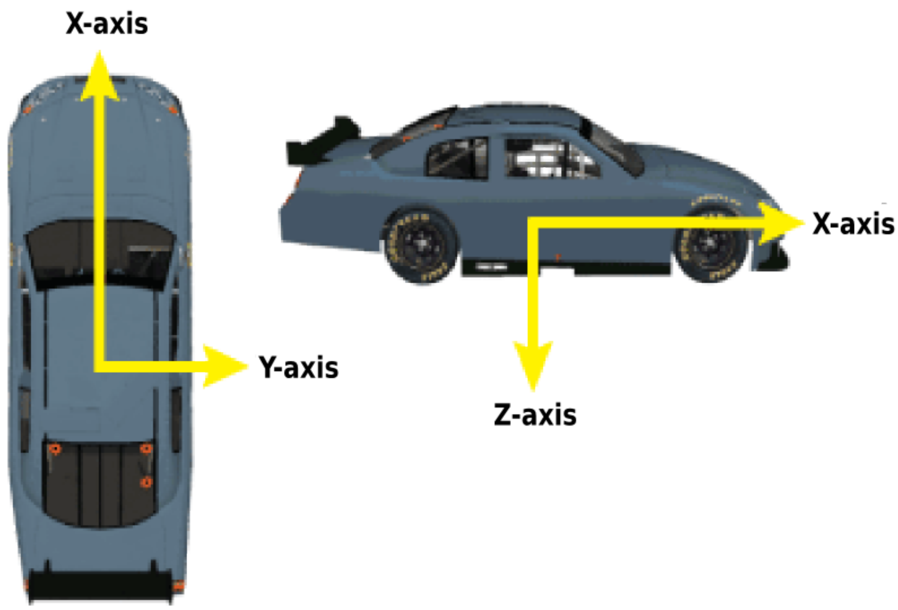

Figure 3.1: A vehicle, showing its X, Y, and Z axes

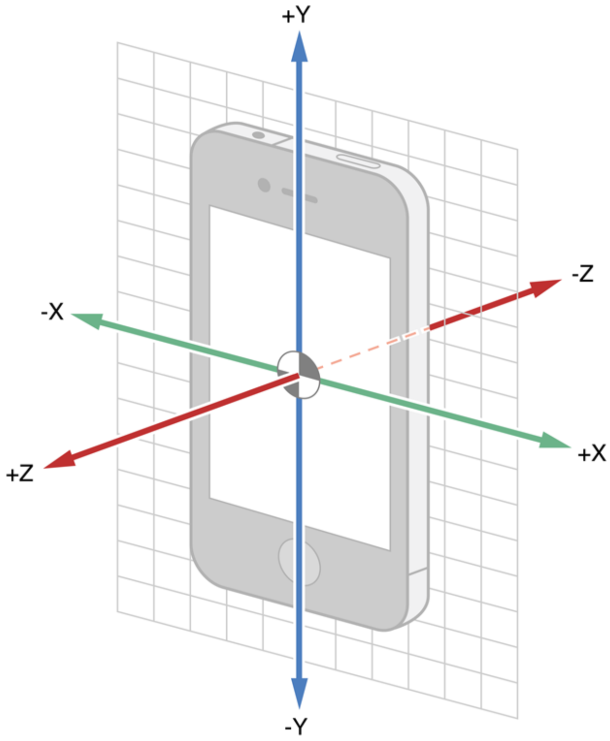

Figure 3.2: A smartphone, showing its x, y, and z axes

3.4 Collection of Hand-Labeled Training Data

Data collected is hand labeled for the purposes of training and testing the classifier. Hand labeling the data is necessary to match accelerometer signals with the class of road that produced each signal. At the training stage, it is used to teach the algorithm what types of signals each class of road produces. At the testing stage it is used to evaluate the accuracy of the classifications produced by the classifier.

During data collection, a passenger in the vehicle labels each segment of road driven on with a semantic label indicating the class of road. Figure 3.3 shows the interface of the Android application used for collecting and labeling acceleration data. The passenger conducting the labeling presses a button on the smartphone each time a particular class of road is driven over. The button press writes the corresponding class to a text file recording the acceleration data. This allows the class of each segment of road to be reliably known when data analysis is conducted.

