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以智慧型行動裝置進行
自動偵測異常路面
Automatic Road Anomaly Detection
Using Smart Mobile Device

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本論文係戴于晉君（學號 R96922047）在國立臺灣大學資訊工程學研究所完成之碩士學位論文，於民國 98 年 7 月 21 日承下列考試委員審查通過及口試及格，特此證明

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Abstract

Maintaining the quality of roadways is a major challenge for governments around the world. Poor road surfaces pose significant safety threats to drivers and motorists. According to the statistics of the Ministry of Justice in Taiwan, there are 220 claims for state compensation caused by road quality problems from 2005 to 2007, and the government paid a total of 113 million NTD in compensation.

This research explores utilizing a mobile phone with tri-axial accelerometer to collect acceleration data while riding in the motorcycle. The data is analyzed to detect road anomaly and to evaluate the quality of the road segments. Acceleration data on motorcycles are collected on twelve road segments, three hours long, with a total length of about 60 kilometers in our experiments. Both supervised and unsupervised machine learning methods are used to recognize the road condition. SVM learning is used to detect road anomaly and to identify its corresponding position from labeled acceleration data. This method achieves a precision of 78.5% in road anomaly detection. To construct a model of smooth roads, unsupervised learning is used to learn the thresholds by clustering data collected from the accelerometer. The results are used to rank the quality of multiple road segments. We compare the rank list from the evaluator with the rank list from human testers who rode on the roads segments. The experiment showed that the automatic rank result is good based on the Kendall tau rank correlation coefficient.

Keywords: accelerometer, mobile device, mobile phone, mobile sensing, road surface anomaly, pothole

摘要

近年來，台灣的道路工程品質往往給人「地無三里平」的刻板印象。根據法務部的從民國94 年至民國96 年的數據顯示，因爲道路品質所引發的國賠事件，賠償金額共爲一億一仟三百多萬元。施工品質不良除了賠上額外的經費，更進一步危害用路人的安全。本研究利用固定在機車置物箱內的行動裝置，收集三軸加速度器在不同路面的資料，進而分析加速度變化與路面狀況的關係。

本研究的目的在於偵測異常路面及評估路段品質。我們收集了騎乘機車時的加速度資料，共十二個路段，三個小時，約六十公里，並利用監督式(supervised)及非監督式(unsupervised) 兩種機器學習的方法評估路面狀況。監督式的機器學習利用已標記的資料，嘗試辨認某個位置是否爲異常路面，由此方法得到78.5% 的異常路面辨識率(precision)。非監督式的機器學習利用分群(clustering)及學習門檻值(threshold)，找出平穩路面的振動模型。實驗最後，以上述兩種方法評估路段狀況，進而建立起一個道路品質的地圖。

關鍵字: 加速度器, 行動裝置, 手機, 行動感測, 異常路面, 路面坑洞

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Chapter 1

Introduction

In this section, we describe the motivation and the basic idea of the anomaly detection system. Then, several research questions are mentioned, and possible difficulties are needed to surmount. Finally, we explain the organization of the entire thesis.

1.1 Motivation

In Taiwan, the road surface is usually rough and people often feel uncomfortable when driving on the roads. Many reasons cause the damage on the roads. Firstly, the construction process of the road is imprudent and jerry-built so that the road decrepitude or destroy faster than normal usage. For example, there are lots of manholes in Taipei city, and these manholes produce uneven road surface between the pavement and the manholes. Moreover, the jerry-built road results in pothole on the road, and it is very dangerous not only for the vehicle itself but also for the safety of the people. Secondly, the weather is wet and hot in Taiwan, so the nature reasons decay the pavement. As a result, people who operate the vehicles feel unsteady and are hurt by the rough surface on the road.

1.1.1 National Compensation due to Poor Road Quality

According to the statistics from the website of the ministry of justice [1], the national compensation events of road construction are about 220, and the total compensation money is about 113 million dollars from 2005 to 2007. However, people getting a little hurt by uneven roads will not choose to ask for compensation, so, implicitly, there are much more accidents happened than 220 events in statistics. Moreover, riders in two-wheel vehicles, like motorcycles or bicycles, are more sensitive to the road condition and usually get hurt worse than in four-wheel vehicles so that these kinds of riders need road information to avoid possible accidents.

1.1.2 Pothole Avoidance

Suppose the road information can be known by the driver and the government, the driver can avoid the potholes of the road and the government can take actions to these anomalous conditions quickly. In order to achieve this goal, if the vehicle is equipped with the accelerometer sensor and collect the acceleration data on the road, it is possible to analyse the road condition and share it with everyone. Thus, assume that the accelerometer is in everyone's phones or mobile device, it behaves like a mobile sen-

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

sor network and makes it easier for people to contribute their driving information and update the road information quickly.

1.1.3 Rapid Change in Road

Another reason for collecting the data by everyone is that the road condition changes everyday. We can not only depend on the road monitoring device of the government but contribute our little effort to make our environment better. This application will be an indirect monitoring tool for putting pressure on the government in order to fix the anomalous road.

Therefore, the road condition is monitored using an efficient and innovative way by every citizen, and driving quality will be improved if the government takes actions to fix the road and is serious about the construction of the road due to the public road monitoring of citizens.

1.2 Research Objectives

Road surface monitoring by mobile device [6, 14] is a good motivation for us to achieve. People who drive cars share their information of roads, reporting damage position of the road to the monitoring center. In order to reach this objective, the mobile device is equipped with GPS and the accelerometer so as to collect the acceleration data and location information of the road. By analysing the acceleration data, the road condition can be indirectly inferred and shared with everyone.

1.2.1 Road Anomaly Detection

The first research question is how to detect the road anomaly with exact location and high precision by using mobile device. The mobile device and sensor are installed on the motorcycle for collecting the data, and the data is transmitted to the server from everybody so as to build a road quality map.

1.2.2 Relabeling Technique

Another question is the labeling problem of the anomalous road. When operating the vehicle, the experimenter tags the anomalous road after feeling the abnormal vibration. Although the experimenter tries to tag the data as soon as possible, the delay always happens. Suppose we want to train a supervised classifier in the experiment, the inaccuracy of the labeling must be improved.

1.2.3 Road Condition Evaluation

In general, the GPS itself only offers the accuracy of 10 meter. A typical pothole usually spreads about one meter. The precision of pothole location can not be accurate than 10 meter. However, if we try to report the road anomaly to the government, the government prefers the information of a road section to a single point. Thus, they utilize the information of the road section to determine which road is needed to be fix immediately.

The detection system makes everyone join the process of road monitoring. If everyone can contribute their a little effort in road monitoring, the road anomaly will disappear soon.

1.3 Challenges

As mentioned in previous section, the accuracy of labeling is a big problem of training a supervised classifier [23]. In our experience, the supervised classifier performs poorly if we use the original labels in the data collection. There are two proposed solutions to solve this labeling problem: unsupervised classifier and relabeling technique.

1.3.1 The Model of Smooth Road

The unsupervised classifier tries to build a model of smooth road. In general, the majority of the data is smooth and even. Thus, by clustering the data into two groups, the smooth data is gathered and used to train a model of smooth road. Challenges in this question are the clustering technique modification and personalization in different vehicles.

1.3.2 Supervised Classifier for Relabeling

Relabeling is a technique that a computer will relabel the original label if possible labels are near original one in the given search window. Under the assumption of the original label is reliable in the given window, a supervised classifier is trained to relabel the possible tags near the original one.

1.3.3 Trade-off between Detection and Use

Other challenges are the limit of sensor frequency and accuracy. The low frequency, 25 Hz in our experiment, of acceleration device is used, and the accuracy of accelerometer on mobile device is worse than an external acceleration device. We try to decide a trade-off between the accuracy of anomaly detection and the convenience for users.

1.4 Thesis Organization

The thesis is organized as follows. In the beginning, the literature review of road surface monitoring and activity recognition from acceleration data are presented in Chapter 2. Secondly, we define our problems and propose solutions in Chapter 3. Thirdly, the overview and the implementation explanation of the anomaly detection system are shown in Chapter 4. Fourthly, we conduct experiments to verify the feasibility and evaluate the validness of the system in Chapter 5. Lastly, we conclude the contributions and mention the future work which can be further explored in Chapter 6.

Chapter 2

Literature Review

This chapter introduces some relate work for road surface monitoring using acceleration data. There are some applications which provide web 2.0 platforms for people to manually report the anomalies on the roads.

