A Method for Estimating Road Surface Conditions with a Smartphone

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Abstract - In recent years, GPS (Global Positioning System) sensors, acceleration sensors and so on have been embedded in smartphones and become popular. We can gather various kinds of information simply and on a massive scale by using such smartphones. A system that creates new information from various kinds of information and shares this information through a network is called a "probe information system". Recently, such probe information systems have attracted attention and been used to share traffic information. In this study, we focus on road surface conditions concerning driving comfort and ride quality. We need to share data, for example when ruts appear in a road, because road conditions are changeable. Therefore, this study proposes a method for estimating and detecting changes in road surface conditions by using a smartphone. The proposed method uses acceleration sensors embedded in smartphones and estimates road surface conditions. Then, the method detects changes in the conditions by comparing the latest estimation results with past results. The proposed method can confirm changes in road conditions changed in winter, even within the same segment.

Keywords: probe information system, smartphone, log data, sensing, estimation of road surface condition

1 INTRODUCTION

Recently small, high-performance sensors have become widespread due to the development of MEMS (Micro Electric Mechanical Systems), and are embedded in various kinds of object in our living environment such as personal computers, beacons, cars and smartphones. Many researchers tackle advanced studies in the field of mobile sensing. Mobile sensing uses sensors embedded in moving objects such as cars, bikes and smartphones, and regards cars and humans as sensors. Moreover, the penetration rate of smartphones is increasing and will continue to do so. Many sensors such as acceleration sensors, gyro sensors and so on are embedded in smartphones. Consequently, we can develop convenient and efficient systems at low cost and gather various kinds of information simply and on a massive scale [1]. The gathered information is called "probe information." A system that generates new information from probe information and shares this information through a network is called a "probe information system" [2]. A conventional sensory system can only gather information on a road that has stationary devices, and it is necessary to increase the number of devices in order to extend the range over which information can be gathered. On the other hand, a probe information system can gather various kinds of information because it gathers information by using cars and humans as sensors without locating stationary devices such as beacon devices [3]-[5]. This study focuses specifically on traffic information.

There are road bumps and road surface conditions affecting driving comfort and ride quality. In winter, uneven surfaces form on roads in snowy regions due to snow and ice. In addition, ruts form on a road due to the temperature rising in the daytime and cooling at night. It is difficult for drivers to drive because road surface conditions change depending on the season or time, even on the same road. Accordingly, it is necessary not only to grasp present road surface conditions accurately but also to detect the changes in road surface conditions. It will become possible to navigate roads that are comfortable for driving and do not change, if we can gather the road surface conditions as probe information and detect the changes in road surface conditions.

However, some related works on estimating road surface conditions have a problem regarding cutting costs, because they need to introduce stationary devices on roads and in-vehicle cameras. Moreover, as mentioned above, we have to consider the change of road surface conditions to grasp them accurately because they change depending on the season or time.

Our study proposes a method for detecting changes in road surface conditions, and solves the problems of introductory costs and robustness by using a smartphone and its acceleration sensors. The proposed method calculates the variance of the vertical component of acceleration values when a driver drives a car. The method classifies road surface conditions into three levels: rough road level 0, rough road level 1 and rough road level 2. Moreover, this method partitions a road from intersection to intersection into multiple segments, and estimates road surface conditions on each partitioned segment. In addition, this method achieves detection of changes in road surface conditions through comparing the result of the latest estimation and past estimations.

2 RELATED WORK

There are some related works on estimating road surface conditions. One is an approach that uses the polarization property of fixed cameras. Another uses in-vehicle cameras. A further work uses acceleration sensors. We explain the details of these works in this section.

Table 1: Characteristics of each road surface condition (Quoted from [6]).

State	Degree of reflectivity	Brightness	Road temperature	Characteristics
Dry	Low	Low	-	Even and a little dark.
Wet	High	Low – Medium	Above -3°C.	Degree of reflectivity is high.
Snowy	High	Low – Medium	Below -3°C.	Degree of reflectivity is high.
Freezing	Low	High	-	Even and bright.