Figure 3.3: Interface of the android application used for data collection and labeling

For the purposes of classification, the term 'road anomaly' is used to describe the presence of a road feature that causes the road to be uneven. This may include, but is not limited to potholes and bumps. The following are the classes of roads defined for use in this study:

- **Good road:** Segments of road surface without the occurrence of potholes and other road surface anomalies. This is a road surface that is considered smooth.
- **Fair road:** Segments of road surface with intermittent occurrences of relatively shallow potholes and other road anomalies.
- **Bad road**: Segments of road surface that have continuous occurrences of potholes and other road anomalies. This class refers to roads that significantly slow down cars and are barely motorable.

The definition of each class of road above is relevant for the human user performing the hand labeling, and not the system. The system does not employ anomaly counting to determine the class a road segment belongs to. Figure 3.4 through Figure 3.6 illustrate examples of the classes of road defined.

Figure 3.4: A stretch of good road

Figure 3.5: A stretch of fair road

Figure 3.6: A stretch of bad road

The accuracy of the hand labeling process while collecting training and test data is instrumental to the success of building a robust classifier. As will be further explained in the following sections, it is one of the bases upon which correct classification can be achieved. The road segments chosen for collection of training and test data were carefully selected to include amounts of all three classes of road. The roads selected for the study are within the Greater Accra and Eastern Regions of Ghana. A circuit is mapped beginning at Kitase junction on the Accra-Aburi road. It follows the highway towards Accra and joins the N1 highway towards at the Tetteh Quarshie Interchange. At Achimota, the circuit joins the Nsawam-Kumasi highway, turning off towards Kwabenya via the Pokuase-

Kwabenya road. It finally reconnects to the start point via the Kwabenya-Berekuso road. Figure 3.7 shows a map of the area with the circuit marked out in Purple. The circuit covers a total of 60km of road. Data collection is done over 50km of the circuit. Table3.2 shows a breakdown of the distances over which data collection was done for each class of road. The data collected was split into two parts. 70% was used to train the classifier. The remaining 30% was used to test the classifier.

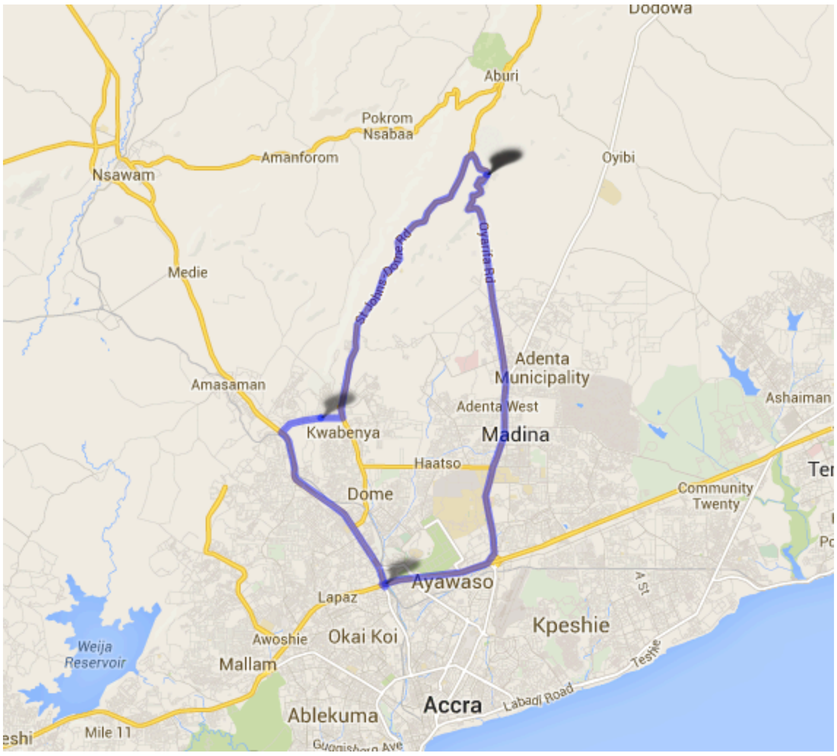

Figure 3.7: Map showing the roads (marked in purple) along which data was collected for the study.

