Automatic Road Anomaly Detection Using Smart Mobile Device

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***Abstract*—Maintaining the quality of roadways is a major challenge for governments around the world. In particular, poor road surfaces pose a significant safety threat to motorists, especially when motorbikes make up a significant portion of roadway traffic. According to the statistics of the Ministry of Justice in Taiwan, there were 220 claims for state compensation caused by road quality problems between 2005 to 2007, and the government paid a total of 113 million NTD in compensation.**

This research explores utilizing a mobile phone with a tri-axial accelerometer to collect acceleration data while riding a motorcycle. The data is analyzed to detect road anomalies and to evaluate road quality. Motorcycle-based acceleration data is collected on twelve stretches of road, with a data log spanning approximately three hours, and a total road length of about 60 kilometers. Both supervised and unsupervised machine learning methods are used to recognize road conditions. SVM learning is used to detect road anomalies and to identify their corresponding positions from labeled acceleration data. This method of road anomaly detection achieves a precision of 78.5%. Furthermore, to construct a model of smooth roads, unsupervised learning is used to learn anomaly thresholds by clustering data collected from the accelerometer. The results are used to rank the quality of the road segments in the experiment. We compare the ranked list from the learned evaluator with the ranked list from human evaluators who rode along the same roadways during the test phase. Based on the Kendall tau rank correlation coefficient, the automatically ranked result exhibited excellent performance.

***Keywords*-mobile device; machine learning; accelerometer; road surface anomaly; pothole;**

I. Introduction

Road surfaces in Taiwan are often quite rough, which can cause discomfort and pose safety risks to the motorists who traverse these roadways. Many explanations can be attributed to these substandard road conditions. For example, road construction in Taiwan is typically done in great haste (perhaps to minimize traffic congestion) which translates directly into lower quality roads. This means that road surfaces wear much faster than would normally be expected. In addition, the weather is usually warm and humid in Taiwan, causing nature to also take its toll on roadways. As an effect, these low quality well worn road surfaces lead to many potholes which are very dangerous for drivers and can also cause considerable vehicular damage. And this is not yet taking into account the thousands of manholes covers which scar the streets of Taipei city. The combination of these covers and poor quality roads produce very uneven road surfaces between the pavement and the manhole, deteriorating the commute of Taipei motorist still further.

According to the statistics from the website of the Ministry of Justice [1], between 2005 and 2007, the number of lawsuits brought to national court involving roadway injury compensation numbered about 220 with a total compensation payout of roughly 113 million Taiwan dollars. Naturally, this figure only represents cases in which compensation was requested, so it is likely the actually damage inflicted is far greater than what is represented by these figures. Moreover, riders of two-wheel vehicles, such as motorcyclists or bicycle enthusiasts, are more sensitive to road conditions and when are involved in road accidents sustain injuries far worse than their automobile driving counterparts. Clearly, it is important that preventative measures be identified and implemented to reduce the toll of this growing epidemic.

Suppose for a moment that road condition information was available to both drivers and the government. Drivers could avoid potholes and the government could take actions to remedy these hazards quickly. In order to realize this goal, a vehicle equipped with an accelerometer sensor could collect acceleration data while traversing roadways such that it could be later analyzed to reveal road anomalies. Now imagine that this sensing system could be deployed to consumer phones and other mobile devices, allowing this now distributed system to behave like a mobile sensory network, enabling wide area coverage for road anomaly reporting.

Road surface monitoring by mobile device [1], [2] is the main objective of our research. In our vision, any motorist utilizing our solution is able to utilize road anomaly information of and report such data to the central road anomaly monitoring center. In order to realize this objective, the mobile device is equipped with GPS and an accelerometer so as to collect acceleration data and location information of the road segment in question. By analyzing the acceleration data, the road conditions can be indirectly inferred.

In our experimental setup, a mobile device and sensor are installed on a motorcycle to collect the needed data. This data is combined over many trials to build a high quality road map. The first research question is how to detect road anomalies at specific locations with high precision via use of a mobile device. Another question is the accurate labeling of anomalies given acceleration data over space-time. As there is a delay between the

[1] http://www.moj.gov.tw

anomaly and the spike in acceleration due to vibration of the motorcycle, accurately labeling of these bumps prior to training with a supervised classifier is essential.