2.1 An Approach Using Fixed Cameras

There is a study that uses fixed cameras on poles on a road to estimate road surface conditions [6]. This method estimates road surface conditions based on the polarization property of images by using fixed cameras. It locates a stationary device at each pole on a road. Then, it irradiates a light onto a road using stroboscopic illumination and captures images continuously with CCD cameras, then estimates road surface conditions by analyzing the captured images. It is possible to gather information regardless of brightness because the method takes images alternately while irradiating light and while not irradiating light. Moreover, this study classifies road surface conditions into four states: dry, wet, snowy and freezing. The characteristics of the four states are shown in Table 1.

This method needs to introduce fixed cameras, and the introductory cost of the devices is high. In addition, it has a problem with granularity of the system structure because the estimation targets are limited to roads that have stationary devices.

2.2 An Approach Using In-vehicle Cameras

Recently, cars mounted with cameras are increasing due to the development of image processing techniques. Cameras used on cars are called in-vehicle cameras, and many researchers consider various kinds of application using these cameras [7]-[10]. The method [7] estimates road surface conditions by using the characteristic of image brightness acquired from in-vehicle cameras. This study assumes that a coefficient of friction is low if the road is bright, and proposes a method for estimating road surface conditions based on the degree of brightness of the road surface. The brightness of the road is derived from images taken by in-vehicle cameras which monitor the area in front of the car.

When reflected sunlight spreads across the surface of a dry road, the brightness signal from in-vehicle cameras becomes constant. On the other hand, when a wet road surface becomes like a mirror because it is covered by water, the brightness signal is non-constant, because the reflective areas of a wet road surface are not evenly ranged.

This study estimates whether the road surface is dry or wet by using these brightness signals. The introductory cost of this method is lower than that of the method that uses fixed cameras. This method also solves the problem of

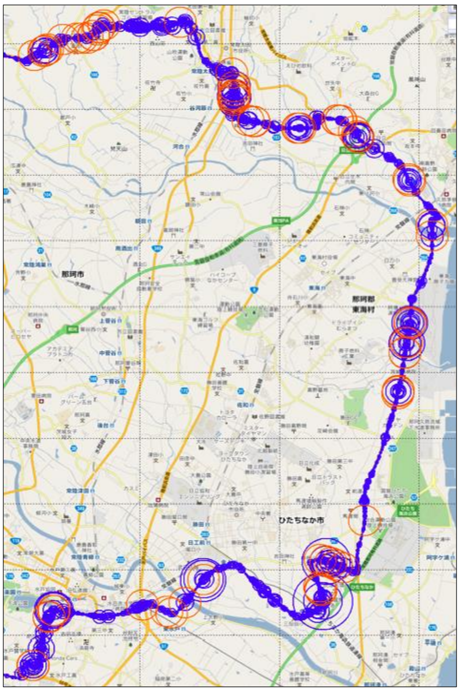

Figure 1: The relationship between estimation result and visual check (Quoted from [16]).

granularity. However, the method cannot estimate conditions in bad weather and at night, because the method uses sunlight. Accordingly, this study has a problem regarding robustness.

2.3 An Approach Using Acceleration Sensors

There are some studies of detecting road bumps using acceleration sensors [11]-[16]. Method [11] is based on iterating multibody analysis and uses a multibody vehicle model. Methods [12]-[14] use three-axis acceleration sensors and a GPS sensor embedded in a vehicle. Methods [15][16] involve placing a smartphone on the dashboard of a car, and can detect road bumps only during driving. The IRI (International Roughness Index), an index of flatness of road surfaces, has a relationship with the RMS (Root Mean Square) of the vertical component of acceleration values. Therefore, the study [16] proposes a method for estimating the height and length of bumps using acceleration sensors. This method estimates the amount of vertical displacement using the double integral of the vertical component of acceleration values, and defines it as the height of a bump. In addition, this method estimates distance travelled forward using a GPS sensor, and defines it as the length of a bump. In Fig. 1, results of estimation of road bumps and actual visual confirmation of road bumps are shown. The results of estimation are shown as blue circles, and visual confirmation is shown as orange circles.

This method can estimate road surface conditions rapidly at low cost by using smartphones. However, road bumps that do not cause fellow passengers to feel vibrations are detected, and road bumps that do cause fellow passengers to feel vibrations are not detected. Therefore, this method has a problem with accuracy. Moreover, a map like the above does not present changes in road surface conditions

Table 2: Advantages and disadvantages of related works.