Table 3.2: Distance Covered During Data Collection

Class	Distance Covered
Good road	30km
Fair road	5km
Bad Road	15km

3.5 Road Surface Classification Algorithm

This section describes the multiclass logistic regression machine learning algorithm used to train the road surface classifier. The classifier works on the premise that the condition of a road segment is reflected in the acceleration experienced along the axes of a vehicle that travels over the said road. This premise is true because the vehicle experiences particular vibrations as a result of the condition of the road surface. Rough road surface features like potholes cause the vehicle to fall sharply, resulting in high-energy events in the stream of acceleration data. The intensity of such energy events corresponds to the intensity of the road surface anomaly experienced. A deep pothole for instance records a higher energy event in an accelerometer signal than a shallow one.

Before the algorithm was implemented, the dataset was cleaned and divided into windows. Data cleaning involves deletion of data segments that show the vehicle was stationary during data collection. The dataset is then divided into windows of length 10 seconds. This essentially divides roads being classified into segments that can each be traversed in 10 seconds. Once the windows are obtained, a number of features are extracted from each window.

The z-axis of the vehicle, if drawn, would begin at the wheelbase of the vehicle and run upwards perpendicular to the ground. We get the intuition that acceleration along the Z-axis of the vehicle can help identify the condition of the road. Potholes that cause the vehicle to bob upwards and downwards cause significant energy events that are recorded by the accelerometer along its z-axis. As a result, various features derived from z-axial readings are extracted.

Similarly we envisage that acceleration along the x and y-axes of the vehicle can be used to identify the condition of a road segment being driven over. As road anomalies are encountered, the vehicle wobbles from side to side, experiencing acceleration along its Y-axis. Features are extracted from the y-axial readings as a result. Lastly, as drivers encounter road anomalies, they tend to slow down to ease the effect of the anomaly on the vehicle and its passengers. This continuous start and stop motion causes high-energy events along the x-axis of the vehicle. The presence of such energy events could potentially point to the occurrence of road anomalies. Again, features are derived from the x-axial readings to capture this phenomenon.

The following is the list of all extracted features:

- **Z-Mean**: The mean of all z-axial reading in each window.
- **Z-Var:** The variance of the z values in each window.
- **Z-SD**: The standard deviation of all z values in the window.
- **Z-HPeak**: The highest z-axial value recorded in each window.
- **Z-LTrough**: The lowest z-axial value recorded in each window.
- **Z-DiffMean**: The mean difference between successive peaks and troughs of z-axial readings in each window.
- **Z-DiffVar**: The variance of the difference between successive peaks and troughs of z-axial readings in each window.
- **Z-DiffSD**: The standard deviation of the difference between successive peaks and troughs of z-axial readings in each window.
- **X-Var:** The variance of the x-axial values in each window.
- **X-SD**: The standard deviation of all x-axial values in the window.
- **X-HPeak**: The highest x-axial value recorded in each window.
- **X-LTrough**: The lowest x-axial value recorded in each window.
- **Y-Var:** The variance of the y-axial values in each window.
- **Y-SD**: The standard deviation of all y-axial values in the window.

The goal of the classification algorithm is to derive a hypothesis function, which when fed a set of features will output a road classification prediction. The hypothesis outputs values between 0 and 1, where 0 represents a 100% chance of the input belonging to one class of road and 1 a 100% probability of the input belonging to another class. We define the class represented by 0 as the negative class and the class represented by one as the positive class. We further define a threshold of 0.5 so that any detection with a probability of under 0.5 belongs to the negative class. Following the same thought process, any prediction with a probability of 0.5 and above is classified as belonging to the positive class. In essence the classification algorithm is a binary classifier, able to predict the probability of input belonging to one of two classes. However, by using the one-versus-rest method, which is explained later on in this section, we are able to build a multi class classifier.