2.1 Pavement Roughness Evaluation

As the vehicle industry grows up, people are concerned about not only vehicle performance but also the comfort level which they feel during the driving. The two main reasons that affect ride quality are the vehicle response to the road and the surface roughness of pavement. International Roughness Index (IRI) is one of most commonly 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 vehicle and road surface. However, Loiszos [13] points out that IRI is often inadequate to describe the ride quality at speeds other than 80 km/hr. Moreover, Sun[20] also says that IRI is an indirect statistic of roughness, since it does not measure the pavement surface directly. Power spectral density (PSD)[13] is proposed to measure the road roughness directly. The vertical displacement data after Fourier transform is often used in PSD to analyse the wavelength, amplitude, and phase. As a result, IRI focuses on the comfort level to the passenger and PSD concerns directly about the analysis of road surface roughness. Gillespie [10] writes a tutorial to explain principle and basic idea of the IRI. In recent years, Wei et al. [22] use a toolkit called Wavelet for analysis and interpretation of road roughness.

2.2 Acceleration Data Recognition

2.2.1 Activity Recognition

In recent researches, activity recognition of human behavior from acceleration data is a popular issue, and such activity information is useful for context-aware service. In order to gain correct context, users often wear acceleration sensors on their wrists, ankles, or waists, so that the computer can learn human activities. A daily life experiment [1] is conducted by using acceleration data. With five biaxial accelerometers on their bodies, subjects also need to annotate current activity by themselves. This work uses the data collected out of lab and trains classifiers to distinguish 20 activities. Theses classifiers are decision table, decision tree (C4.5), Naive Bayes, and IBL. Finally, it achieves an overall accuracy rate of 84%.

Feature extraction of acceleration raw data is also an important problem. A triaxial accelerometer is used in Ravi's [16] experiment. This work selects four features in each axe, these features are mean, standard deviation, energy, and correlation. The acceleration data in a window is transformed by the discrete FFT, so that the sum of squared DFFT component magnitudes is defined as energy. For each pair of axes, the correlation can be calculated so as to differentiate one dimensional activity, such as walking, from two dimensional activity, such as stair climbing. Huynh et al. [11] analyzes how the performance of different feature set across different window sizes works in real world data. For each data window, this paper calculates the magnitude of mean, energy, variance, spectral entropy, and discrete FFT coefficients. The experiment results show some important conclusions. Firstly, FFT features often acquire high precision among other features. Secondly, different FFT coefficients will produce high precision in different activities. Moreover, short window size gains a high precision in activity 'standing' and low precision in activity between 'skipping' and 'hopping'.

Unsupervised activity recognition are also mentioned in [24, 21]. Both works uses the common sense as the base for training the activity recognizers. A fall detection system [2] is trained from the tri-axial accelerometer. This system is designed to take care and monitor the elder if something emergent happens.

2.2.2 Terrain Analysis for Mobile Robots

Terrain analysis is an important issue for auto-control of mobile robots. Different terrains need different controlling setting when robots meet an unknown environment. Planetary exploration rovers must have this ability to deal with unexpected situation.

Some researches use computer vision method or laser scanner data to recognize different terrain surfaces.

Using an accelerometer to analyse terrain is a direct and computing-saving method comparing to the computer vision method. A vibration-based method for terrain analysis is proposed by Brooks et al[3]. The accelerometer is installed on the wheel and vibration data is collected on a laboratory testbed. Brooks transforms vibration data into spectral domain and trains the priori distribution of different terrain. Terrain characterization and classification [15] are conducted on a Pioneer robot with a 2-axis accelerometer and a KVH fiber optic gyro. This experiment uses neural network to decide five types of terrain, which are gravel, grass, sand, pavement, and dirt. The trafficability characteristic is also discussed in this work. In recent works, Giguere [9] uses an iRobot with a inclined metallic rod, which equips with a single-axis accelerometer, to collect data. Six indoor and Four outdoor surface data are collected, and neural network are employed to classify ten different surfaces.

2.2.3 Fault Detection for Vehicle

In vehicle industry, there are some fault detection [7] techniques of the vehicles. These works assume that the road is good and try to build a detection principle if some parts of the vehicle are malfunctioned.

2.3 Road Surface Monitoring

2.3.1 Road Surface Monitoring Using Mobile Device

Road surface monitoring with sophisticated device are introduced in the previous section. However, the road quality are changed quickly by the time and the usage load. It is hard to monitor the road quality in real-time using standard monitoring cars, which are expensive and few. Recently, the Pothole Patrol[6] system uses three-axis accelerometer and GPS to detect and report the road surface conditions. This system is installed with a fixed orientation on the dashboard of a four-wheel vehicle, collecting data by seven cabs around the Boston area. Another system, TrafficSense[14], uses GPS, accelerometer, and microphone to collect data during driving, trying to monitor traffic and road conditions. One of the contribution of TrafficSense is that it uses Euler angle to reorient the acceleration data for arbitrary placement of the accelerometer. The above two works use simple device to accomplish road monitoring.

2.3.2 Websites for Monitoring Non-emergency Issues

Several websites aim to build a bridge between the government and people in order to collaboratively improve their living environment. Such websites collect issues from local residents and report the problems to related administrative units.

SeeClickWatch[1] introduces an easy-to-use interface on both web and mobile device for users in US. Some active users are likely to contribute their efforts to report problems. SeeClickWatch offers a function that when a particular area has a fixing or

[1] `http://www.seeclickfix.com/`

reporting event, a watch service will send email alerts to whom monitor this area.

FixMyStreet[2] provides a similar service in UK for achieving a goal of citizens online democracy. Volunteers can report local problems, such as potholes on the road, unlit lampposts, or abandoned beds. In order to fix the problem, FixMyStreet will send an email to relevant council.

In Taipei, the city government released a website, RCIS, [3] in April 2009. If someone wants government to fix road anomaly, the user can easily report the problem on the RCIS. Although RCIS suffers from its performance and laking of auto-response to the users who are concerned about some events, it indeed offers a good communication way between the government and citizens.

[2] `http://www.fixmystreet.com`

[3] `http://rcis.taipei.gov.tw`

Chapter 3

Anomaly Detection of Road Surface

This thesis emphasizes on the anomaly detection of road surface. These road anomalies, such as potholes, sunk-in manholes, missing pavement, or railway joints, causes abnormal vibration on the vehicles. By setting up the device on vehicles, users can collect the acceleration data of roads when they drive. After obtaining history data, the detection system analyses the vibration patterns of acceleration data so as to differentiate the anomalous vibration from the normal one.

3.1 Assumption

Before entering the part of problem definition, three assumptions need to be mentioned. We assume that the vibrating patterns for each vehicle during driving are similar. Those vibrating patterns will not change fast in a short time so that the same pattern of anomaly can be retrieved in the future. The second assumption is that the vehicle is in good condition of its suspension system. Under the normal state of the suspension system, the acceleration data collected by accelerometer on the vehicle will obtain similar value. These 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 the accelerometer.

3.2 Problem Definition

The main goals of this thesis are to classify the road surface and further evaluate road conditions. At the first stage, we emphasize on an issue about how to locate the anomalies on the road by analysing the sequence of acceleration data. Next, the conditions of each road section can be calculated using the statistics of acceleration data or the results derived from the first phase. Therefore, the road profile can be obtained by solving these two problems.

3.2.1 Road Surface Classification

There are two basic categories for describing the road surface: smooth road and anomalous road. The smooth road offers a good quality of driving surface when the vehicles pass through it, and the anomalous road is the complement of smooth road which appears to be more uneven than smooth one. Besides, the definition 1 clarifies more details and explanations on the road anomalies, and the types of road surface are listed and explained in the table 3.1.

(a) A severe pothole on the road (b) An anomalous pavement and manhole

Figure 3.1: Road Anomalies

Definition 1. Anomalous Road *($\mathcal{R}_\alpha$)*

The anomalous road is a description for road surface which is of bad flatness. The causes of bad flatness are potholes (figure 3.1(a)), manholes (figure 3.1(b)), or missing pavement on the road. Therefore, drivers feel uncomfortable when passing via road anomalies.

