CROWD-SOURCING BASED ROAD SURFACE EVALUATION USING MOBILE SENSING

BY

WITSARUT ACHARIYAVIRIYA

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF ENGINEERING (INFORMATION AND COMMUNICATION TECHNOLOGY FOR EMBEDDED SYSTEMS)
SIRINDHORN INTERNATIONAL INSTITUTE OF TECHNOLOGY
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A Thesis Presented

By

WITSARUT ACHARIYAVIRIYA

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Abstract

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WITSARUT ACHARIYAVIRIYA

B.Eng in Electrical Engineering, Chiang Mai University, 2014
M.Eng in Information and Communication Technology for Embedded System, SIIT, 2016

Road conditions monitoring system is one of important tools for Intelligent Transportation System (ITS). The monitoring system can facilitate road administrator to assess deterioration of road surface for maintenance, and assist driver for safety. Recently, smartphones were used as monitoring tools because of sensor-rich and Internet-enabled capability. Our research is aimed to developed tools for monitoring road distress based on smartphone sensors. In this research, we proposed virtual re-orientation method for smartphone during driving. accelerometer, magnetometer and GPS positioning were used to determine relative orientation between smartphone and vehicle. Additionally, we proposed road conditions detection system based on support vector machine. Road bump and pothole conditions was focused. In the end of this paper, the result of system assessment by field test data reveal that our proposed system work successfully.

Keywords: Crowsourcing, road conditions, smartphone orientation

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CHAPTER 1
INTRODUCTION

1.1 Intelligent Transportation System (ITS)

Vehicular traffic on the roads is the key role of today life. To improve the quality of traffic, road monitoring system is a very important tool for retrieve information of road conditions. For this reason, Intelligent transportation system (ITS) have been developed (ITS Thailand n.d.). Many of research are involve with analyzing GPS data in term of population transfer behavior(Somkiadcharoen et al. 2015; Horanont & Phithakkitnukoon 2014), monitor the traffic congestion(An et al. 2015), estimate arrival time local bus (Yu et al. 2011), schedule bus interval(Bie et al. 2015). ITS are including the interactive among transportation component (Birk et al. 2010; Birk et al. 2009) such as vehicles, road infrastructure, driver or user, building, etc. To monitor more specify, deploying dedicated sensors in vehicle such as GPS, accelerometer, gyro-sensor, or magnetometer are need. Analyzing this road conditions information is very helpful in term of managing, planning, and maintenance for vehicular traffic

1.2 Smartphone in ITS

Smartphone is one of the important elements in modern life that people carry at all time. It became a multifunction tool that people can communicate or access to many services easily. The capability of sensor-rich and Internet-enabled of smartphone is the important key for ITS in term of sensor's data collection. From the extensive use of smartphones, the framework for collected sensor's data in wide range are proposed which is referred to Crowdsourcing. The idea of crowdsourcing is resulted in development of various field of research such as safety planning(Carley et al. 2016), environment monitoring(Monahan & Mokos 2013), etc.

According to the survey of safety of traveling [], the second cause of the accidents in Thailand came from road distress. It reaches to 26 percent of road accidents lower than the reason of undisciplined driving. To reduce the number of accidents, road maintenance play in a key role in term of safety that need some tools for evaluate and monitor the road distress. Currently, the tool to assess the road quality are still costly and time-consuming. Therefore, the comprehensive evaluation of road networks is become a difficult task. To solve this problem, ITS took a major role in developing the tool leveraging from sensor-rich and Internet-enabled of smartphone to gather crowdsourced data. smartphones have become a tool to assess or monitor the road quality that the ubiquity of smartphones make more comprehensive evaluation of road networks.

1.3 Emerging technology in ITS

In term of detection and emerging technology in ITS, many frameworks were proposed such as tracking the safe and unsafe driving behavior (Eboli et al. 2016), detection of road distress based on vibration (Eriksson, Girod & Hull 2008; Castellanos & Fruett 2014; Yi et al. 2015; Douangphachanh et al. 2013), classification of road conditions and driving conditions (Chaovalit et al. 2013). These researches are all involved with analyzing acceleration data. Some of research are involving with 3-axis accelerometer that is very important to mount smartphone into the correct posture. It became a difficult task to keep a specific orientation. In this paper, we propose the virtual reorientation frameworks for free installation of smartphone. This framework can support many research that need to corrected the smartphone orientation.