	Estimation target	Estimation accuracy	Introductory cost and estimation granularity	Robustness	Inadequate detection of changes in road surface conditions
Fixed cameras [6]	Wet, dry, snowy and freezing roads	Y	N	Y	-
In-vehicle cameras [7]	Wet and dry roads	Y	Y	N	-
Acceleration sensors [16]	Road bumps	N	Y	Y	N

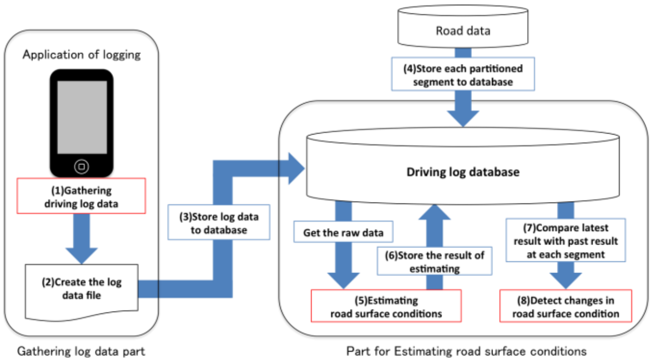

Figure 2: An overview of the proposed system.

depending on season or time. In winter, information on whether the condition of rough roads is constant or changeable is important to help drivers select the best route. Accordingly, this study has a problem with inadequate detection of changes in road surface conditions

2.4 Summary of Related Works

In Table 2, we show the advantages and disadvantages of the related works mentioned in this section.

The approach using fixed cameras has problems such as introductory cost and estimation granularity. The approach using in-vehicle cameras solves these problems. However, this method has a problem of robustness. The approach using acceleration sensors is able to estimate the height and length of road bumps. This method solves the problems of introductory cost, granularity and robustness because it uses a smartphone. However, it has a problem with accuracy, and inadequate detection of changes in road surface conditions.

For these reasons, in this study we propose a method for solving problems such as introductory cost, estimation granularity and robustness by using smartphones. This method can detect changes in road surface conditions from hour to hour. The proposed method estimates road surface conditions and gathers results of estimation, and compares the latest results with past results.

3 PROPOSED METHOD

In this section, we explain an approach for solving problems in the related works and the purpose of this study and give a detailed overview of the proposed method.

3.1 Purpose and Approach

The related works have problems such as introductory cost, estimation granularity, scale of robustness and inadequate detection of changes in road surface conditions. We propose a system that can gather driving log data at low cost and is robust, and which compares latest estimation and past estimations to solve the problems with the related works. Therefore, in this study, our method gathers driving log data by using the sensors of smartphones, and estimates road surface conditions using only the gathered log data. Moreover, the method manages the estimated results in a database, and detects changes in road surface conditions by comparing the latest estimation with past estimations. Smartphones are often used on a car dashboard because it has features such as audio and navigation applications. Therefore, smartphones can reduce the burden for drivers when we gather driving log data. In addition, sensors embedded in smartphones can robustly gather driving log data because they can be used in all weathers and at all times. This study aims to estimate road surface conditions and to detect changes in road surface conditions by using driving log data gathered by smartphones.

3.2 An Overview of the Proposed System

Smartphones on car dashboards gather vertical components of acceleration values, location information such as latitude and longitude, and time stamps during driving. Gathered driving log data are managed in a database, and we estimate road surface conditions and detect changes in them by using the driving log data. An overview of the proposed system is shown in Fig. 2.

The proposed system consists of two stages: gathering log data and estimating road surface conditions. First, the system gathers the vertical components of acceleration values, location information, dates and time stamps by using the acceleration sensor and GPS sensor of a smartphone (1). Next, the system generates a log data file, and stores log data in the database (2), (3). Our method partitions a road from intersection to intersection into multiple segments, and creates a road segment table that is then stored in the database as a preliminary preparation (4). In the second stage, the system estimates road surface conditions using gathered log data, and manages the estimated results as attribute data of segments with dates and time stamps (5), (6). Finally, the system compares the latest result of estimation with past results of estimation at each segment, and detects changes in road surface conditions (7), (8).