In order to locate and recognize the road anomalies, the acceleration data a collected on the vehicles is an primary index for classification. To be precise, the acceleration data $a =< a_x, a_y, a_z >$ is a vector which contains the acceleration values of three orthogonal directions. Each a is associated with a road point p, an instant speed σ, and a certain time t. We use GPS data to represent the position of a road point p, and it makes $p =< \lambda, \rho >$ where λ is the latitude and ρ is the longitude. As a result, the input data is defined as $\mathcal{X} =< a, \sigma, p, t >$. The problem is to discover a function which takes $\mathcal{X}$ as the input and outputs a corresponding labels of road $\mathcal{Y}$. The function of mapping single road point can be expressed as follows:

Road Type	Description
Smooth Road	The smooth road often refers to well-paved road. People see that there is no hole or bump on this kind of road, and feeling comfortable when driving in it.
Pothole	According to the Merrian-Webster Online Dictionary, a pothole is a pot-shaped hole in a road surface. There are several reasons which produce a pothole. Firstly, the flawed base of the pavement causes the leaks of road material when it rains. Secondly, the over usage by the vehicles cracks the pavement and results in a pothole.
Manhole	The manhole provides a way for workers to go underground and maintain some public utilities. However, the surface of manhole and the joint between normal road and manhole produce anomalous vibration to the vehicles due to careless construction. As a result, a passing through manhole may produce uncomfortable feeling to the driver.
Speed Bump	The speed bump forces driver to drive slowly when passing it. Moreover, the speed bump produces unsteady value for vertical and front acceleration data, and it generates different acceleration segment comparing to the pothole.
Anomalous Pavement	Anomalous pavement includes missing pavement and rising pavement. Missing pavement produces small holes on the road and rising pavement generates small bumps on the road. As a result, anomalous pavement causes a little uncomfortable feeling for the driver.
Railway Crossing	When vehicle passes the railway, severe vibration are appeared and causes passenger feel unwell. The abnormal vibration of railway crossing persists for longer than other anomalous road conditions.
Bridge Joint	Due to the expansion of construction materials in temperature, the bridge keeps some space between two sections. This causes a little vibration for vehicles.

Table 3.1: Labels for Road Surface

$$\mathcal{Y} = \mathcal{F}(\mathcal{X}) : \begin{cases} 1 & \text{if } \mathcal{X} \text{ is the data of anomalous road point} \\ 0 & \text{if } \mathcal{X} \text{ is the data of smooth road point} \end{cases} \tag{3.1}$$

However, if the function 3.1 only takes single input $\mathcal{X}$, the time characteristic will not take effect. In order to consider time issue, the segmentation of input data with a specified window size $\mathcal{N}$ is necessary. Moreover, it should assign at least half of the window size to the overlapping window size. The approach of separating the input data is to put the nearby $\mathcal{N}$ data together according to their time.

Definition 2. Input Data Segment *($\mathcal{X}_s$)*
The input data segment $\mathcal{X}_s$ contains a time series of input data $\mathcal{X}$, and this segment is defined as $\mathcal{X}_s = \{\mathcal{X}_1, \mathcal{X}_2, ..., \mathcal{X}_\mathcal{N}\}$, where $\mathcal{N}$ is the segmentation size. It divides $\mathcal{N}$ data $\mathcal{X}$ into segment $\mathcal{X}_s$ by their time.

Therefore, we convert the set of the input data $\mathcal{U}$ = $\{\mathcal{X}_1, \mathcal{X}_2, ..., \mathcal{X}_m\}$, where m is the size of $\mathcal{U}$, into the set of the input data segment $\mathcal{U}_s = \{\mathcal{X}_{s,1}, ..., \mathcal{X}_{s,k}\}$, where k is the size of $\mathcal{U}_s$. Thus, we modify the function 3.1 to the segmentation version.

$$\mathcal{Y}_s = \mathcal{F}_s(\mathcal{X}_s) : \begin{cases} 1 & \text{if } \mathcal{X}_s \text{ is the anomalous segment } \mathcal{X}_s^a \\ 0 & \text{if } \mathcal{X}_s \text{ is the smooth segment } \mathcal{X}_s^s \end{cases} \tag{3.2}$$

3.2.2 The Quality of Road Section

Vibration of the vehicle occurs when operating the vehicle. Furthermore, the strength and patterns of vibration will change because of the different road conditions and the vehicle speed. We assume that every vehicle has its own model of vibration and changes slowly in a short time. Another assumption is that the strength of vibration increases with the speed of the vehicle on the smooth road. If we can build a model of smooth road, the road anomaly is discovered by comparing with the model.

The second problem of this thesis is how to build the model of smooth road and how to use this model for the comparison. Suppose there is a set of input data segments, $\mathcal{U}_s = \{\mathcal{X}_{s,1}, ..., \mathcal{X}_{s,k}\}$, the goal is to learn a model $\mathcal{M}_s$ from all the smooth segments in $\mathcal{U}_s$. In our definition 3, this model changes with the speed so that we have a model set containing models which are varied with the speed.

Definition 3. The Model of Smooth Road ($\mathcal{M}_s$)
Since different speeds result in different vibration patterns, the model of smooth road at speed σ is $\mathcal{M}_s^\sigma$. Therefore, it makes the model of smooth road $\mathcal{M}_s$ is a collection of models with different speed σ. As a result, $\mathcal{M}_s$ for a certain vehicle is equal to the collection $\{\mathcal{M}_s^{\sigma,1}, ..., \mathcal{M}_s^{\sigma,n}\}$, where n is the size of different speed.

After training the model of smooth road, the classifying function 3.2, $\mathcal{F}_s(\mathcal{X}_s)$ transforms into the classifying function 3.3 with model of smooth road, $\mathcal{F}_s^\sigma(\mathcal{X}_s|\mathcal{M}_s)$.

$$\mathcal{Y}_s = \mathcal{F}_s^\sigma(\mathcal{X}_s|\mathcal{M}_s) : \begin{cases} 1 & \text{if } \mathcal{X}_s \notin \mathcal{M}_s^\sigma \text{ and } Speed(\mathcal{X}_s) = \sigma \\ 0 & \text{if } \mathcal{X}_s \in \mathcal{M}_s^\sigma \text{ and } Speed(\mathcal{X}_s) = \sigma \end{cases} \tag{3.3}$$

Once we have the classifying function with model of smooth road, the quality of road section is ready to be examined. From the definition of International Roughness Index (IRI)[10], 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 per mile (that is, ”inches/mile”). We modify the definition slightly into our own; therefore, our roughness index is defined as the cumulative anomalous segments per kilometer (ie., ”number/kilometer”). The details of roughness is in the definition 4.

Definition 4. Roughness Index Function *($\mathcal{I}(\mathcal{U}_R)$)*
Suppose $\mathcal{U}_s$ is divided into $\{\mathcal{U}_{R,1}, ..., \mathcal{U}_{R,n}\}$ according to the road section, the function $\mathcal{I}(\mathcal{U}_R)$ outputs the road anomalies per kilometer of road section covered by $\mathcal{U}_R$. The road anomalies is calculated by the function 3.2. That is,

$$\mathcal{I}(\mathcal{U}_R) = \frac{\sum_{i=1}^{n} \mathcal{F}_s^{\sigma}(\mathcal{X}_{s,i}|\mathcal{M}_s)}{Length(\mathcal{U}_R)} \tag{3.4}$$

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

The roughness index function in equation 3.4 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 are good, fair, inferior, and dangerous, and three thresholds need to be learned for assigning semantic labels to the road section.

Definition 5. The Semantic Descriptors for Road Section *($\mathcal{S}_{descrp}$)*

A road section has a set of data segments $\mathcal{U}_R$, and corresponding roughness value is calculated by the roughness index function. Once the roughness value is calculated, the semantic descriptor $\mathcal{S}_{descrp}$ is assigned to the road section. These semantic descriptors $\mathcal{S}_{descrp} = \{\mathcal{S}_g, \mathcal{S}_f, \mathcal{S}_i, \mathcal{S}_d\}$ are good, fair, inferior, and dangerous respectively.

3.3 Proposed Solution

In this section, we present the approaches and algorithms for solving road surface classification and estimating the quality of road section. At first, we explain the preprocessing approaches for the input data. Secondly, the method for classification is proposed. Lastly, the estimation of road condition is introduced so that we can use the mobile phone to monitor the road conditions.

3.3.1 Input Data Preprocessing

Input data preprocessing in data cleaning and data format changing is necessary. Moreover, the re-labeling issue is discussed because the synchronization of several sensors is uneasy. Later, filtering method helps us gain useful data. Finally, the segmentation of the input data not only reduces the computation time but also increases information in classification.