For the chosen classification algorithm, logistic regression, the hypothesis function is defined as:

$$h_\theta(x) = g(\theta^T x) \qquad (1)$$

[12]

where x is a vector of features for a given road segment, θ is a vector of parameters that must be learned, and the function $g(z)$ represents the sigmoid function. The sigmoid function ensures the output of the hypothesis is a value between 0 and 1. This is vital because the expected output must be probabilistic. The sigmoid function is defined as:

$$g(z) = \frac{1}{1+e^{z}} \qquad (2)$$

By first defining parameter and feature vectors θ and x respectively, the function $\theta^T x$ can be defined as:

$$\theta^T x = \theta_0 x_0 + \theta_1 x_1 + \theta_2 x_2 + \cdots + \theta_n x_n \qquad (3)$$

Given:

$$x = \begin{bmatrix} x_0 \\ x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} where\ x_0 = 1 \qquad \text{and} \qquad \theta = \begin{bmatrix} \theta_0 \\ \theta_1 \\ \theta_2 \\ \vdots \\ \theta_n \end{bmatrix}$$

The elements x_0 through x_n of the feature vector *x,* refer to values of individual features, while the elements θ_0 through θ_n of vector θ refer to values of individual parameters. To complete the hypothesis function we must determine the parameter vector θ. This can be achieved by minimizing the logistic regression cost function $J(\theta)$ defined below:

$$J(\theta) = \frac{1}{m} \left[\sum_{i=1}^{m} y^{(i)} \log h_\theta \left(x^{(i)}\right) + \left(1 - y^{(i)}\right) \log(1 - h_\theta(x^{(i)})) \right]$$

[12]

That is, we must computer:

$$\min_{\theta} J(\theta)$$

Minimization of the cost function results in a parameter vector that when plugged back into the hypothesis defines a decision boundary that ultimately performs classification.

The logistic regression algorithm is essentially a binary classifier, able to distinguish between two classes of input. To achieve a multi class classifier we use a one-versus-rest approach. This involves distinguishing between one class and all other classes. Given three classes A, B and C, we find the probability of an input belonging to class A, versus the remaining classes B and C. We then find the probability of the input belonging to a class B versus A and C. Lastly we compute the probability of the input belonging to class C versus class A and B. The input is then attributed to the class that outputs the highest probability. Due to the fact that this study attempts a multi class classification involving three classes, three hypotheses and three cost functions are defined. Once minimized, each cost function defines the values of theta to complete the corresponding hypothesis function. Each hypothesis is then used to classify input using the one-versus-rest method.

Once the classifier has been trained, a series of tests are conducted to evaluate the performance of the system developed. The data points in test set are used to test the classification algorithm. Each feature vector is passed as input to the algorithm and the output is measured against its label. The performance of the algorithm is then analyzed statistically by comparing the outcome after the application of the algorithm to the previously obtained ground truth.

4.0 Experimentation and Testing

The purpose of this section is to describe the experimentation stage of the study. It also describes efforts to evaluate the performance of the methods used to gather and process data, and the classification algorithm developed to classify road surface quality. The methods used in experimentation are as described in the methodology section of the paper.

4.1 Data Collection and Hand Labeling of Data

Data was collected along the intended segments of road indicated in the methodology of the study. The methods used to collect and hand label data proved effective. Figure 4.1 through Figure 4.4 illustrate the tri-axial acceleration data collected from driving over the three different classes of road defined in the study. Figure 4.1 displays sample z-axial accelerometer data collected over a good road. It represents one window of data. As can be seen, the variability between the successive peaks and troughs is not large, as they lie between g-forces of $8.8m/s^2$ and $10.6m/s^2$. This phenomenon points to the relatively smoothness of good roads. Figure 4.2 shows z-axial readings collected over a fair road. The variability experienced between successive peaks and troughs is larger than that experienced on good roads. The highest peak recorded in the window displayed is $11.8m/s^2$ while the lowest trough recorded is $7.5m/s^2$. This illustrates the intermittent occurrence of road anomalies on fair roads. A similar analysis of Figure 4.3, which displays one window of z-axial acceleration readings on a bad road, shows the greatest variability experienced throughout the study. The highest peak in the window displayed recorded a g-force of 13.2m/s^2 while the lowest trough recorded a g-force of 4.4m/s^2. Figure 4.4 illustrates the z-axial acceleration readings collected across one window of each class of road. It clearly illustrates the different energy events that occur in each class of road.