1.3 Contribution

We proposed the virtual reorientation frameworks of smartphone by using the common sensors that available on smartphone that is accelerometer, magnetometer, and GPS. This framework is works successfully under flat road conditions.

Our system was evaluated by testing on 2 road characteristics that is highway and local road. The result of experiment shows an accurate estimation of smartphone orientation angles. In term of initialize time, the system take around 15 seconds while driving on straight road.

We applied the virtual reorientation frameworks in road distress detection system. the detection system was tested by focusing on detection of 2 road conditions that is pothole and road bump. The system has false positive detection less than 20 percent.

CHAPTER 2
THEORETICAL BACKGROUND AND LITERATURE REVIEW

2.1 Analog and Digital Signal

The type of signal that we know and familiar in everyday life are form of a continuous signal, known as analog. Analog signal representation of some other time varying quantity. For example, audio signal, temperature, air pressure, etc. in the term of digital signal referred discrete signal which have a certain level of quantity. This digital signal is what computers use to communicate and collaborate.

2.2 Digital Signal Processing

Digital signal processing based to perform numerical calculations on sampled values of the signal. the processor unit can be a personal computer or a specialized digital processing chip. Although in DSP process consider a digital signal, but in general, these signals are formed in the original analog sources. Acquisition of digital signals representing an analog signal that we are interested in going through the process of converting analog signals to digital or Digitization, which includes sampling (sampling), and the quantization. (Quantization) in the digital form before further processing.

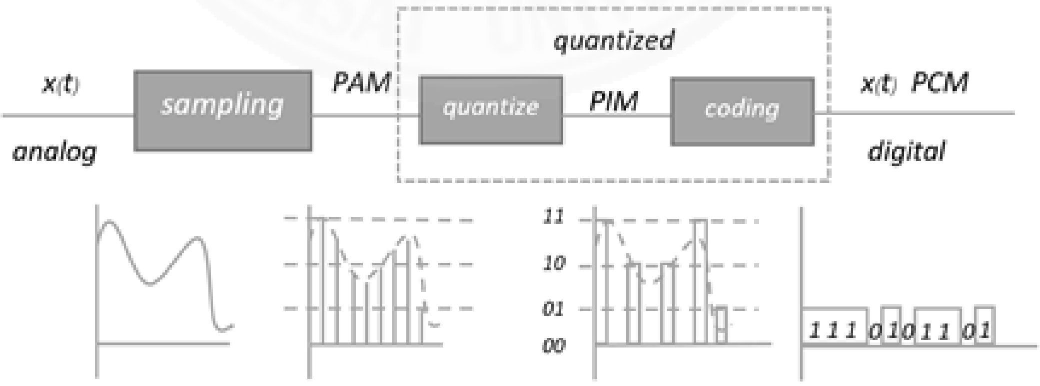


Fig 2.1 the process of analog to digital conversion

2.2.1 Sampling

Analog signals which is continuous signal of the measures will be converted into a digital signal which is a discrete signal can be done by sampling. In the sampling process, analog signal is cut periodically with the frequency of sampling (Sampling Frequency, fs) or time of sampling (Sampling Time, Ts). To convert digital signal back to original signal completely, there is limitations which is mentioned in the Shannon's sampling theorem that is the sampling frequency must higher than 2 times of the original signal frequency so called Nyquist Rate**.**

2.2.2 Quantization

when Analog signal is sampled, the height of obtained pulse is equal to the values of analog signals. At the sampled time the obtained pulse are call Pulse Amplitude Modulation (PAM). This PAM pulse can be any size depend on the size of original analog signal at that time. Then adjust the PAM pulse into in a predetermined level that triggers this process quantization. Encoding of PAM depend on number of signal level. For example, If the signal difference is set in four levels, it can use a binary code two bit to represent the signal levels. In general, there are many ways to quantize This signal such as Counter Quantization, Serial Quantization, and Parallel Quantization.

2.2.3 Coding

the number of levels we have divided the amplitude into, must be encoded in binary. This process is known as Encoding. Here we find the use of taking 2^n levels in amplitude. Any radix 2 number (having number of values equal to 2^n), can be encoded into binary using n-bits, where each bit represents either zero or one. Any value within this 2^n can then be represented by an n-bit number.