3.3 Estimating Road Surface Conditions

In this section, we explain how to gather driving log data, estimate road surface conditions and detect changes in road surface conditions.

Table 3: Structure of log data table.

Attribute	Detail	Attribute	Detail
Id	Id of log data	pitch	3-axis gyro values
date	Value of date	roll	
time	Time stamp	yaw	
accx	3-axis acceleration values	speed	Speed of car
accy		lat	Latitude
accz		lon	Longitude
		direction	Direction

Table 4: Definition and classification of rough road levels.

	Feature	Measure of continuous bounce
Rough road level 0	A flat road on which no bounce is felt.	Small
Rough road level 1	A road on which bounce is felt in certain spots due to asphalt damage.	Medium
Rough road level 2	A road on which bounce is felt continuously, such as a dirt road.	Large

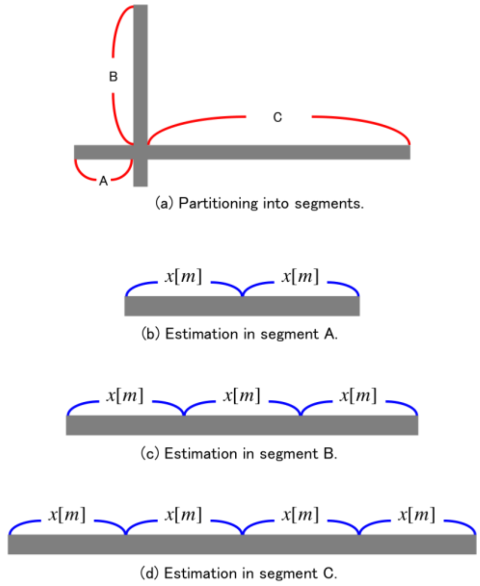

Figure 3: An illustration of partitioning into segments and estimating in the partitioned segment.

3.3.1. Gathering Driving Log Data

Our method gathers driving log data by using smartphones on car dashboards. Log data to be gathered are date, time stamp, 3-axis acceleration values, 3-axis gyro values, speed of car, latitude, longitude and direction. Smartphones gather this information every 100 [Hz]. The driving log data are stored in a raw data table in the database, through the mail function of smartphones. The structure of the log data table is shown in Table 3.

This study focuses on the vertical component of acceleration values because it is the piece of log data most affected by the impact of road bumps. Accordingly, we estimate road surface conditions using changes in the vertical component of acceleration values.

3.3.2. Estimating Road Surface Conditions

There are various kinds of road surface condition. They are classified as point information and line information if we focus on driving comfort and ride quality. Point information is the expected partial change when cars pass over a manhole or road bump. The method for detecting them is explained in a paper by Yagi [15][16]. On the other hand, line information is the states of a segment, such as a minor bounce segment or bad ride quality segment, when we focus on units from intersection to intersection. This estimation method is not touched on in any related works. If we grasp road surface conditions, drivers can use a navigation system to avoid a bad ride quality segment in advance. This study defines segment conditions using the three levels shown in Table 4.

Differences appear when we observe driving on a single segment of road. We can expect that variability of acceleration values is low when we drive on a road classed as rough road level 0.

Table 5: Structure of segment table and example data.

Attribute	seg_id	str_lon	str_lat	end_lon	end_lat
Detail	Id of the segment	Longitude of start point	Latitude of start point	Longitude of end point	Latitude of end point
Example	1	41.843252	140.768283	41.840409	140.767791
-	…	…	…	…	…

We can expect that variability of acceleration values is a little higher when we drive on a road classed as the rough road level 1, and very high when we drive on a road classified as rough road level 2. The proposed method classifies roads into three levels by calculating the variance of the vertical component of acceleration values in a constant segment and setting thresholds. The thresholds are explained in Section 4.2. We need to estimate road surface conditions at every fixed interval when we use thresholds. However, lengths of actual roads and driving routes vary. In addition, we need to compare estimation results for each individual segment to detect changes in road surface conditions. For these reasons, the proposed method partitions a road from intersection to intersection into multiple segments and further partitions those segments into sub-segments of constant length. It then estimates road surface conditions of each partitioned segment, in order to solve the problem of varying length of segments. Figure 3 shows an illustration of partitioning into segments and estimating in each partitioned segment, and Table 5 shows an example of segment table data.