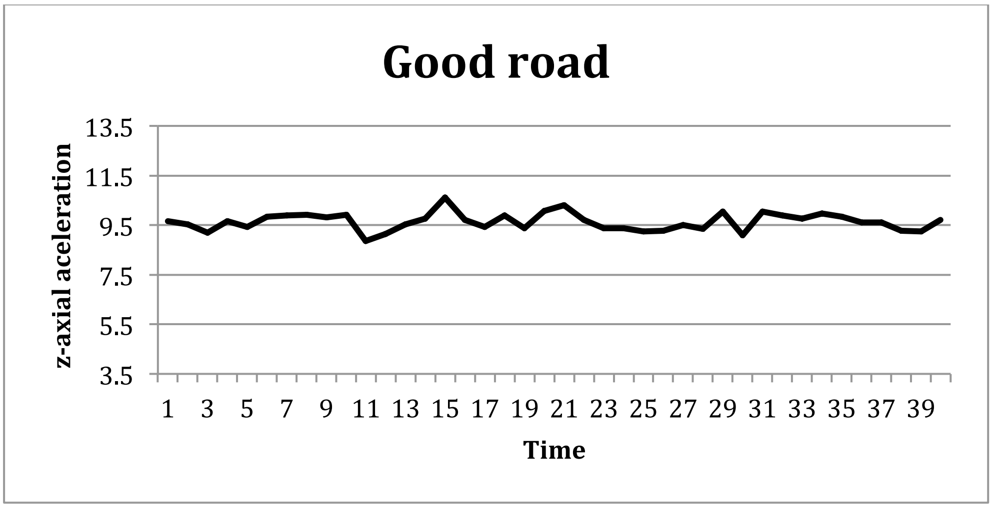

Figure 4.1: Graph displaying one window of z-axial readings collected on a good road

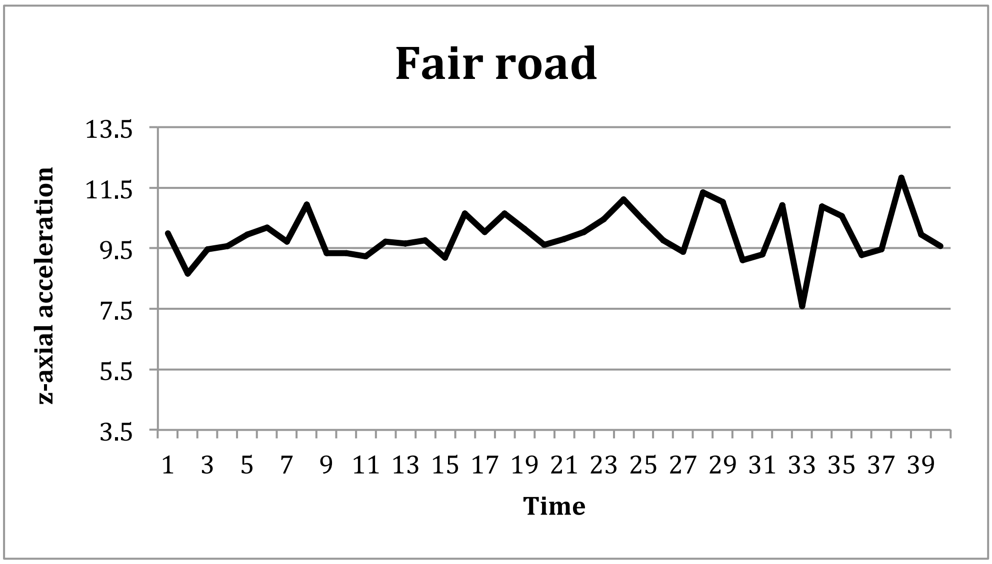

Figure 4.2: Graph displaying one window of z-axial readings collected on a fair road