Creating an additional challenge is the accuracy of the GPS unit itself, which gives location within 10 meters. To draw a comparison, the typical pothole spans less than one meter. When reporting road surface anomalies to the government, precise locations would be preferred. While this is not strictly achievable, by comparing the analyses of different road sections, repair candidates can be readily identified.

The accuracy of labeling is also a concern with respect to the training of the supervised classifier [3] for the road anomaly detection system. In our experience, the supervised classifier performs poorly if we use the original labels in the dataset. There are two proposed solutions to solve this labeling problem: relabel the data or utilize an unsupervised classifier. Our relabeling method recomputes new labels if they fall within close proximity of the original, but align more closely with the acceleration data in the given search window. If however, the original label is reliable (judged to be correct) within the given window, a supervised classifier is trained to relabel the false tags near the original. As an alternative to the relabeling of the data, a unsupervised classifier can be built which models smooth roads. This is a straightforward procedure as a majority of the data is collected over smooth even surfaces. Thus, by clustering the data into two groups, the smooth data can be gathered and used to train a model of smooth roads. Challenges in this approach include optimization of the clustering technique and personalization to account for different vehicles.

The rest of this paper is organized as follows. Section II discusses related work of road anomaly detection. Section III defines the problem of detecting potholes, while the following section IV shows the architecture of the detection system. Section V reports experimental results. Finally, section VI concludes and summarizes contributions.

II. Related Work

Road surface monitoring with sophisticated devices is introduced in the previous subsection. However, as road quality can change quickly over time and with varying usage loads, it is hard to monitor road quality in real-time using standard monitoring cars, which are expensive and few. Recently, the Pothole Patrol[1] system uses a three-axis accelerometer and GPS to detect and report road surface conditions. This system is installed at a fixed orientation on the dashboard of an automobile. Data is collected by seven cabs around the Boston area. Another system, TrafficSense[2], uses GPS, an accelerometer, and a microphone to collect vehicle-based road data, monitoring traffic and road conditions. One of the contributions of TrafficSense is that it uses the Euler angle to reorient the acceleration data allowing for arbitrary placement of the accelerometer. These two approaches utilize simple device to accomplish road monitoring.

Several websites aim to collect issues from local residents and report the raised issues to the appropriate administrative units. SeeClickWatch[2] (based in the US) introduces an easy-to-use interface on both the web and mobile devices with which users may report problems to governmental agencies regarding their local environment. FixMyStreet[3] provides a similar service in the UK for promoting online democracy. Volunteers can report local problems, such as roads with potholes, unlit lampposts, or discarded mattresses at the roadside. Issues identified by users of the FixMyStreet system are forwarded to relevant council. In Taipei, the city government released a website, RCIS, [4] in April 2009, which provides a platform where users can report roadway hazards. Although the RCIS system has reportedly suffered from inconsistent problem handling and lacks some features such as automated follow-up of reported issues, it indeed offers a good outline of a communications pathway between government and citizens.

Two main factors which affect riding quality are vehicle response to the road and the surface roughness of the pavement. The International Roughness Index (IRI) is one of most commonly used statistical measures of road roughness. IRI defines a scale, which is acquired on the quarter-card simulation at a speed of 80 km/hr, for the response between a vehicle and the road surface. Loiszos [4] claims that IRI is often inadequate to describe the ride quality at speeds other than 80 km/hr. Gillespie [5] writes a tutorial to explain the principles and basic ideas of IRI. In recent years, Wei et al. [6] use a toolkit called Wavelet for analysis and interpretation of road roughness. Sun[7] points out that IRI is an indirect statistic of roughness, since it does not measure the pavement surface directly. To address this latter issue, Power Spectral Density (PSD)[4] is able to measure the road roughness directly. The vertical displacement data after Fourier transform is often used in PSD to analyze the wavelength, amplitude, and phase. To make a distinction, IRI focuses on the comfort level to the passenger and PSD is directly concerned with the analysis of road surface roughness.