Actual lengths from intersection to intersection are different, as shown in Fig. 3 (a). Therefore, the proposed method continues to calculate every $x\,[m]$ until it reaches the end of a segment, as shown in Fig. 3(b), (c) and (d). ‘$x\,[m]$’. The variable used for calculating the interval of variance is explained in Section 4.2. The estimated results at

Table 6: Structure of table of estimation results and example data.

Attribute	est_id	seg_id	date	time	estimation
Detail	ID of estimation result	ID of a segment	Date of estimating result	Time stamp of estimation result	Output integer of estimation result
Example	1	1	2014/03/20	12:09:40:666	0
-	…	…	…	…	…

every x $[m]$ are output as three integers (0: rough road level 0, 1: rough road level 1, 2: rough road level 2). We define the calculation order as i, the result of estimating every x $[m]$ as $Var(i)$, the calculation count of variance as n and the ID of each segment as seg_id. Then, the result of estimating each segment, $Est(seg\_id)$, is calculated as follows (after the decimal point is rounded):

$$Est(seg\_id) = \frac{\sum_{i=1}^{n} Var(i)}{n} \quad \cdots(1)$$

This $Est(seg\_id)$ is stored in the database table of estimation results with an estimation result ID, date and time stamp, as shown in Table.

In this way, we classify roads of various lengths into three levels. Moreover, recording estimation results in units of segments enables comparison of the results of each individual segment.

3.3.3. Detecting Changes in Road Surface Conditions

We detect changes in road surface conditions by using a table to compare estimation results with any past data that have the same segment ID and time. We divide time into three periods: 0:00-8:00, 8:00-16:00 and 16:00-24:00.

We compare estimation results using the following process. We define the number of estimation results with matching segment ID and time as n, the order of managed data as i and the result of estimation as $Est(i)$. Then, the average value of past results $Past\_Est(seg\_id)$ is calculated as follows (after the decimal point is rounded):

$$Past\_Est(seg\_id) = \frac{\sum_{i=1}^{n} Est(i)}{n} \quad \cdots(2)$$

The reliability of estimation results is high when there is a wide range of past data to refer to. However, this changes depending on season. In summer, road surface conditions do not change frequently. For this reason, it is appropriate to compare the average of the past month's results with the latest result to detect the latest changes. In contrast, in winter, in snowy regions, road surface conditions change frequently, meaning that comparing the average of the past month's results with the latest result is not effective. Therefore, this study detects changes in winter road surface conditions by comparing the result from the same time on the previous day, and the average of the past week's results, with the latest result. In this way, the range of reference data varies according to season and purpose. Therefore, we define that range is set by the user, based on these variables.

Figure 4: Image of setting a smartphone.

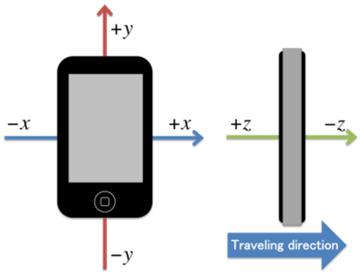

Figure 5: Acceleration axis.

Next, we compare latest estimation $Latest\_Est(seg\_id)$ with past estimation $Past\_Est(seg\_id)$. We can assume that road conditions remain constant if $Past\_Est(seg\_id)$ is equal to $Latest\_Est(seg\_id)$. However, if $Past\_Est(seg\_id)$ is not equal to $Latest\_Est(seg\_id)$ we can assume that road surface conditions have changed within the past few hours.

4 EXPERIMENTS AND DISCUSSIONS

In this section, we explain the experiments we conducted to confirm the effectiveness of the proposed method, and discuss the results. We fixed the vehicle speed in the following experiments.

4.1 Implementation

We implemented a system that gathers log data, estimates road surface conditions using this data, and visualizes the results. We used Java and JDBC (Java Database Connection) to implement the processing of estimation of road surface conditions and detection of changes in these conditions, and we also used JavaScript to implement an application for visualizing estimation results.