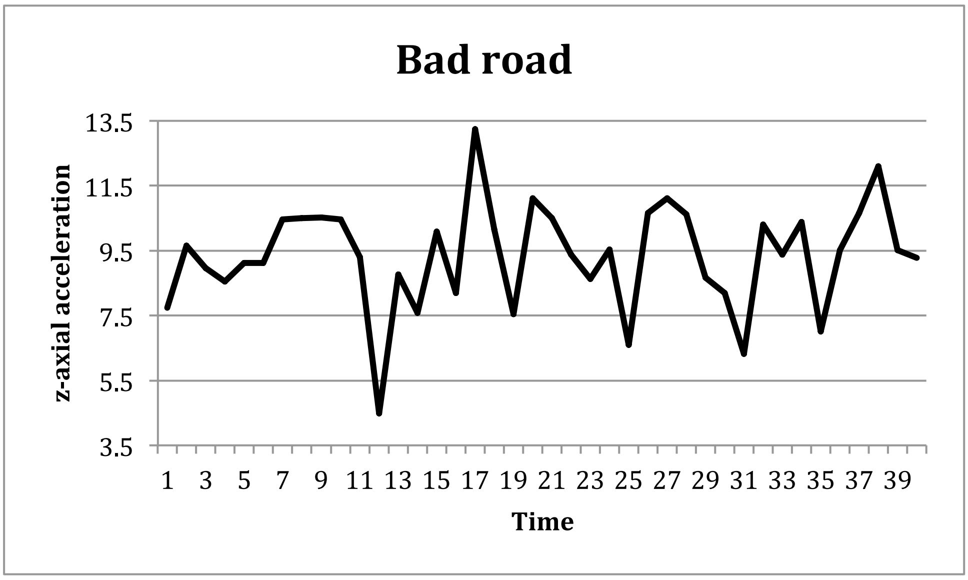

Figure 4.3: Graph displaying one window of z-axial readings collected on a bad road

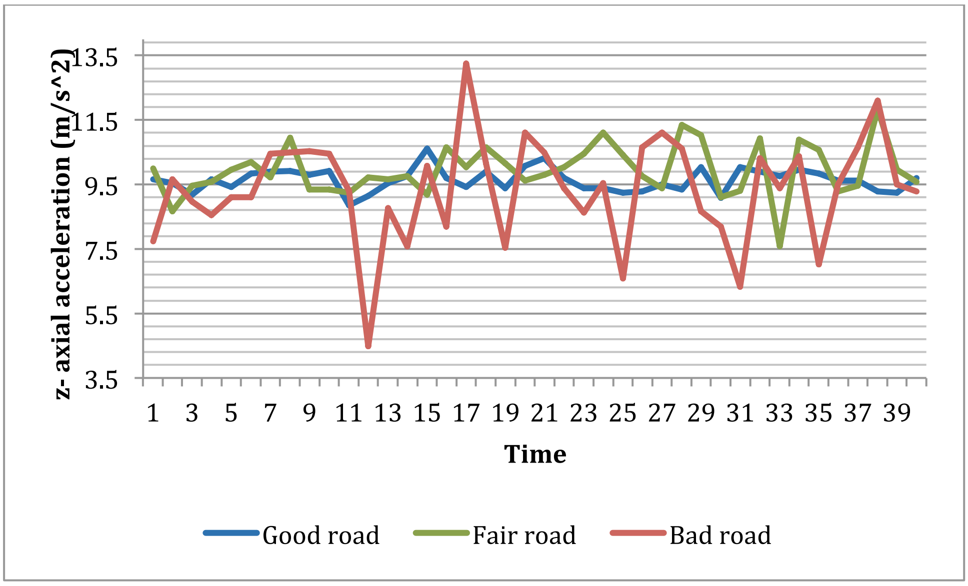

Figure 4.4: Graph displaying one window of z-axial readings collected on all three classes of road. The difference between the data produced by each class is observed.

4.2 Feature extraction and selection

The features described in the methodology section of the study were extracted for use in building the algorithm. As previously discussed, the appropriate selection of features to be used in the development of the algorithm is essential to its success. Further, for the development of a robust classifier, the features extracted should show a distinction between the different classes. To test this, various features extracted from the different classed of road were graphed to illustrate the levels of distinction.