Using an accelerometer to analyze terrain is a less computationally intense method as compared to the computer vision method. A vibration-based method for terrain analysis is proposed by Brooks et al[8]. The accelerometer is installed on the wheel and vibration data is collected on a laboratory testbed. Brooks transforms vibration data into the spectral domain and trains the priori distribution of different terrain types. Terrain characterization and classification [9] are conducted on a Pioneer robot with a 2-axis accelerometer and a KVH fiber optic gyro, using a neural network to decide five types of terrain, which are gravel, grass, sand, pavement, and dirt. In a recent work, Giguere [10] uses an iRobot with a inclined metallic rod equipped with a single-axis accelerometer to collect vibration data, and neural network are employed to classified six indoor

[2] http://www.seeclickfix.com/
[3] http://www.fixmystreet.com
[4] http://rcis.taipei.gov.tw

(a) A severe pothole on the road (b) A pavement anomaly and manhole cover

Figure 1. Road Anomalies

and four outdoor surfaces.

III. Approach

Road anomalies, as shown in Figure 1, such as potholes, sunk-in manhole covers, or missing pavement, cause the abnormal vibration of vehicles. By installing acceleration data collection systems within these vehicles, operators can collect vibration data induced by road conditions as they commute. After obtaining this information, the detection system analyzes the vibration patterns of the acceleration data so as to differentiate anomalous vibrations from background vibrations experienced on a smooth road.

Three assumptions are made in this paper. We assume that the vibration patterns across data collection events for a given stretch of road are similar. That is, road quality will not change significantly during the timescale of our data collection. The second assumption is that the suspension system of the test vehicle is in good condition. Under the constant normal state of the suspension system, the acceleration data collected by accelerometer installed on the vehicle will give similar values. This acceleration data can be viewed as an indirect index of the quality of the road surface. The final assumption is that the coordinate system of the accelerometer is fixed with the vehicle, so the acceleration value of the vehicle is similar to that of the accelerometer.

Our main goals are to classify road surfaces and further evaluate road conditions. At the first stage, we focus on the issue of locating road anomalies via acceleration data analysis. Next, the conditions of each road section can be calculated using the statistics generated from the acceleration data or the results derived from the first phase. We submit that a road profile can be obtained by solving these two problems. There are two basic categories for describing the road surface: smooth roads and rough roads (roads containing surface anomalies). A smooth road offers a high quality driving surface to vehicles traversing over it, while a rough road is its complement.

Once we have the classifying function with a model of a smooth road, the quality of a road section is ready to be examined. From the definition of International Roughness Index (IRI)[5], the measure of roughness is based on the measure of vertical deviations over a section of the road. To be precise, the roughness of IRI is defined as the cumulative deviations in vertical inches per lateral mile. We modify the definition slightly, defining roughness as the number of road anomalies per kilometer. The details of roughness is in the definition 1. The input data segment $\mathcal{X}_s$ contains a time series of input data $\mathcal{X}$, and this segment is defined as $\mathcal{X}_s = \{\mathcal{X}_1, \mathcal{X}_2, ..., \mathcal{X}_\mathcal{N}\}$. Furthermore, the set of input data segments is defined as $\mathcal{U}_R = \{\mathcal{X}_{R,1}, ..., \mathcal{X}_{R,n}\}$, where n is the size of $\mathcal{U}_R$. $\mathcal{F}_s^\sigma(\mathcal{X}_{s,i}|\mathcal{M}_s)$ is the classifying function with the smooth surface model $\mathcal{M}_s$ under speed σ.

Definition 1: Roughness Index Function ($\mathcal{I}(\mathcal{U}_R)$)

$$\mathcal{I}(\mathcal{U}_R) = \frac{\sum_{i=1}^{n} \mathcal{F}_s^\sigma(\mathcal{X}_{s,i}|\mathcal{M}_s)}{Length(\mathcal{U}_R)} \tag{1}$$

where $\mathcal{X}_{s,i} \in \mathcal{U}_R$ and n is the size of $\mathcal{U}_R$.

The roughness index function given in equation 1 is an indicator for estimating the quality of the input road section. We further offer semantic labels to describe the given road section. These semantic labels have values "good", "fair", "inferior", and "dangerous". In addition, three thresholds are learned to assign semantic labels to road sections.