2.3 Digital Filter

In signal processing, the function of a filter is to remove unwanted components of the signal, such as random noise, or to extract useful parts of the signal, such as the components lying within a certain frequency range. There are two main kinds of filter, analog and digital. An analog filter uses analog electronic components such as resistor, capacitor, and inductor. For digital filter, it uses a digital processor to perform numerical calculations on sampled values of the signal. In this topic, we focus on digital filter that the basic theory of the operation of digital filters are described below.

Suppose the original analog signal (V) is the voltage signal that waveform is described by the function

$$V = x(t)$$

Where t is time.

When the signal was sampled at the time interval (T), the obtained signal(x_n) can be written as

$$x_n = x(nT)$$

Where n is the number of sampling times.

Therefore, the digital signal can be represented by the sequence

$$x_0, x_1, x_2, x_3, \dots , x_{n-1}$$

Corresponding to the time

$$0T, 1T, 2T, 3T, \dots, (n-1)T$$

In the following, we will look at some examples of simple digital filters.

Gain filter

$$y_n = Kx_n$$

Where K is constant.

Delay filter

$$y_n = x_{n-d}$$

Where d is delayed sample

N-term average filter

$$y_n = \frac{x_n + x_{n-1} + x_{n-2} + \cdots + x_{n-N-1}}{N}$$

Where N is the number of term.

2.4 Recursive and non-recursive filters

The previous examples of digital filter, the current value of output is only depending on current and previous input data. In this type of filter is called non-recursive, non-recursive filters are also known as finite impulse response (FIR). There is another type of filters that is Recursive filter or infinite impulse response (IIR). The output of recursive filter is depending on both input and previous output data. the example of moving average filter designed by recursive filter and non-recursive filter are shown below.

2.4.1 Moving average FIR filter

$$y_n = C_0 x_n + C_1 x_{n-1} + C_2 x_{n-2}$$

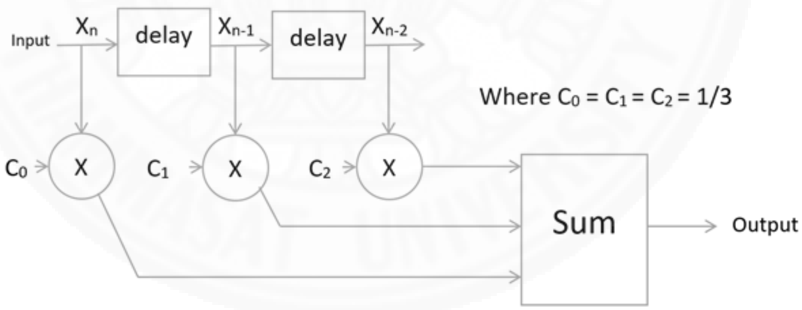


Fig 2.2 diagram of Moving average FIR filter

2.4.2 Moving average FIR filter

$$y_n = \alpha x_n + (1 - \alpha) y_{n-1}$$

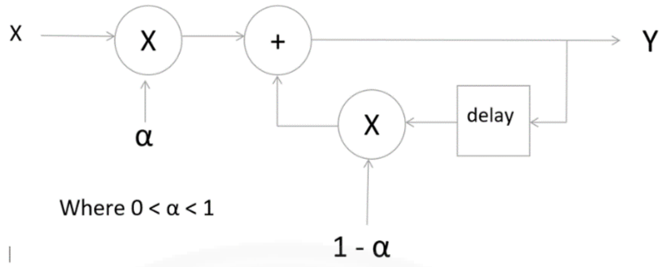


Fig 2.3 diagram of Moving average IIR filter

2.5 Machine learning

Machine learning is a branch of artificial intelligence developed from the recognition. Related to the study and design of algorithms that can learn and predict data itself. The algorithm is driven by models built from a set of sample data (training data) to predict result or event based on environmental data (features). Instead of working on a sequence of instructions a computer program. Machine learning can be divided roughly into 2 categories according to the type of "training data" or "data input" that are supervised learning and unsupervised learning. In addition, machine learning can also be an assortment of "work" based on output of machine which are classification, regression, clustering, etc.

supervised learning is a machine learning technique which created a model from training data. The training data compose of 2 components that is features and result. The function of this machine learning type is to create model that can link the features to the result.

unsupervised learning is a machine learning technique which created a model that fits the data set. The difference between this technique and supervised technique is no need to specify the result of training data. This learning technique consider the relation among of data set which is closely related to the problem of density estimation in statistics.