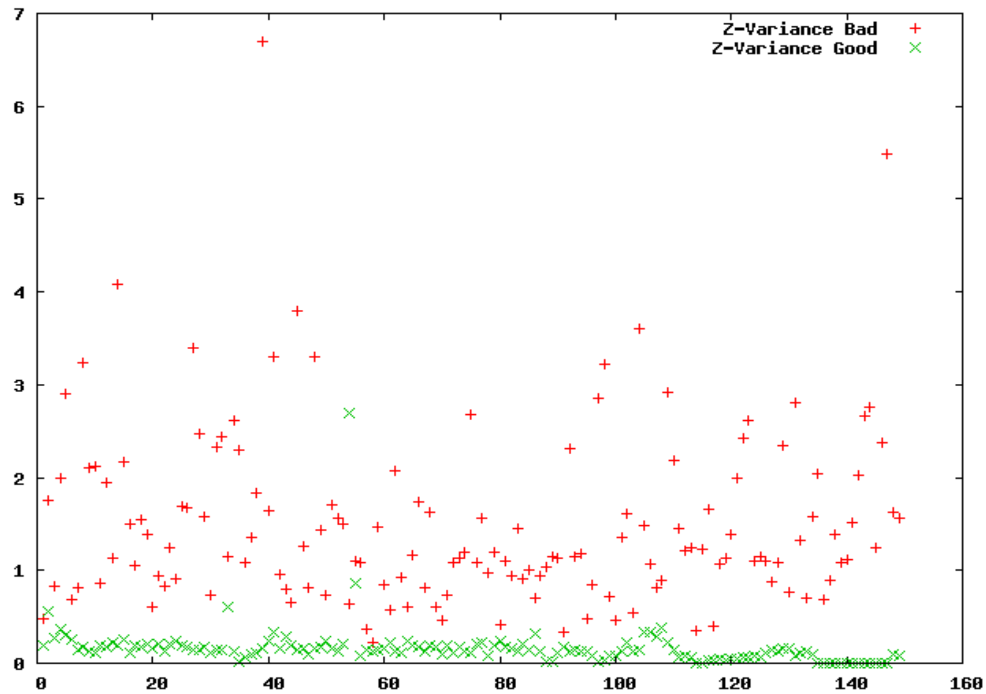

Figure 4.5: Graph displaying one windows of Z-Var features extracted from z-axial acceleration data collected on good and bad roads.

Figure 4.5 illustrates the Z-Var feature for good roads (x) and bad roads (+) over 150 windows. As can be seen in the graph, there is a marked difference between the features extracted from data collected in each class. This is a desirable phenomenon, as it indicates that the feature is a potential determinant of the class of a road segment.

The training set used to train the classifier comprises training examples randomly selected from the dataset. A total of 70% of the dataset was selected to make up the training set. The dataset was split into 10second windows with one feature set extracted from each window. The examples were grouped by class and 70% of each class randomly selected to make the training set. The following table shows the number of examples that were used for building and testing the classifier:

Table 4.1: Size of Training Examples

Class	**Total number of feature sets (examples) extracted**	**Number of training examples**	**Number of test examples**
Good road	221	221	95
Fair road	109	76	33
Bad road	214	149	65

4.3 Fitting of parameters $\boldsymbol{\theta}$

Once the feature vector was developed, the last step of the algorithm was to find the values of θ for which the cost function $J(\theta)$ is minimized. Due to the fact that this study attempts a multi class classification involving three classes, there was a need to minimize three cost functions. We attempted minimization of each cost function by using the minimization function *fminunc* available in the Octave GNU library.

After the cost functions were minimized, the derived values of θ were plugged into the respective hypothesis functions. The completed hypotheses were then tested to determine their accuracy.

To achieve the best possible classifier, various combinations of features were used to train different classifiers. Each classifier was built using the same training set and evaluated using the same test set. The following is the feature vector that was used to train the most robust classifier achieved.

$$x = \begin{bmatrix} 1 \\ Z\text{-}Mean \\ Z\text{-}Variance \\ Z\text{-}D \\ Z\text{-}HPeak \\ Z\text{-}LTrough \end{bmatrix}$$

The tables below illustrates the accuracy of the classifiers built:

Table 4.2: Accuracy of Binary Classifiers

Classifier	**Accuracy**
Good vs. Bad	92%
Good vs. Fair	83%
Bad vs. Fair	Under 50%

Table 4.3: Accuracy of One-versus-rest Classifiers

Classifier	**Accuracy**
Good vs. Bad/Fair	87%
Bad vs. Good/Fair	52%
Fair vs. Bad/Good	Under 50%

Table 4.2 above indicates that with a high level of reliability, two binary classifiers were able to classify road segments. These were the Good vs. Bad and Good vs. Fair binary classifiers. However the Bad vs. Fair classifier was unable to reliably classify road segments.

Table 4.3 indicates that with a reasonable level of reliability, the Good vs. Bad/Fair one-versus-rest classifier was able to classify test features. However, the Bad vs. Good/Fair and Fair vs. Good/Bad one-versus-rest classifiers were unable to reliably classify test features.