Labeling

The labeling process is a difficult problem in this thesis. Assuming that the pothole stretches for 1 meter in general, the contacting time between the pothole and the vehicle with 36 km/hr speed is 0.1 second. That means the tagging system must be precise in 0.1 second, and location system should be accurate in 1 meter. However, people often tag the pothole after passing it, and it produces a time delay for tagging. Not only the tagging system but also the GPS location system are inaccurate enough for labeling the pothole. As a result, it is very hard to tag corresponding acceleration data signals and locate the exact position of the pothole, and we should come up with an approach for solving these problems.

In order to improve the labeling accuracy, the re-labeling process is proposed. We use a labeling window to seek suspicious data near original label, and replacing the original label with the new one. There are three methods for re-labeling. Firstly, we watch the raw data directly and re-label the new one. Secondly, we pre-defines some heuristics and search suspicious one. Lastly, we train a classifier for re-labeling because it is believed that the suspicious data is near the original one. Therefore, the accuracy of labeling improves so that the precision of anomaly detection increases.

Filtering

Filtering helps us gain useful and trustful data from the original one. Suppose the vehicle is stopped, the data obtained at this time cannot be analysed for measuring the road roughness. We abandon those data by checking the speed σ in $\mathcal{X}_s$. Next, a simple high pass filter method [19], equation 3.5, is used since the low frequency data, like gravity, does not affect the result of anomaly detection. Thirdly, the data collected at the turning point is discarded because the inclination of vehicle's body changes the acceleration value.

$$y(t) = \alpha y(t-1) + \alpha(x(t) - x(t-1)) \tag{3.5}$$

Segmentation

Considering the nearby data of single input data, the segmentation offers information about a sequence of acceleration data in stead of a single one. The road anomaly is hard to be observed only by a single acceleration data $\mathcal{X}$. Here, we propose two methods for segmentation. Firstly, we put nearby data into the same segment with a maximum window size N. Secondly, we divide the data according to the length L. If the maximum length of each pair in segment exceeds L, the new segment is formed and collects nearby data. Moreover, the overlapping of the window is needed, and it is usually set as at least half of the segment size.

3.3.2 Method for Road Surface Classification

The purpose of road surface classification is to recognize and locate the road anomaly. The input data segment $\mathcal{X}_s$ contains the acceleration values a_x, a_y, a_z in three directions, the instant speed σ, and position $p =< \lambda, \rho >$. We extract features from $\mathcal{X}_s$ and further use these features for classification.

Feature Extraction

Good Features are important indicators for classification. We consider the data of accelerometer a_x, a_y, a_z and the instant speed σ when reading this data for feature extraction. Gadelmawl et al. [8] defines about 59 of roughness parameters for measuring road surface. We choose some of them and modify these parameters into the version of acceleration. Furthermore, the first-order difference of the acceleration data and the histogram of the acceleration are also considered. The table 3.2 shows an overview of our features.

Features	*Descriptions*
$\mathcal{R}_{q1,i}$	the first quartile in i-axis
$\mathcal{R}_{me,i}$	the median in i-axis
$\mathcal{R}_{q3,i}$	the third quartile in i-axis
$\mathcal{R}_{m,i}$	the mean in i-axis
$\mathcal{R}_{r,i}$	the range in i-axis
$\mathcal{R}_{std,i}$	the standard deviation in i-axis
$\mathcal{R}_{p,i}$	the maximum peak in i-axis
$\mathcal{R}_{pm,i}$	the mean of peak in i-axis
$\mathcal{R}_{v,i}$	the minimum valley in i-axis
$\mathcal{R}_{vm,i}$	the mean of valley in i-axis
$\mathcal{R}_{sk}$	Skewness
$\mathcal{R}_{ku}$	Kurtosis
$\mathcal{S}_{m}$	the mean of segment speed
$\mathcal{S}_{std}$	the standard deviation of segment speed
$\mathcal{H}_{i}$	histogram of i-axis
$\mathcal{D}_{sum,i}$	the sum of absolute difference value in i-axis

Table 3.2: Features extracted from input data segment $\mathcal{X}_s$

Classification Method

The training process is notified after extracting required features. LIBSVM [5] is a library package for support vector classification. Given a set of training data $\mathcal{U}_s$, the support vector machine wants to construct a hyperplane that optimally separates the training data into desired number of categories. Therefore, the model of road surface is learned for future classification.

3.3.3 The Model of Smooth Surface

This section introduces an unsupervised method for building the model of smooth surface. 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 [4, 18] of every $\mathcal{H}_s$ and use this distance as a measure for clustering. Hierarchical clustering [12] is proposed to obtain the data of smooth road. Under the assumption that the data of smooth road is the majority, half of the data is collected to form the model of smooth surface.

The Distance of Histogram

Finding a distance, or similarity of two histograms [4, 18] is an important issue in pattern recognition. There are two methods for estimating the distance of two histograms: vector and probabilistic. We choose the vector way to calculate the distance between histograms. The histogram $\mathcal{H}(\mathcal{X}_s)$ is considered as a b-dimensional histogram vector of the input data $\mathcal{X}_s$; therefore, city block or Euclidean distance measure can be used to calculate the distance of these vectors.

We let $\mathcal{V}$ be the discrete value of the measurement with a size b, $\mathcal{V} = \{v_1, ...v_b\}$ Suppose the vector of histogram is $\mathcal{H} =< \mathcal{H}_1, ..., \mathcal{H}_b >$ and the acceleration value of input data is $\mathcal{A}(\mathcal{X}_s) = \{a_1, ..., a_n\}$, we then can compute the histogram vector according to the equation 3.6. Finally, the Euclidean distance method is chosen to calculate the distance between two vectors of histogram.

$$\mathcal{H}_i(\mathcal{A}(\mathcal{X}_s)) = \sum_{j=1}^{n} c_{ij} \;\; where \; c_{ij} = \begin{cases} 1 & \text{if } a_j = v_i \\ 0 & \text{otherwise.} \end{cases} \quad \text{and } 1 \leq \text{i} \leq \text{b} \tag{3.6}$$

Model Building

Being different from the method of supervised classification mentioned above, we propose an unsupervised method for learning the model of smooth surface $\mathcal{M}_s$ from the set of the input data segment $\mathcal{U}_s$. The model of smooth surface is a finite set of models $\mathcal{M}_s^{\sigma}$ with different speed 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 proposing a method of model building in algorithm 1.

Algorithm 1: The algorithm of building the model of smooth surface

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

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

3.3.4 Evaluation of Road Quality

There are two methodologies for the evaluation of road quality. Firstly, by using the road surface classification, the number of anomalies can be calculated. Second, by using model of smooth surface $\mathcal{M}_s$, we set a threshold to determine whether the input data segment is anomalous or not. As a result, both methodologies can output the anomaly number of the road segment to the roughness index function in definition 4 so as to obtain the road condition of the given road section.

Every road segment has a grade of road quality, and this quality is calculated by the roughness index function in equation 3.4. After computing grades of the given road segments, we obtain a rank list for road segments. The list shows the best road segment to the worst one in the increasing order. However, we do not know whether the rank list is good or not, so Kendall tau correlation coefficient [25, 17] is proposed to measure the correlation between the rank list $\mathcal{L}_e$ of evaluator system and ground truth list $\mathcal{L}_g$. Both $\mathcal{L}_e$ and $\mathcal{L}_g$ are the same size $\mathcal{N}$. A rank list $\mathcal{L} =< r_1, ..., r_{\mathcal{N}} >$ contains distinct $\mathcal{N}$ ranks which range from 1 to $\mathcal{N}$. For example, if the size of $\mathcal{L}$ is 3, one of possible lists is $\mathcal{L} =< 1, 3, 2 >$.

Concordant pairs are two ranking pairs that are ranked in the same order. On the contrary, *Discordant* pairs are two ranking pairs that are ranked in the opposite orders. Suppose there are two rank lists $\mathcal{L}_1 =< 1, 2, 3, 4 >$ and $\mathcal{L}_2 =< 2, 1, 3, 4 >$, the ranking pairs $< 1, 3 >$ and $< 2, 3 >$ are concordant pairs. The ranking pairs $< 1, 2 >$ and $< 2, 1 >$ are discordant pairs.