4.2 Preliminary Experiment

We conducted a preliminary experiment to set the calculation interval of variance and the thresholds that are explained in Section 3.3.2. To gather log data we implemented a logging application on iOS. We set the smartphone horizontally on the dashboard, as in Fig. 4. In this case, the y-axis of acceleration becomes the vertical component of acceleration values, as shown in Fig. 5.

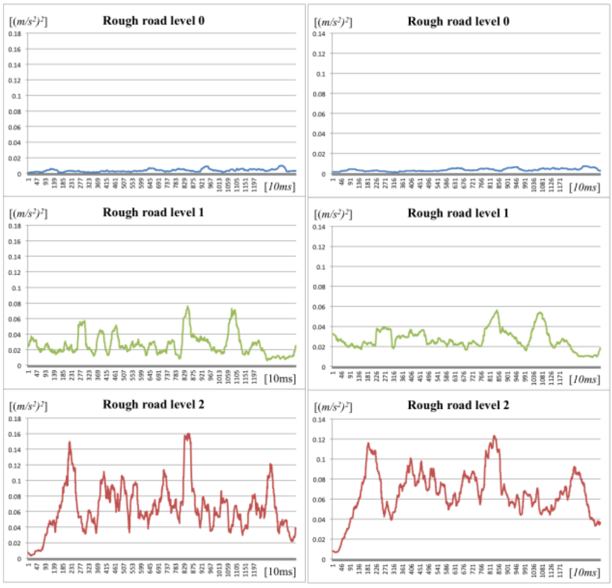

Figure 6: Variance in every 5 and 10 meters.

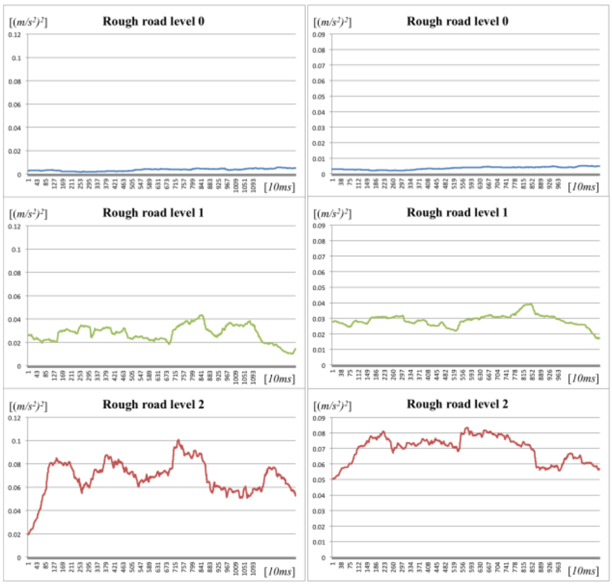

Figure 7: Variance in every 20 and 40 meters.

We drove on three levels (rough road level 0, level 1 and level 2) of road while running the logging application, examined the suitable interval of calculation of variance, and then set thresholds. We examined changes in variance when we changed the calculation interval between every 5 meters, every 10 meters, every 20 meters and every 40 meters. Variances of the vertical component of acceleration values for each road level and calculation interval are shown in Fig. 6 and 7.

These results show that variances when we drove on the three levels of road were different, and the magnitude relation of variance of each level is non-constant in the cases where the calculation intervals of variance are every 5 meters, every 10 meters and every 20 meters. Therefore, we cannot define thresholds that classify the rough road level distinctively. On the other hand, magnitude relation of variance of each level is constant in the case where the variance calculation interval is every 40 meters. Accordingly, we can classify roads into three levels if we set

Table 7: Detail of estimation results.

		Estimation result of rough road level		
		Level 0	Level 1	Level 2
Correct data of rough road level	Level 0	31	0	0
	Level 1	3	10	0
	Level 2	0	0	5

(a) Segment (b) Every 40 meters

Figure 8: Estimation result of a segment and of every 40 meter interval within the segment.

thresholds. For these reasons, we set the variance calculation interval at every 40 meters to classify roads into three rough road levels by threshold. In addition, we repeated this preliminary experiment, and set the threshold to discriminate between rough road level 0 and 1 at $0.0190[(m/s^2)^2]$, and level 1 and 2 at $0.0428[(m/s^2)^2]$.