A. Data Preprocessing

The labeling process is a challenging in this experiment. Assuming that a typical pothole stretches for 1 meter, the traversal time of the vehicle across the pothole at 36 km/hr is then 0.1 second. That means the tagging system must be precise to within 0.1 seconds, and location system should be accurate to 1 meter. Labeling inaccuracy is also an issue as during the test phase, the ability of human subjects to tag potholes accurately in time to within 0.1 seconds is limited. Not only this, but the inherent inaccuracy of the GPS also makes obtaining useful data about pothole location an issue. As a result of these factors, it is difficult to tag corresponding acceleration data signals and by doing so locate the exact position of the pothole. We explore several approaches in dealing with these issues.

In order to improve the labeling accuracy, the re-labeling process is proposed. We use a labeling window to seek suspicious data near the original label, and replace the original label with a new one. In all, we explored three methods for this re-labeling. First, we watch the raw data directly and re-label the new label. Second, we pre-define some heuristics and eliminate suspicious ones. Lastly, we train a classifier for re-labeling. This last method is based on the idea that the suspicious data is near the original label. Therefore, the improvement in the accuracy of labeling yields an increase in the precision of anomaly detection.

Filtering helps us gain useful and trustworthy data from the original source. Suppose the vehicle is stopped, the data obtained at this time cannot be analyzed for measuring the road roughness, thus we can simply remove this data by checking the speed σ in $\mathcal{X}_s$. Next, a simple high pass filter method [11] is used as the low frequency data, like gravity, does not affect the result of anomaly detection. Then the data collected as the vehicle is changing directions is discarded due to the inclination of the vehicle's body (as the motorcycle leans to one side) to change the acceleration value.

Considering the nearby data of a single input acceleration data point ($\mathcal{X}$), segmentation offers information about the sequence of acceleration data around this point making it easier to identify road anomalies. Here, we propose two methods for segmentation. First, we fold nearby data into the same segment with a maximum window size N. Second, we divide the data according to the length L. If the maximum length of each pair in a given segment exceeds L, the new segment is formed and collects nearby data. Moreover, we implement overlapping windows, where the overlap width is set as at least half of the segment size on average.

Good features are important indicators for classification. We consider the data of the accelerometer a_x, a_y, a_z and the instantaneous speed σ when reading this data for feature extraction. Gadelmawl et al. [12] define about 59 roughness parameters for measuring road surfaces. We use some of these parameters with modification. Furthermore, the first-order difference of the acceleration data and the histogram of the acceleration are also considered.

B. Model Building

The purpose of road surface classification is to recognize and locate road anomalies. The input data segment $\mathcal{X}_s$ contains the acceleration values a_x, a_y, a_z in three axes, the instantaneous speed σ, and position $p =< \lambda, \rho >$. We extract features from $\mathcal{X}_s$ and further use these features for classification. The training process is initiated after extracting the required features. We make use of LIBSVM [13], a library package for support vector classification. Given a set of training data $\mathcal{U}_s$, the support vector machine constructs a hyperplane that optimally separates the training data into the desired number of categories. Therefore, the model of the road surface is learned for future classification.

The smooth surface model is important as it contributes to the discovery of road anomalies. Considering that every input data segment $\mathcal{X}_s$ has histogram $\mathcal{H} = \{\mathcal{H}_x, \mathcal{H}_y, \mathcal{H}_z\}$ for acceleration in three orthogonal directions, we measure the distance of the histogram [14], [15] of every $\mathcal{H}_s$ and use this distance as a measure for clustering. Hierarchical clustering [16] is proposed to obtain the data of the smooth road. Under the assumption that the data of the smooth road is in the majority, half of the data is collected to form the smooth surface model. Finding a distance, or similarity of two histograms [14], [15] is an important issue in pattern recognition. There are two common methods for estimating the distance of two histograms: vector and probabilistic. We use the vector method to calculate the distance between histograms and use Euclidean distance to calculate the distance between these vectors.

Departing from the method of supervised classification mentioned above, we propose an unsupervised method for learning the smooth surface model $\mathcal{M}_s$ from the set of the input data segments $\mathcal{U}_s$. The smooth surface model is a finite set of models $\mathcal{M}_s^\sigma$ with different speeds σ. The continuous speed value is quantized into a discrete set $\mathcal{U}_\sigma = \{\sigma_{10-20}, \sigma_{20-30}, ..., \sigma_{50-60}\}$, where σ_{x-y} represents the speed from x km/hr to y km/hr. As a result, we seek to learn the model $\mathcal{M}_s = \{\mathcal{M}_s^{\sigma_{10-20}}, ..., \mathcal{M}_s^{\sigma_{50-60}}\}$, and propose a method of model building in algorithm 1.