Definition 6. Kendall Tau Correlation Coefficient *(τ)*
Suppose $\mathcal{C}$ is the total number of concordant pairs and $\mathcal{D}$ is the total number of discordant pairs, the Kendall tau correlation coefficient τ of two rank lists $\mathcal{L}_1$ and $\mathcal{L}_2$ with size $\mathcal{N}$ is defined as follows:

$$\tau(\mathcal{L}_1, \mathcal{L}_2) = \frac{\mathcal{C} - \mathcal{D}}{\mathcal{N}(\mathcal{N} - 1)/2} \tag{3.7}$$

The Kendall Tau correlation coefficient ranges from -1 to 1. If τ is 1, then it means that two ranks are highly correlated and in the same order. Suppose τ is 0, it means that two ranks have no correlation. However, if τ is -1, it means that two ranks are in the opposite order but highly correlated. As a result, we will use Kendall tau in equation 3.7 as a measure to judge the performance of the rank list produced by evaluator system for road segments.

Chapter 4

Implementation

This chapter introduces the overall architecture of the anomaly detection system, and implementation details will be mentioned.

4.1 Hardware and Software Setup

This section presents the preparations of devices and programs for the experiments. Sensors of this experiment are a GPS, an accelerometer, a smartphone device, a sound recorder, and a two-wheel vehicle. After the installation, the rider operates a motorcycle around Taipei City so as to collect necessary data for road surface analysis.

4.1.1 Hardware Setup

In our system, several sensors and devices are used in order to collect both location and acceleration data. There are four necessary devices which are used in our experiment.

HTC Diamond, in figure 4.1(a), is the main platform for the storage of all the sensor data, and it also has a built-in accelerometer with a maximum 25 Hz data frequency. Secondly, an external GPS sensor, NCS Navi R150+ GPS logger in figure 4.1(b), is used to collect precise location data. Thirdly, the recorder, in figure 4.1(c), is used for the labeling process because it is dangerous for the rider to use its hands to label the anomaly. Lastly, a motorcycle, in figure 4.1(d), which travels the city to collect the acceleration data on the vehicle.

Hardware Placement

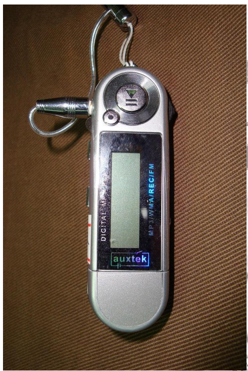
The HTC Diamond is installed inside the store box of the motorcycle, so the coordinate of accelerometer is the same with the coordinate of motorcycle as seen in the figure 4.1(d). Moreover, the x, y, and z-axis of the accelerometer represents the direction from left to right, from bottom to top, and from front to rear of the vehicle respectively. The figure 4.2 shows the coordinate of motorcycle and accelerometer. Lastly, both the GPS device and the recorder are hanged on the neck of the riders. The GPS device needs an open environment to receive correct data and the recorder can collect the labels from the voice of the rider.

4.1.2 Software Setup

There are two important parts of the detection system: the client side and the server side. The sensors are brought by the users and send information back to the server for analysis. At this time, all the information is processed on the server side, and the client side is only responsible for collecting the data. Once many users are willing to collect

(a) The platform collects the acceleration data

(b) The external GPS device



(c) The sound recorder for labeling process

(d) The motocycle for data collection

Figure 4.1: Equipments in the experiment

the data, the status of the road is monitored by everyone.

Data Collection

The mobile device is an excellent tool for everybody to collect the data on the road. There are many advantages of using mobile devices. Firstly, the pervasive characteristic is an important issue for us to not only share the road condition immediately but also avoid the road anomalies. Moreover, it is easy to carry the device with the user in any kind of vehicles. The low power usage of the accelerometer also provides a benefit for users to contribute their acceleration data. However, the GPS device may cause too much power loss, but other possibility is to use Wi-Fi location tracking to save power.

The software on the mobile device is written in c-sharp language because it is simple to build an interface for data collection. The accelerometer and GPS data are both stored on the mobile device. When the device connects to the Internet, the data records will be transmitted to the server for analysis.

Data Analysis

After gathering data from sensors, several modules are built for data analysis. We build these analysis modules on an Unix-like system, and obtaining data via a specified port. At first, these data should be preprocessed before learning the model. Several preprocessing modules are needed: data filtering, segmentation, and feature extraction. Secondly, the learning model should be trained before classifying. We use two learning models: LIBSVM and model of smooth road. LIBSVM is a supervised learning library and needs labels for training a model. The model of smooth road obtains majority of the original data using hierarchical clustering method, and several thresholds are trained from the data of smooth road. Finally, road anomaly detection system uses two models to decide the road condition, and a road quality evaluator is proposed to evaluate the quality of the road segment.

Figure 4.2: The coordinate and inner placement of the motorcycle

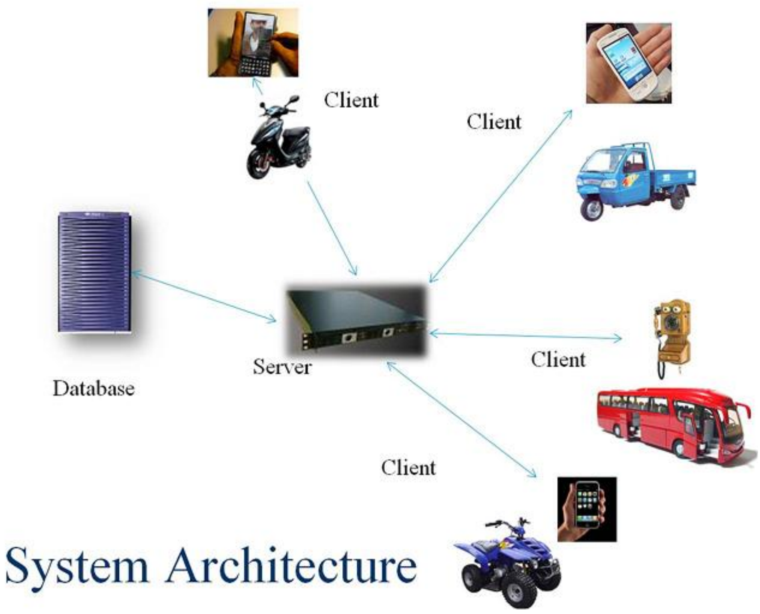


Figure 4.3: The architecture of the detection system

4.2 System Architecture

This section introduces the architecture of the detection system. The system can be divided into two parts: the user side and the server side. The figure 4.3 shows the overall picture of the detection system. Our goal is to create an environment of mobile sensor network. Every client contributes its information from its own sensors, and the server gathers these information and forms a map of road quality.

4.2.1 User Side

Every user has a mobile device that collect the data, such as GPS information, or acceleration data. Some preprocessings of the data will be done at the client side. For example, the filtering segmentation, and feature extraction are handled at the client side. Once the user has these data, the data are synchronized and transmitted back to the server.

People use mobile device to share their knowledge about the environment, and using other people's information to avoid possible disaster. This is a primary advantage and motivation for everyone to join this mobile sensor network. People can report the road anomalies by passing messages or pictures to the websites. Besides, people can install the detection system on the mobile device to automatically monitor the road conditions.

4.2.2 Server Side

There are two main services of the server. Firstly, the server gathers data from different places, trying to analyse and aggregate them together. When client passes the data to the server, the server will analyse the data of certain client. Each client will have a unique model of its vehicle, so if the vehicle is changed, the client should notify the server. We use a Unix-like system in our server side, and the server program is written using the python language.

Secondly, the server provides necessary information for the users to avoid the road anomalies. While the user on client side operates a vehicle and connect to the server, the server will broadcast the road condition to the clients for safety. Furthermore, if some place occurs emergent situation on the road, the server will send the information to the relevant government unit.

Chapter 5

Experimental Design and Results

In this chapter, we present the design and results of the experiment. At first, the process and description of data collection are shown. The relabeling process is used to improve the accuracy of labels. Secondly, we evaluate road anomaly detection system using two differnt speed of three data sets. Finally, the road segment evaluator is built for reporting the quality of every road segment. The results of evaluator are compared with the users who actually rides across the same road.

5.1 Data Collection

In order to collect necessary data, three sensors are installed on the motorcycle. Firstly, the accelerometer in the mobile device provides the vibration data between the road and the vehicle. Moreover, the frequency of the accelerometer is 24 Hz. Secondly, the GPS device offers the location information of the vehicle in latitude and longitude every second. Lastly, the voice recording pen records the voice of anomalous labels if the vehicle passes the uneven road. These three data will be combined together by their time.

5.1.1 Data Description

Three data sets are collected in the same motorcycle, and each data set contains four paths with two different maximum speeds. These two maximum speed are 30 km/hr and 40 km/hr respectively. We try to keep the same speed during the data collection. Then, two paths remain 30 km/hr and the other paths remain 40 km/hr in one data set. The passing roads of three data sets can be found at the table 5.1. It costs 3 hours to collect the data, which has twelve different roads listed in table 5.1 and the total distance of 52 kilometers. Moreover, the data is collected in dry weather at the midnight. Data set 1 is obtained on 16 May 2009, data set 2 is on 25 May 2009, and data set 3 is on 27 May 2009.