Classification is algorithms use to identify the object which category an object belongs to. Users must create a model that can identify for any data type. Typically, it can be done by supervised learning technique. The examples of classification algorithm are support vector machine, random forest, and nearest neighbors.

Regression is algorithms use to forecast a continuous-valued attribute associated with dataset. There are various kinds of regression techniques available to make predictions which the most commonly used regressions are linear regression, logistic regression, polynomial regression, etc.

Clustering is algorithms use to split the input dataset by into proper groups without pre-specified group. The algorithms performed based on similarity object in the dataset. This technique is done by unsupervised learning. For examples of clustering algorithm, K-means, mean-shift, DBSCAN, etc.

2.6 Support vector machine(SVM)

Support vector machines are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis. The concept of support vector machine derived from plotting the dataset into a feature space. Then, determine the best line(hyperplane) that can divide dataset in different groups apart. For more understanding, the theoretical concept of support vector machine are shown below (Fletcher 2009).

Assign L training points, where each input x_i has D attributes (dimensions of input vector) and belong in one of two classes y_i. Therefore, the mathematical expression of training data $\{x_i, y_i\}$

can be written by

$$\{x_i, y_i\} \ where\ i = 1,2,3, \dots, L\ and\ y_i \in \{-1, +1\}, x_i \in R^D$$

Here we assume the data is linearly separable, meaning that we can draw a line on a graph of $x_1 vs\ x_2$ separating the two classes when $D = 2$ and a hyperplane on graphs of $x_1, x_2, x_3, \dots, x_D$ for when $D > 2$. This hyperplane can be written as

$$w \bullet x + b = 0$$

Where w is normal to hyperplane and $\frac{b}{||w||}$ is perpendicular distance from the hyperplane to the origin.

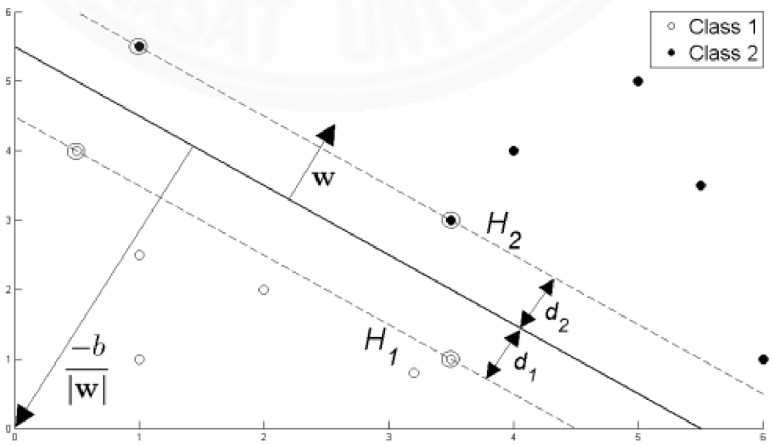


Fig. 2.4 An illustration of the hyperplane

Referring to Fig.2.4, implementing a SVM boils down to selecting the variables w and b so that our training data can be described by:

$$x_i \bullet w + b \geq +1, for\ y_i = +1$$

$$x_i \bullet w + b \leq -1, for\ y_i = -1$$

2.7 Road conditions monitoring system

Road monitoring system is one of the important component of ITS. Many research was proposed this system in various model that we categorized into 2 types. The first type is custom embedded devices based system. In this kind of models, the testing car was equipped with an external device that designed for the purposed of collecting and analyzing driving situations. (Eriksson, Girod, Hull, et al. 2008) proposed the system to detect pothole and another anomaly of road surface based on acceleration data so call Pothole Patrol. 7 taxis were installed with custom device that includes 3-axis accelerometer and GPS sensor. To identify pothole, the ratio of x-axis (lateral component) and z-axis (vertical component) acceleration is performed by thresholding. when Internet connection is available, the detected results were uploaded to central server and filtered by clustering based on location. In the same way,(Castellanos & Fruett 2014) proposed the system to localize comfort disturbances of public transportation system. Jerk-acceleration Threshold Detection (JATD) and Comfort Index with Acceleration Threshold Detection (CI-ATD) were used to analyze acceleration data and assess the comfort of journey.