Algorithm 1: The algorithm of building the smooth surface model

Input: $\mathcal{U}_s$: a set of input data segments
Output: $\mathcal{M}_s$: a smooth surface model

foreach $\mathcal{X}_s \in \mathcal{U}_s$ **do**
  foreach $\sigma \in \mathcal{U}_\sigma$ **do**
    if *Speed*($\mathcal{X}_s$) $= \sigma$ **then**
      $\mathcal{M}_s^\sigma.Add(\mathcal{X}_s)$
    end
  end
end
foreach $\mathcal{M}_s^\sigma \in \mathcal{M}_s$ **do**
  $\mathcal{HC}$ = HierarchicalCluster($\mathcal{M}_s^\sigma$)
  $\mathcal{M}_s^\sigma$ = FilterMajority($\mathcal{HC}$)
end

IV. Implementation

In our system, several sensors and devices are used to collect both location and acceleration data. There are four main components which make up our experimental testbed. The HTC Diamond is the main platform for the storage of all the sensor data, which also has a built-in accelerometer with a 25 Hz maximum data frequency. For collecting precise GPS location data, an external GPS sensor, the NCS Navi R150+ GPS logger, is used. To label road surface anomalies, a voice recorder is used as it minimizes the required interaction for the rider. Lastly, a motorcycle is required which travels the city collecting the needed data.

The HTC Diamond is installed inside the storage box of the motorcycle, so that the coordinate system of accelerometer is the same as that of the motorcycle. Moreover, the x, y, and z-axes of the accelerometer represent the directions of left to right, top to bottom, and front to rear of the vehicle, respectively. Figure 2 shows the coordinates of the motorcycle and the accelerometer. Both the GPS device and the recorder are hung around the neck of the rider. This is done as the GPS device requires an open environment to achieve good satellite signal strength while the voice recorder must be in close proximity to the rider to collect the voice labels of surface anomalies.

Mobile devices make an excellent choice for collecting data on the road. The pervasive nature of mobile devices enables the immediate sharing of road condition information among a large user base. Moreover, it is easy to carry such devices in any kind of vehicle. The low power requirement of the accelerometer reduces the burden of collecting continuous acceleration data while users are mobile. While the GPS device has a larger power requirement, a possible alternative to GPS for location data acquisition would be to use Wi-Fi triangulation.

In our setup, users have a mobile device that collects the required information, such as GPS and acceleration data. Some pre-processing of the data can be done at the client side. Such client side tasks include filtering, segmentation, and feature extraction. The data can then be synchronized and transmitted back to the server. In addition to the installation of the anomaly detection system on the device to automatically transmit road data to the central server, users may also use their mobile devices to report road anomalies by passing messages or pictures to the website.

Our server implementation, a Unix-like system in which the server program is written using the python language, provides two main services. First, the server receives data from different sources and provides for analysis and aggregate of these datasets. When a client passes data to the server, the server will analyze the data taking into account the vehicle model of the client. Therefore, if a client uses a different vehicle, this user should give notice of the change to the server. Second, the server provides information to clients which allows them to more readily avoid road anomalies. While the user on the client side operates a vehicle connected to the server, the server will broadcast the road conditions to the client. Furthermore, via the analysis on the server side of road conditions, information regarding certain areas which are considered emergency situations can be sent by the server to the relevant governmental agencies.

Besides the collecting and distributing of data in the sensory network, data analysis on the server side is an important part of our work, thus several modules are built for this purpose. Before learning the model, the data must be preprocessed in three phases as previous mentioned: data filtering, segmentation, and feature extraction. The learning model should be trained before classifying. We use two learning models: LIBSVM and a smooth road model. The latter is obtained by utilizing a majority of the original data (which is collected while traversing road segments free of road surface anomalies) using the hierarchical clustering method in which several thresholds are trained. Finally, the road anomaly detection system uses two models to decide road conditions, and a road quality evaluator is proposed to evaluate the quality of a given road segment.