Labeling is the most important thing during the data collection. The road anomalies are tagged if the experimenter feels unstable when passing certain position. In our experiment, the labeling tool is an audio recorder, and it collects the label voice of the experimenter. There are three labels used in the data collection: potholes, bumps, and the smooth road. Both potholes and bumps are road anomalies. In most situation, the smooth road is the majority labels among three labels, so the experimenter only tags the road anomalies in the voice recorder.

The tags in the voice recorder are extracted by human after the experiment. Those tags are listed with their types and happening time in second. Therefore, we need to synchronize three kinds of data: the location information from GPS, the acceleration data, and tags of the voice recorder. All of the data start at the same time, so the synchronization process uses their time as a measure for data integration.

Data Set	#1	#2	#3
Figure	Fig. 5.1(a)	Fig. 5.1(b)	Fig. 5.1(c)
Road 1	Sec. 4, Jhongsiao E. Rd.	Sec. 1, Fusing S. Rd.	Sec. 2, Sinhai Rd.
Road 2	Lane 216, Jhongsiao E. Rd.	Sec. 3, Civic Blvd.	Sec. 3, Keelung Rd.
Road 3	Sec. 4, Ren-ai Rd.	Sec. 1, Shinsheng S. Rd.	Sec. 4, Roosevelt Rd.
Road 4	Sec. 1, Jianguo S. Rd.	Sec. 3, Sinyi Rd.	Sec. 3, Shinsheng S. Rd.
Distance	3933m	5052m	3985m

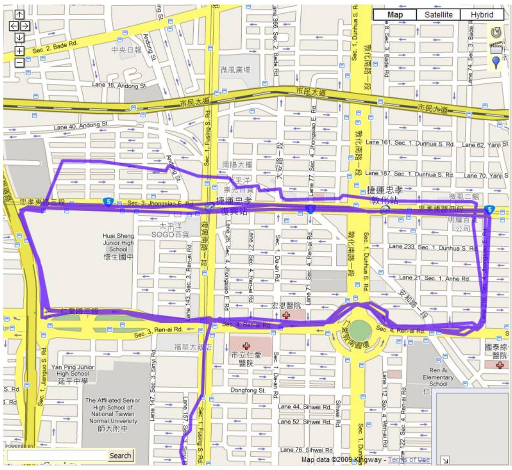
Table 5.1: The road coverage of the data sets

5.1.2 Data Observation

Before jumping to the experimental result, some observations from the acceleration data are listed in this section.

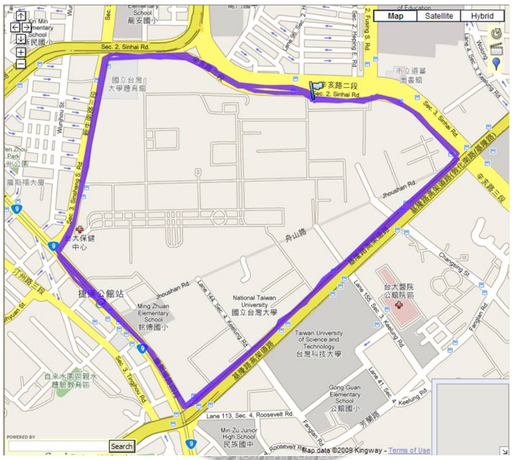
Label Shifting

The accuracy of labeling is a big problem for the training process because it is too fast to tag the anomalous road at the same time. Considering the experimenter wants to tag the label while passing anomalous road, the experimenter feels the unstable vibration and then tags the data. Although the experimenter tries to tag the anomalous road as soon as possible, the shifting of label still can not be avoided. Moreover, due to the different responding time to the different anomalous road, the experimenter has different delay time of tagging. This brings about a problem that the label shifting can



(a) data set #1

(b) data set #2



(c) data set #3

Figure 5.1: The map of data sets

not be solved by simply moving data in a constant time.

Another cause of label shifting is the different starting time of three sensors. The experimenter tries to open three sensors simultaneously, but a little time shift still occurs because of the human control. The data frequency of the acceleration data is high so that any little shift results in the inaccuracy of the labeling.

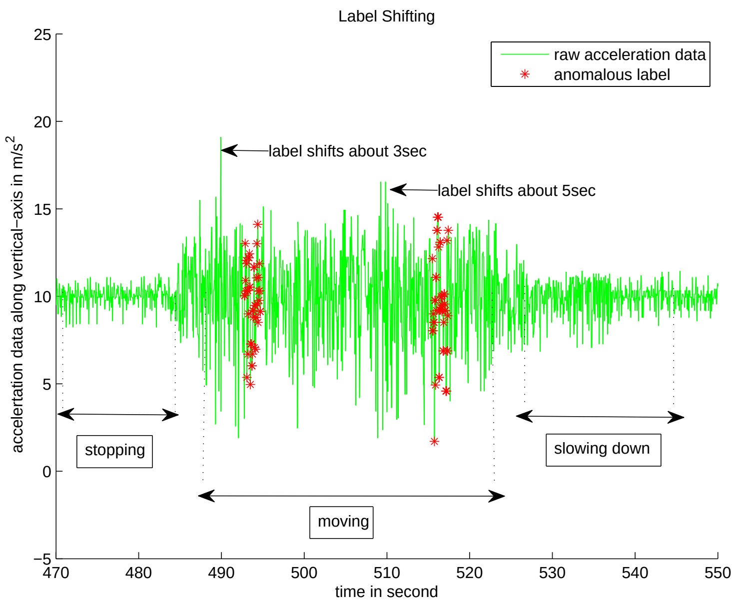


Figure 5.2: A typical label shifting problem of the raw data

As we can see in the figure 5.2, the shifting situation happens. The y axis of the figure 5.2 is the vertical acceleration data, and it contains the gravity of 9.8 m/s^2 from Earth. In stopping situation, the vertical data has a little vibration due to the engine of the vehicle. When the motorcycle enters the moving mode, the vertical vibration becomes much larger than stopping one. The asterisk sign in the figure represents the anomalous label tagged by the experimenter. By our intuition, the vertical acceleration value increases sharply if the motorcycle bumps into a road anomaly. Interestingly, two peaks which are much higher than other peaks are not tagged but they are near two anomalous labels respectively. Thus, the shifting problem happens and these two labels need to be shifted to the correct position.

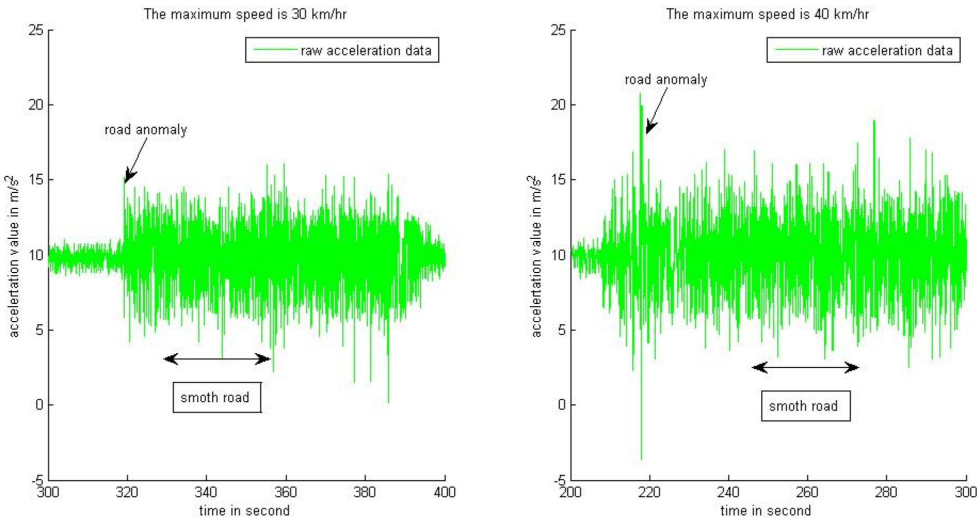


Figure 5.3: The anomalies and smooth road in different speed

The Data of Road Anomalies

In figure 5.3, the acceleration data near the road anomaly usually has a higher peak or lower valley than the smooth one. These impulses stick out of the nearby data and clearly indicate that they are road anomaly. Moreover, both two figures in figure 5.3 shows the vertical acceleration data when the vehicle passes the same road with different speeds. The right figure has a higher strength of road anomaly in 40 km/hr than the strength of road anomaly in 30 km/hr.