5.0 Conclusion

This chapter presents a summary of the research findings and compares these findings to related literature. It further discusses the limitations of this study as well as future work that can be done to improve it.

5.1 Summary

This study attempts to classify entire segments of road using acceleration data collected from moving vehicles. We define a segment of road as a stretch of road that can be traversed in 10 seconds. As has been stated previously, to the best of our knowledge, the approach this study takes to classify roads is a novel one. We attempted to achieve this by first collecting hand labeled accelerometer data from moving vehicles using a Google Nexus One smartphone. Next, we processed the data and divided it into windows, each of length 10 seconds. Appropriate features were then extracted from the each window. The feature sets were divided into training and test sets using a 70:30 ratio respectively. We then trained various classifiers using the logistic regression algorithm.

After conducting experiments using the methods described we conclude that using a binary logistic regression machine learning algorithm:

- We are able to reliably distinguish between good and bad roads with a true positive rate of 92%
- We are able to reliably distinguish good and fair roads with a true positive rate of 83%
- We are unable to reliably distinguish between bad and fair roads

Again, the study concludes that using a one-versus-rest logistic regression machine learning algorithm:

- We are able to reliably distinguish good roads from fair and bad roads with a true positive rate of 87%
- We are unable to reliably distinguish fair roads from good and bad roads combined
- We are unable to reliably distinguish bad roads from good and fair roads.

Although this assertion requires further experimentation to reliably prove, we get a sense that the lack of reliability of the second and third one-versus-rest classifiers stems from the lack of reliability displayed by the Bad vs. Fair binary classifier. This assertion is made because both unreliable one-versus-rest classifiers attempt to distinguish between bad and fair roads – a binary classification that was itself unreliable.

5.2 Comparison to related literature

The attempt to identify individual road anomalies using accelerometer signals collected from vehicles has been attempted many times with varying levels of success. This has been discussed in detail in the related work section of this study. The findings of this study have been in line with related literature. We have been successful at using accelerometer data and a logistic regression machine learning algorithm to reliably classify road surface quality. What this study did differently from related literature was to identify entire segments of roads as opposed to individual anomalies.

5.3 Limitations

This section describes the limitations that were experienced during the implementation of this study. It discusses the fundamental constraints experienced and the potential sources of inaccuracy to the study. The following were perceived limitations of the study:

True Nature of roads

The study attempts to classify roads by analyzing entire road segments. This approach has to deal with the reality that in one segment of road tested, multiple classes of roads may be experienced. We try to minimize the chance of this phenomenon by choosing a small window size. We believe it however limits the accuracy of the classifier.

Mislabeling of Data

The limitation of the true nature of roads gives rise to the difficulty in proper labeling of collected data. The labeling process is done in real time during data collection. This means the passenger conducting the labeling must tag each change in road condition as it occurs. Assuming that on a particular class of road A, a quick transition is made to another class B, followed by another quick transition to the initial class A. The labeler is unable to capture the occurrence of the class B road. This causes a mislabeling which could affect the robustness of the classifier developed.

Taxonomy of road quality

The proper definition of classes is essential to the development of a reliable classification algorithm. The nature of roads however makes it difficult to define and adhere to a scheme of classification. In this work we attempted to clearly define each class of road. We explored various ways of doing this including the Road Roughness Index, which classifies roads based on the number of anomalies that occur on a defined length of road. The case however is that it is often impossible to count the number of anomalies encountered on some segments of road that we encountered during data collection. It therefore is incumbent on the person conducting data labeling to interpret the classes of roads encountered while keeping in mind the definition of each class in the study.

5.4 Future Work

This section makes suggestions as to the improvements that can be made to this study to increase the robustness of the classifier. The overall robustness of the classifier can potentially be improved by improving each of the following:

- **Taxonomy**: An improvement to the classification scheme used in this study can be beneficial to the robustness of the classifier. An alternative to creating a scheme will be to run a clustering algorithm on accelerometer data with the expectation that the data organizes itself into clusters, thereby defining classes.

- **Feature selection:** The features selected and extracted from the data set for this study represent only a handful of possible features that can be used to build the classifier. Further experimentation with features may lead to the development of a more robust classifier.

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