Figure 2. The architecture of the detection system

Table I
THE ROAD COVERAGE OF THE DATASETS

Dataset	Dataset #1	Dataset #2	Dataset #3
Road 1	Sec. 4, Jhong-siao E. Rd.	Sec. 1, Fu-sing S. Rd.	Sec. 2, Sin-hai Rd.
Road 2	Lane 216, Jhong-siao E. Rd.	Sec. 3, Civic Blvd.	Sec. 3, Kee-lung Rd.
Road 3	Sec. 4, Ren-ai Rd.	Sec. 1, Shin-sheng S. Rd.	Sec. 4, Roo-sevelt Rd.
Road 4	Sec. 1, Jian-guo S. Rd.	Sec. 3, Sin-yi Rd.	Sec. 3, Shin sheng S. Rd.
Distance	3933m	5052m	3985m

V. EXPERIMENTS

Three datasets, collected by the same motorcycle, each contains four road segments traversed at two different maximum speeds of 30 km/hr and 40 km/hr, respectively. In these different speed runs, we try to maintain the given maximum speed throughout the duration of the run. These three datasets are summarized in table V. It took approximately 3 hours to collect the data divided among twelve different roads segments, with a total distance of 52 kilometers. The data is collected in dry weather and late at night (past midnight) to virtually eliminate weather and traffic interference during data collection. Dataset 1, 2, and 3 are obtained on the 16th, 25th, and 27th of May 2009, respectively.

Labeling is an important part of the data collection process. The road anomalies are tagged if the experimenter experiences a sudden bump when passing a certain position. In our experiment, the labeling tool is an audio recorder and it collects the voice of the experimenter which is then manually converted to anomaly class labels. There are three labels used in the data collection: potholes, bumps, and smooth road. A large majority of the road surface is smooth road, so the experimenter need only tag road anomalies (e.g. potholes and bumps) with the voice recorder. These labels need to be synchronized with the location information from the GPS and the acceleration data from the accelerometer. Since all three data types are taken over the same time period, data integration is performed with time as a unifier.

As we can see in figure 3, a shifting situation occurs. The y-axis of the figure represents the vertical acceleration, which includes acceleration of 9.8 m/s^2 due to gravity. When the vehicle stops, the vertical data exhibits a small vibration due to the engine of the vehicle. When the motorcycle then begins moving, the vertical vibration becomes much larger than the vibration experienced at the rest state. The asterisk symbol in the figure represents the anomalous label tagged by the experimenter.

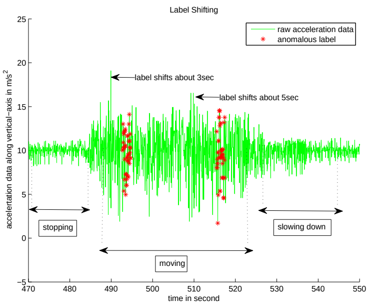

Figure 3. A typical label shifting problem of the raw data

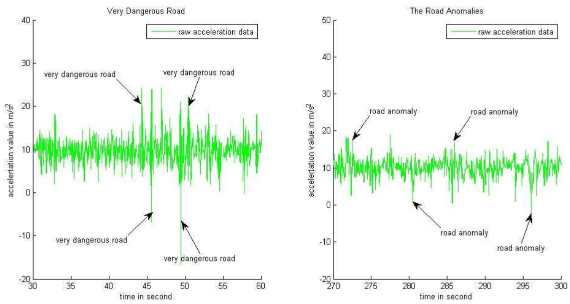

Figure 4. Dangerous stretches of road versus typical road with anomalies

By our intuition, the vertical acceleration value increases sharply while the motorcycle reacts to a road anomaly. Interestingly, the two peaks (which are much higher than the others) are not tagged, but they lie near the two anomalous labels, respectively. Thus a shifting action must occur to ensure that these two labels are located at the correct position. Roads which are extremely bumpy show immense peaks and valleys as compared to nearby background acceleration data. Under these conditions, the vertical acceleration value can be twice or three times higher than that of a smooth road (see figure 4). Roads which fit this extreme pattern are an imminent danger to drivers and are easier to discover by our methods than roads which contain only minor surface anomalies.

Figure 5 shows a sequence of histograms with a moving window. These histograms are formed by continuous vertical acceleration data, and each histogram contains 24 data points and overlaps with 3/4 of the data of nearby histograms. The horizontal axis is the vertical acceleration value measured in m/s^2 and the vertical axis is the number of acceleration data points which fall into the specified acceleration bin. We observe the distribution of histogram becomes widened in histogram 4 and has lower peak than most histograms, which means histogram 4 is an anomalous data.