Not only vertical acceleration but also front-rear acceleration are affected by the road anomaly. As we can see in the figure 5.4, road anomaly r_1 and r_2 vastly change the value of both vertical and front-rear acceleration. This evident shows the relationship between vertical and front-rear acceleration when meeting the road anomaly.

The very dangerous road results in the immense peak and valley from nearby data.

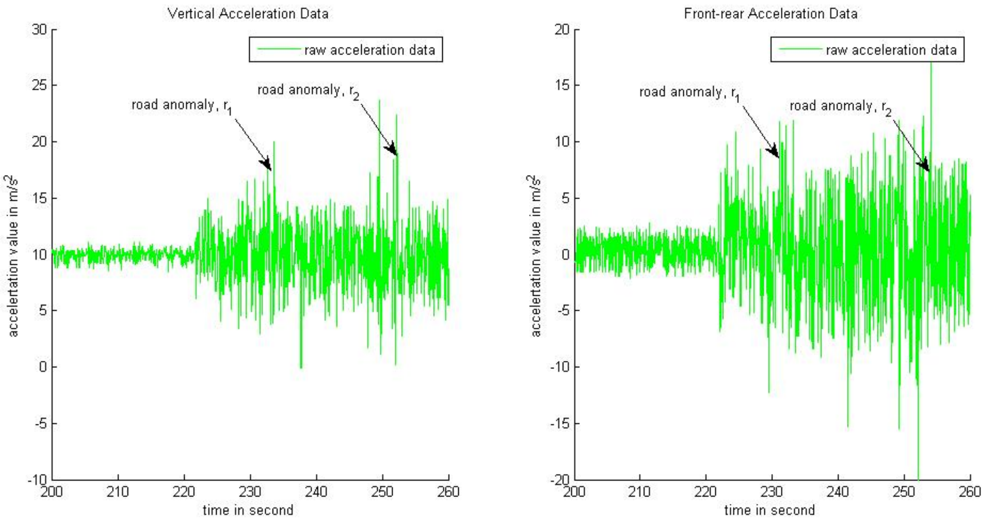


Figure 5.4: The relationship between vertical and front-rear acceleration data

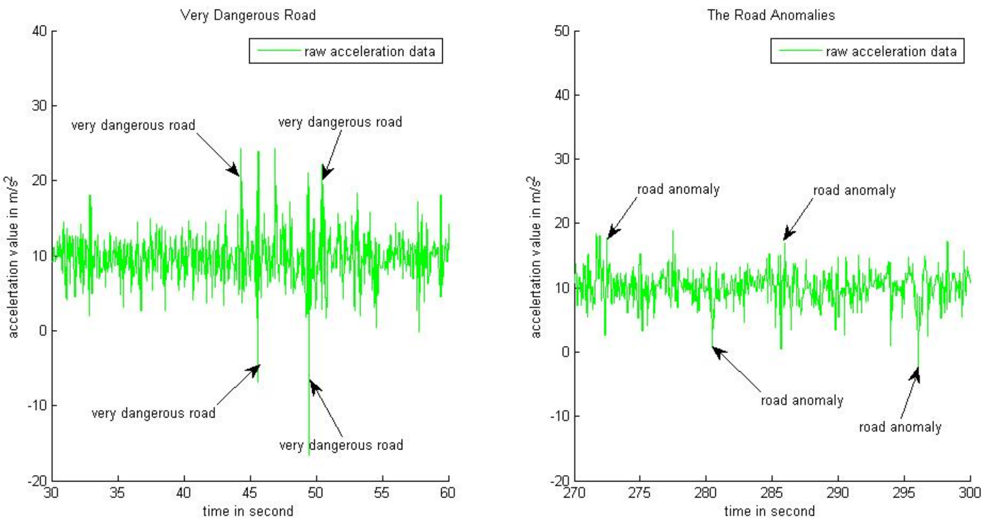


Figure 5.5: Highly dangerous road and typical road anomalies

These kinds of data differ from the common road anomalies, causing threat to the drivers for safety reason. In figure 5.5, very dangerous road has the vertical acceleration value twice or three times higher than the smooth road. These kinds of dangerous road are easier to discover than common road anomalies.

The Data of Smooth Road

The data of smooth road has different strength of peak and valley in vertical acceleration data when passing the smooth road with different speeds. In figure 5.3, the left figure is the data of the speed 30 km/hr and the right one is the data of the speed 40 km/hr. The data of right figure in smooth road has higher peaks and valleys than the left one. It shows that the vibration strength on the same road changes with the speed.

Table 5.2 shows the statistics of the data set #2. The standard deviation of the acceleration data in both vertical and front-rear direction increases as the speed increases. According to the minimum and maximum value, the peaks and valleys also become larger as the speed increases. We obtain an evidence that the values of vertical and front-rear acceleration of the smooth road are affected by different speeds.

Statistics	*Vertical direction*				*Front-rear direction*			
Speed	*Min*	*Max*	*Mean*	*Std*	*Min*	*Max*	*Mean*	*Std*
10-20	-1.44	19.17	9.92	1.06	-10.42	11.07	0.53	1.80
20-30	-1.44	20.48	9.89	2.36	-14.46	15.49	0.18	3.25
30-40	-5.74	23.91	9.92	2.65	-22.98	24.24	0.37	4.39

Table 5.2: The statistics of data set #2

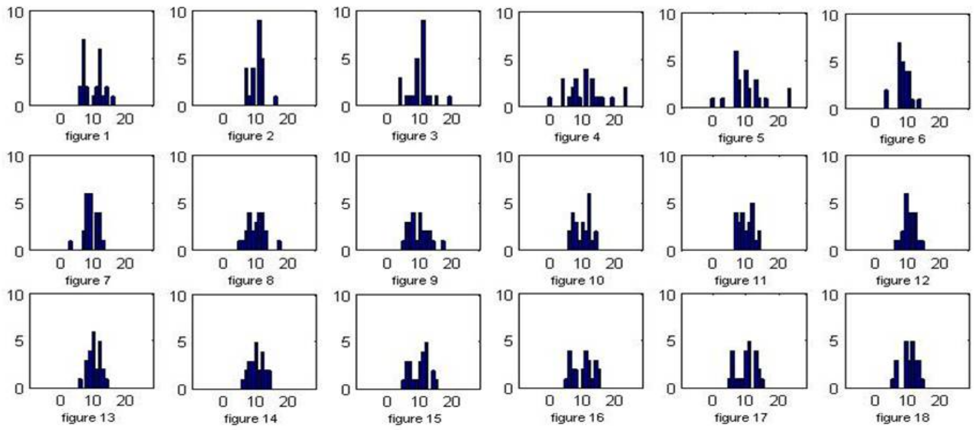


Figure 5.6: Histograms of a sequence of data segments in windows size 24

The histogram of a Data Segment

Figure 5.6 shows a sequence of histograms with moving window. These histograms are formed by continuous vertical acceleration data, and each histogram contains 24 data and overlaps 3/4 data with nearby histograms. The horizontal axis is the vertical acceleration value measuring in m/s^2 and the vertical axis is the number of acceleration data that falls in specified acceleration bin.

We observe that the road anomaly happens from the histogram 3 to histogram 8. At first, the histogram becomes widened in histogram 3 and has lower peak in histogram 4. Moreover, the remaining histograms are formed by passing the smooth road, they are denser and much centralized than the histograms of road anomalies.

5.2 Evaluation

In this section, the anomaly detection and the quality evaluation of road sections are presented. The anomaly detection uses LIBSVM, a machining learning library, for the classification of road surface. The quality evaluation of road sections is based on the results of anomaly detection, computing the grade of road sections according to the number of anomalies per kilometer.

5.2.1 Anomaly Detection using LIBSVM

LIBSVM[4] is used in our experiments for the classification of road surface. The important stages of supervised learning are feature extraction and selection, labeling, learning, and testing. We will focus on the feature selection and labeling problem of the anomaly detection.

Feature Selection

First of all, the acceleration data is segmented with different window size. These window sizes are 12, 24, 36, and 48, representing 0.5, 1, 1.5, and 2 seconds respectively. Secondly, the features are extracted from each segment, and they can be selected from table 3.2. In the experiment 1, we choose the following features in table 5.3 among three axis and total acceleration value.