Another ongoing development is smartphone based system. Since capability of smartphones was developed rapidly with more added sensing capability such as accelerometer, gyro-sensor, GPS positioning etc., it has potential to use as a tool for collect, analyze and transfer data. Smartphone probe car(SPC) was proposed (Yi et al. 2015). SPC is used to assess road anomalies in term of pothole and road bump using vertical acceleration component. To rate the road anomaly level, underdamp oscillation model(UOM) was used to determine road anomaly index. (Douangphachanh et al. 2013) proposed the system to monitor road roughness conditions and estimate International Roughness Index(IRI) from acceleration. Their study showed that IRI have a linear relationship of vibration and average speed of vehicle.

Both types of system have a different prominent feature that custom embedded devices can be designed to perform specific tasks, which can reach a higher sampling rate of sensor reading and lower power consumption. in term of smartphone, it is more flexible for use in a large scale. In our work aim to designed the monitoring system that can collected by crowdsourcing that smartphone can provide enough capability of Internet-enabled and build-in sensors.

2.8 Transportation mode detection

The role of smartphone has become an integral component of modern life. Since smartphones can be portable to everywhere and every activity, activity tracking system has been developed in various field such as sport tracking, step counting and especially transportation tracking system. the proposed method to identify transportation mode using build-in GPS receiver. (Reddy et al. 2010) used decision tree and Hidden Markov Model by considered GPS and acceleration data. (Gong et al. 2012) analyzed GPS data combined with Geographical Information System (GIS) to distinguish mode of transportation based on location and moving speed. Speed and location in each transportation mode are associated with user activity. Analyzing GPS data can help system to identify more accurately.

Since smartphone have limited resources, considering about power consumption is needed. One of the high-energy consumed devices is GPS receiver. In contrast to using GPS, transportation mode can be extracted by accelerometer that consume less energy. The proposed method extracted the mode of transportation by smartphone acceleration. Using decision tree to classify user activity such as walking, running, standing was proposed by (Miluzzo et al. 2008). (Eftekhari & Ghatee 2016) proposed method to detect motorize and non-motorize mode using accelerometer, magnetometer and gyroscope. This method reveals 95.2% accuracy for motorize mode detection and 97.1% accuracy for stationary states in motorize mode.

Detection of transportation mode can be applied with road detection system, driving behavior, or navigation system. Those systems can be automatically run when the motorize mode is detected. According to mentioned research, transportation mode detection can be work successfully which is more than 90% accuracy.

2.9 Smartphone orientation estimation

Orientation of smartphone is one of important conditions that many research assumed the mounting conditions of smartphone. Knowing the current orientation of smartphone while driving can eliminate this tricky conditions. There is some research proposed the method for estimate smartphone orientation. (Mohan et al. 2008) estimate orientation based on Euler Angles. They applied the deceleration of braking event to estimate heading direction. Likewise, using quaternion method was proposed by (Tundo et al. 2013). (Khaleghi et al. 2015) proposed compensating method for smartphone orientation estimation during driving. The proposed method estimates heading direction during walking(Roy et al. 2014; Mohssen et al. 2014). (Huu et al. 2016) extended the holding styles in user heading estimation.

CHAPTER 3
CHALLENGES AND STRATEGIES

3.1 System architecture

The model of this system is interactive between 2 main components which is Mobile Sensing Unit (MSU) and Central Server Unit (CSU) in purposed of retrieve a driving information Fig. 3.1. SSU is smartphone mounted on vehicle and run application to retrieve sensor's data that provide acceleration, magnetic field, and GPS-positioning. Sensor's data will send to store and analyses at CSU. Strategies and Challenges in each module will be described below.