A. Experiment 1

The acceleration data is segmented according to window size. These window sizes are 12, 24, 36, and 48, representing 0.5, 1, 1.5, and 2 seconds, respectively. Selected features for experiment 1, including triaxial and overall acceleration, are listed in table II.

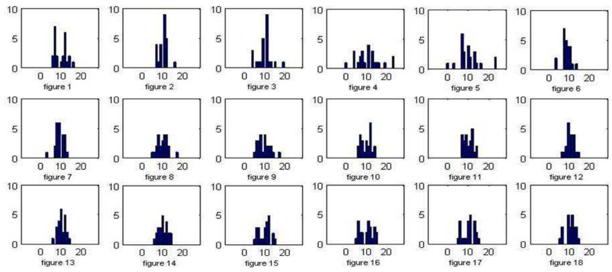

Figure 5. Histograms of a sequence of data segments with windows size 24

Due to the label shifting issue, a relabeling process is proposed to improve the label accuracy. Instead of manually relabeling the raw data directly, the computer uses a simple heuristic function to relabel the data. Recalling that the original labels are collected via voice recorder, we assume that these labels are reliable and that the correct labels are near the original ones. Thus, the seek window is predefined for the computer to seek out suspicious data near the original label. We define two thresholds that are used for relabeling, which are the maximum absolute value of the vertical acceleration data from the equilibrium point and the maximum absolute value of the front-rear acceleration data from the equilibrium point. These thresholds are learned directly from the statistics of our dataset. In this way, we are able to achieve an increase in label accuracy due to the relabeling process.

Table V-A are the results with dataset #3 in experiment 1 using LIBSVM. The precision measures the correctness in the identification of road anomalies, and it shows the confidence of road anomalies detected by the classifier. The recall of road anomalies is simply the number of road anomalies detected so far, reported as a percentage of the known existing road anomalies. The accuracy shows the validity of the two classes, road anomalies and smooth road.

As the window size increases, the accuracy and precision also both increase. Although larger window size generally has a better result, the position of road anomalies becomes imprecise. A road anomaly, like a pothole, has a footprint of under 1 meter across. So accuracy to within about 1 meter would likely be sufficient to specify road anomaly location. However, because the motorcycle moves

Table II
SELECTED FEATURES FOR EXPERIMENT 1

Experiment 1	
Features	*Descriptions*
$\mathcal{R}_{m,i}$	mean accel., i-axis
$\mathcal{R}_{r,i}$	range of accel., i-axis
$\mathcal{R}_{std,i}$	standard deviation of accel., i-axis
$\mathcal{R}_{p,i}$	maximum accel., i-axis
$\mathcal{R}_{v,i}$	minimum accel., i-axis
$\mathcal{S}_m$	mean speed

Table III
THE CLASSIFICATION RESULTS IN DATASET 3 WITH DIFFERENT WINDOW SIZES AND SPEEDS

Data Set#3	*Speed*					
	30 km/hr			40 km/hr		
Size	*Prec.*	*Rec.*	*Accu.*	*Prec.*	*Rec.*	*Accu.*
12	75.3%	61.4%	96.9%	90.0%	47.3%	95.2%
24	94.7%	74.8%	96.6%	97.6%	62.4%	94.4%
36	96.2%	81.9%	96.4%	95.4%	71.1%	93.7%
48	96.0%	73.6%	94.1%	96.0%	76.5%	93.9%

Table IV
RANKS OF ROADS, THE ROAD WITH SMALLEST NUMERICAL SCORE IS THE BEST (MOST SMOOTH)

Dataset #3	Rank			
	A	B	C	total
Sec. 2, Sinhai Rd.	4	4	4	4
Sec. 3, Keelung Rd.	1	1	2	1
Sec. 4, Roosevelt Rd.	3	3	3	3
Sec. 3, Shinsheng S. Rd.	2	2	1	2

at about 10 meters per second (36 km/hr), if a window size of 48 is chosen for example, the road anomaly can only be localized to within a circle of radius 10 meters. Moreover, precision is much important than recall in this problem. The large user base will facilitate the discovery of road anomalies even when recall is low. Experiment 1 shows that the average precision is about 78.5% and the average recall is 70.5%.