Relabeling

Due to the label shifting problem of the data, the relabeling process is proposed to improve the accuracy of the data. Instead of relabeling the raw data directly by human, the computer uses simple heuristic function to relabel the data. Recalling that the original labels are collected in voice recorder, we assumes that these labels are reliable and the correct labels are near the original one. Thus, the seeking window is predefined for computer to seek suspicious data near the original label.

There are many heuristic functions can be used for relabeling. We define two thresholds that used for relabeling. Firstly, the maximum absolute value of the vertical acceleration data from the equilibrium point. Secondly, the maximum absolute value of the front-rear acceleration data from the equilibrium point. These thresholds are learned directly from the statistics of the our data set by human. Thus, the accuracy of the labels increases because of relabeling process.

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

Table 5.3: Selected features for experiment 1

Results of Experiment 1

Table 5.4, table 5.5, and table 5.6 are the results with different data set in experiment 1 using LIBSVM. The precision measures the correctness of the road anomalies, and it shows the confidence of road anomalies detected by the classifier. The recall of road anomalies means how many road anomalies have been detected so far, and it shows the percentage of road anomalies already detected. The accuracy shows the validness of two classes, road anomalies and smooth road.

In this experiment, different window sizes affect the result of the detection system. As the window size increases, the accuracy and precision increase. Although longer window size has a better result, the position of road anomaly becomes imprecise. In general, the motorcycle moves about 10 meter per second in the speed of 36 km/hr and a road anomaly, like a pothole, usually spreads only 1 meter long. Suppose the window size of 48 is chosen, the road anomaly could be in a circle with 10-meter radius.

Moreover, the precision is much important than the recall in this problem, because if everyone contributes a little information, the road anomalies are soon discovered. Due to the aim of mobile sensor network, we only need to emphasize on the performance of the precision for road anomalies.

Finally, the experiment 1 shows that the average result of precision is about 78.5% and the average result of recall is 70.5%. In the next section, we further use the anomaly detection system for evaluating the quality of the road section.

Data Set #1	*Speed*					
	30 km/hr			40 km/hr		
Window Size	*Precision*	*Recall*	*Accuracy*	*Precision*	*Recall*	*Accuracy*
12	55.1%	30.9%	92.2%	34.9%	68.5%	89.0%
24	72.6%	55.0%	88.4%	40.1%	89.8%	79.4%
36	79.9%	66.2%	88.0%	45.1%	93.0%	74.4%
48	81.4%	70.7%	86.5%	51.2%	94.8%	74.8%

Table 5.4: The classification results in data set 1 with different window size and speed

Data Set #2	*Speed*					
	30 km/hr			40 km/hr		
Window Size	*Precision*	*Recall*	*Accuracy*	*Precision*	*Recall*	*Accuracy*
12	78.4%	61.0%	95.3%	86.6%	63.9%	92.8%
24	74.6%	84.1%	93.0%	90.3%	85.6%	93.8%
36	82.3%	93.5%	94.4%	94.9%	91.4%	95.3%
48	81.4%	96.0%	93.5%	94.0%	94.5%	95.2%

Table 5.5: The classification results in data set 2 with different window size and speed

Data Set #3	*Speed*					
	30 km/hr			40 km/hr		
Window Size	*Precision*	*Recall*	*Accuracy*	*Precision*	*Recall*	*Accuracy*
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 5.6: The classification results in data set 3 with different window size and speed

5.2.2 Quality Evaluation of Road Section

After the classification of the road anomaly, the evaluation of road quality is proposed and compared. In this section, the model of smooth road is built and used to determine the number of anomalies in the given road section. The quality evaluation system gives the rank result of roads. Further, we compare the rank result of the system with the rank result of three users who ride the motorcycles to pass the same road.

The Model of Smooth Road

The different suspension system of motorcycles and the different weight of motorcycles cause the different model of smooth road. We keep historical data and try to train a model of smooth road.

By the assumption that the majority of the collected is the smooth road, we seek to cluster the smooth road together and build a model of smooth road. In figure 5.6, histograms of smooth road are dense and centralized. Thus, the features of histogram are extracted for clustering process.

At first, the data is divided according to their speed because the vibration range of smooth data increases as the speed increases. Next, the maximum and minimum value of the histogram are extracted for clustering. Hierarchical clustering is used to separate the data into two different size clusters. Under the majority assumption, we wish to have two size: 90% and 10% of the original data.

Once the data of smooth road is obtained, we start to establish the model of the smooth road. Some model parameters are learned from the data of smooth road, and this model is used to decide whether an input segment is anomalous or not.

Road Quality Evaluation by Users

Three inspectors ride across the roads in data set #3 and give the rank for those roads. The rank results of three inspectors are listed in the table 5.7. 1 means the best road and 4 means the worst road, and the total rank list $\mathcal{L}_g$ is calculated according the ranks of three inspectors.

	Data Set #3	Rank 1	Rank 2	Rank 3	Total Rank
Road 1	Sec. 2, Sinhai Rd.	4	4	4	4
Road 2	Sec. 3, Keelung Rd.	1	1	2	1
Road 3	Sec. 4, Roosevelt Rd.	3	3	3	3
Road 4	Sec. 3, Shinsheng S. Rd.	2	2	1	2

Table 5.7: Ranks of roads, the road with smallest grade is the best

Road Quality Evaluation by the System

According to our roughness index function 3.4, the roads in data set #3 can be sorted according to their grade of roughness index function. At first, The evaluation system uses the model of smooth road to determine the number of anomalies, and calculating the length of the given road section.

The table 5.8 shows the rank result $\mathcal{L}_e$ of the evaluation system. The system computes the grade by the equation 3.4 and sort the roads according to the grade. The ranking result is slightly different in the first and second place between three inspectors and the system. Moreover, the inspectors say that they are also hard to decide the first place from Roosevelt Rd. and Shinsheng S. Rd. This means our evaluation system produces an acceptable rank result.

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

Table 5.8: The grade and rank decided by the evaluation system

The Correlation Between Two Lists

After getting two rank lists $\mathcal{L}_g$ and $\mathcal{L}_e$ produced by three inspectors and by the system, the Kendall tau $\tau(\mathcal{L}_g, \mathcal{L}_e)$ of two rank lists is 0.67 because $\mathcal{C}$ is 5, $\mathcal{D}$ is 1, and size $\mathcal{N}$ of rank list is 4. Therefore, we obtain a good rank correlation value of these two rank lists.

Chapter 6

Conclusion

This thesis explores the possibility of road anomaly detection with mobile device on motorcycles. Two different approaches, supervised and unsupervised learning, are proposed to detect the road anomalies. The quality evaluation of road sections is based on the result of the detection system, trying to calculate the number of anomaly per kilometer according to equation 3.4.

While some websites aim to monitor the city by volunteers who provide information via the internet or their cell phone, the automatic detection system in the cell phone on any kinds of vehicles offers a better way to monitor the city without consciousness. This increases the willings of people to share their information of the mobile device, and making the road information update much quickly than the expensive and few road examination cars of the government.

The motorcyclists are happy with the road quality information especially when the weather is rainy and the time is in the evening. The line of sight of motorcyclists is often dim and unclear under above situations so that it is easy to happen car accidents. As a result, providing such road contexts makes motorcyclists safer and more comfortable during riding.

The low frequency of accelerometer produces a good result of the detection system when the position of the road anomaly does not need to know precisely. These are the limits of accelerometer and GPS sensor for knowing the exact position of the road anomaly. This thesis uses the model of the smooth road to evaluate the quality of roads, an approach which can learn new model on different vehicles.

6.1 Summary of Contributions

At the beginning, both supervised and unsupervised machine learnings are used for detecting the road anomalies. The SVM method achieves a precision of 78.5% for 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 system also obtains a good result according to the Kendall tau rank correlation coefficient of two rank lists produced by human and by our system. Lastly, we verify the possibility of using mobile device to automatically monitor road conditions. A prototype of mobile sensor network for road surface monitoring is designed so that a monitoring map for road quality will be established for sharing information of road conditions to everyone.

6.2 Future Work

There are some works needed to improve in the future. Firstly, the high frequency accelerometer can be used in road surface monitoring in order to obtain better performance. Secondly, this application could be much convenient if the mobile device is not fixed on the vehicle but in the pocket of the user. It is can be done by the reorientation of the coordinate of the accelerometer. Lastly, the full implementation of the server for road surface monitoring should be finished so that people join the monitoring process and contribute their efforts to make our environment better.

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