4.3 Experiment to Evaluate Accuracy

We conducted an experiment to evaluate the accuracy of estimation of road surface conditions using the calculation interval and thresholds established in Section 4.2. We analyzed the estimation result of each segment by using a visualization application. Then, we defined a video captured by an in-vehicle camera tracking on an actual road as correct data, and compared the estimation results with the correct data. The results of this experiment are shown in Table 7.

The shaded areas of Table 7 show the number of segments for which estimation was accurate, and the remaining squares show the number of segments for which estimation was not accurate. These results show that rough road level 0 and level 2 were successfully estimated but there were false estimations when a rough road level 1 was estimated as level 0. We analyzed the log data of false estimations to find the cause. The estimation result of a segment in which false estimation occurred is shown in Fig. 8(a). The estimation result of every 40 meter interval in the segment is shown in Fig. 8(b). A rough road level 0 is indicated by a blue line, and level 1 is indicated by a green line in the figures.

The segments in these figures are segments of a rough road level 1, as defined using in-vehicle video capture. In fact, the estimation results of every 40 meter interval show

(c) Snowy day (January 23th) (d) Later fine day (January 29th)

Figure 9: Estimation result of a snowy day and later fine day.

that rough road level 1 was estimated at multiple sites, as shown in Fig. 8(b). However, the estimation result produced using the proposed method shows the segment as a rough road level 0.

4.4 Elementary Experiment for Detecting Changes

We conducted an elementary experiment to determine whether or not road surface conditions change depending on date and time. We used a visualization application to analyze driving log data in winter when road surface conditions often change. Estimation results of driving log data collected when we drove on a snowy segment at night are shown in Fig. 9(c), and estimation results of driving log data collected when we drove in the same segment in good weather on the following day are shown in Fig. 9(d). Rough road level 0 is indicated by a blue line, level 1 by a green line and level 2 by a red line in these figures.

On the day in which the data used in Fig. 9(c) was collected, some roads were covered in snow due to snowfall on the previous day. The red line in Fig. 9(c) indicates a bumpy road surface caused by snow. Accordingly, there was a high degree of bounce throughout the segment. However, a change in the estimation result of this segment can be seen in Fig. 9(d), because the temperature increased and the snow melted in the daytime.

4.5 Discussion

In this section, we discuss the experiment results and other factors affecting vertical acceleration values.

4.5.1. Discussion of Experiment Results

The experiment to evaluate accuracy revealed that the accuracy rate of estimating road surface conditions using the proposed method was about 94 percent. For this reason, we could confirm that we can effectively classify a road into three rough road levels by using the variance of the vertical component of acceleration values. Moreover, we were also able to confirm that rough road level 0 and 2 can be estimated accurately. So we think the proposed method can indicate road surface conditions to a user more clearly than the method used in study [16]. However, there was some false estimation of rough road level 1. This is thought to be due to the fact that in level 1 bounce occurs only in certain spots. The length of some segments is long because the proposed method partitions a road from intersection to intersection. In addition, it is not always true that bounce is felt continuously, even in a road that is level 1. Therefore, the proposed method confuses level 1 with level 0 when it estimates the road as segments. Accordingly, we need to consider ways to improve our method, such as adding new parameters and further partitioning longer segments.

From the results of the elementary experiment for detecting changes, we think the proposed method is able to detect changes in rough road levels in winter, even within the same segment.

4.5.2. Discussion of Factors Affecting Acceleration Values

There are many factors that have an influence on vertical acceleration values. One of the factors is type of vehicle. Length of wheelbase and strength of suspension differ depending on the type of vehicle, and we think these aspects have an influence on vertical acceleration values. The other factor is a individual driving style. We think acceleration values change in a different way depending on driving technique and experience. We need to check the relationship between these factors and vertical acceleration values in the future.

5 CONCLUSION

In this study, we proposed a method for estimating and detecting changes in road surface conditions using a smartphone. In addition, we implemented the system of the proposed method and conducted experiments to confirm its effectiveness. In the future, we will consider a method to improve estimation accuracy and implement a system for detecting and visualizing changes in road surface conditions. We will also consider the influence of vehicle speed. Additionally, we have to research the relationship between IRI and rough road levels estimated by the proposed method.

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