B. Experiment 2

Experiment 2 aims to build a smooth road model and rank road segments. By the assumption that the majority of the collected data is smooth road, we seek to cluster the smooth road segments together and build a smooth road model. The data is first divided according to speed, as the vibration range of smooth data increases with speed. Next, the maximum and minimum values of the histogram are extracted for clustering. Assuming that 90% of the original data is smooth road which is consistent with our observations of the data, hierarchical clustering is used to separate the data into two clusters. Once the smooth road portion of the data is obtained, we can start to build the smooth road model.

Three inspectors ride across the roads in dataset #3 and give the ranked results for those roads. The ranked results of the three inspectors are listed in the table IV. Label “1” means the smoothest road while “4” means the most rough. The total ranked list $\mathcal{L}_g$ is calculated according to the ranks of the three inspectors.

According to our roughness index function 1, the roads in dataset #3 can be sorted according to their grade given by the roughness index function. The evaluation system then uses the smooth road model to determine the number of anomalies and calculates the length of a given road section. Table V shows the ranked result $\mathcal{L}_e$ of the evaluation system. The system computes the grade by the equation 1 and sorts the roads according to that grade. The ranked result is slightly different (for the first and second most smooth roads) between three inspectors and the system. When questioned, the inspectors related that the difference between the smoothness of Roosevelt Rd. Shinsheng S. Rd. was very subtle and difficult to rank. With this explanation, our evaluation system appears to produce an acceptable rank result. However, to investigate the ranked list performance further, we take the two ranked lists $\mathcal{L}_g$ and $\mathcal{L}_e$ produced by three inspectors and by the system and calculate the Kendall tau $\tau(\mathcal{L}_g, \mathcal{L}_e)$ of two rank lists. The correlation is 0.67 as $\mathcal{C}$ is 5, $\mathcal{D}$ is 1, and size $\mathcal{N}$ of rank list is 4. Therefore, we obtain a good rank correlation value between these two sets of ranked lists.

Table V
THE GRADE AND RANK DECIDED BY THE EVALUATION SYSTEM

Dataset #3	Grade of the System (number per km)	Rank
Sec. 2, Sinhai Rd.	161.1	4
Sec. 3, Keelung Rd.	51.8	2
Sec. 4, Roosevelt Rd.	80.1	3
Sec. 3, Shinsheng S. Rd.	40.7	1

VI. CONCLUSION

This paper explores the possibility of road anomaly detection via motorcycle-based mobile device. Two different approaches, supervised and unsupervised learning, are proposed. The SVM method achieves a precision of 78.5% in detecting road anomalies correctly. In the second stage, a ranking system for road segments is built, and the roughness index function for measuring quality of road segments is proposed. The ranking system offers good performance according to the Kendall tau rank correlation coefficient of two distinct ranked lists produced by human and by our system. Lastly, we verify the possibility of using a mobile device to automatically monitor road conditions. A prototype of a mobile sensor network for road surface monitoring is designed so that a monitoring map for road quality can be established to facilitate sharing road condition information.

While some websites aim to monitor road conditions by enlisting volunteers who provide information via the internet or cell phone, the automatic detection system can work with a wide range of vehicle types and offers a better way to monitor road conditions without manual user intervention. Not only does this approach potentially increase participation and thus coverage, but also offers a solution much less costly than that of traditional custom built road investigative vehicles typically employed by governmental transportation agencies. It is important to underscore that a more complete and accurate dataset of road surface anomalies can help to highlight issues to the appropriate parties which can lead to improved roadways and increased public safety.

There are some aspects of the work which could be improved upon in the future. First, a higher frequency accelerometer could be used for road surface monitoring in order to obtain better measurement performance. Second, it would be more convenient if the mobile device was not fixed to the vehicle, but rather allowed to be placed in the pocket of the user. This can be done by the reorientation of the coordinates of the accelerometer. Lastly, the full implementation of the server for road surface monitoring could be publicly deployed so that more users could join the monitoring process, making a contribution to the project while helping to improve roadways.

ACKNOWLEDGMENT

Thanks to all the contributors and supporters of this study, from idea discussion and data collection (operating at their own peril) to algorithm implementation and finally paper review.

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