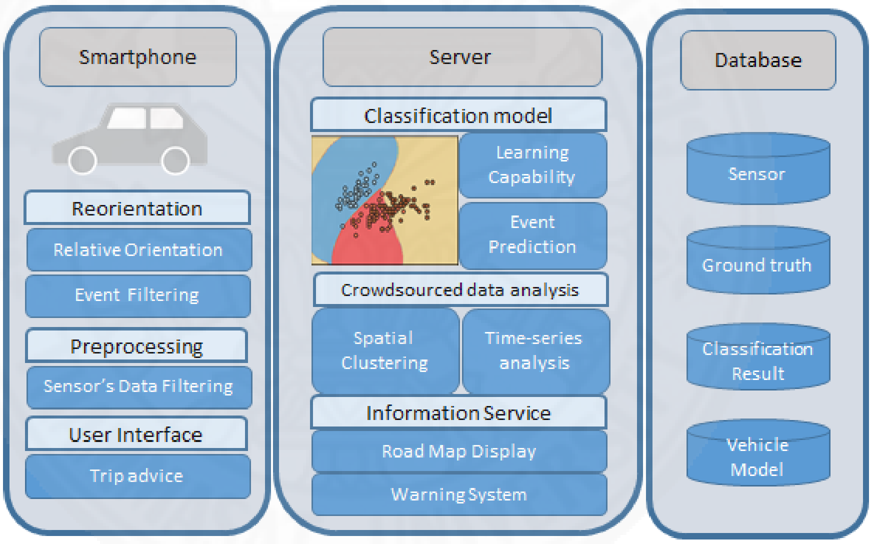


Fig. 3.1 road conditions monitoring system framework

3.2 Smartphone virtual reorientation

when smartphone installed or placed in vehicle, sensors frame is changed depend on the orientation of smartphone that not match with vehicle frame. Basically, smartphone orientation can be identified by taking advantage of gravitational field and magnetic field. However, it is difficult to measure these values accurately while driving. The vibration of driving can distort gravitational field read by accelerometer. Events filtering can be one solution that use to avoid the situation causing error.

3.3 Events classification

There are several research methods proposed to detect or classify driving conditions such as turning, braking, accelerating, or anomaly event. Generally, acceleration is often used as main features to classify by applying machine learning. GPS positioning and speed combined with road map data can help to digest a driving events. Some road conditions are ambiguous to identify such as road bump and pothole because of similarity of vibration characteristic.

3.4 Learning capability

Vehicle types and driving style for individual affect characteristic of vibration significantly. To make system robust to these conditions the classification model should have capability to adjust itself to suit the conditions. adaptive learning of classification model can perform when driving through the road that already explore. Increasing of driving hour make system more precise.

3.5 Crowdsourced data analysis

when system is deployed in large scale, there are many road conditions reported to server. These amounts of data need to be analyze to conclude. For example, clustering by location can be used to determine road anomaly when anomaly is reported frequently in the same area. Time-series can be analyzed to monitor the degradation of the road or traffic flow.

CHAPTER 4
ROAD CONDITIONS CLASSIFICATION

4.1 Road conditions characterization

There are several road conditions, such as potholes, speed bumps, road joint, etc., on common roads that have different vibration characteristics. In this paper, three types of road conditions are defined, good road, bad road and road bump. The good road is a road that has a flat and smooth surface. It has a low vibration in both the vertical axis and lateral axis of the vehicle. Fig. 4.1 (top) shows the condition of the road that is considered good road and this road segment was used to collect the training data. In contrast, a bad road is a road that has a rough surface and full of potholes. The assumptions of this experiment are that same as found in (Eriksson, Girod, Hull, et al. 2008; Gunawan 2015) that potholes affect only one side of the vehicle so that it should have a high vibration in both vertical axis and lateral axis of vehicle. In terms of road bumps, it causes a high vibration only in the vertical axis.

Fig. 4.1 Road condition characteristic good road(top) and bad road(under)

4.2 Sensor's data acquisition

The acceleration, orientation and position from the smartphone's GPS sensor was collected. The smartphone was placed on the vehicle floor on the passenger side and the y-axis acceleration was set to be the same as the vehicle forward direction. In this section, the process of data collection is briefly described.

The 3-axis acceleration and 3-axis orientation data, shown in Fig. 4.2, were collected by smartphone at a frequency of 50Hz (20ms) and the position data was collected every second. Third party android application was used to measure and transmit this data directly to laptop via Wi-Fi. To address the road condition and describe the signal behavior, the physical characteristic of the road was recorded carefully. While the sensor's data was collected, ground truth was simultaneously manually recorded based on the location.

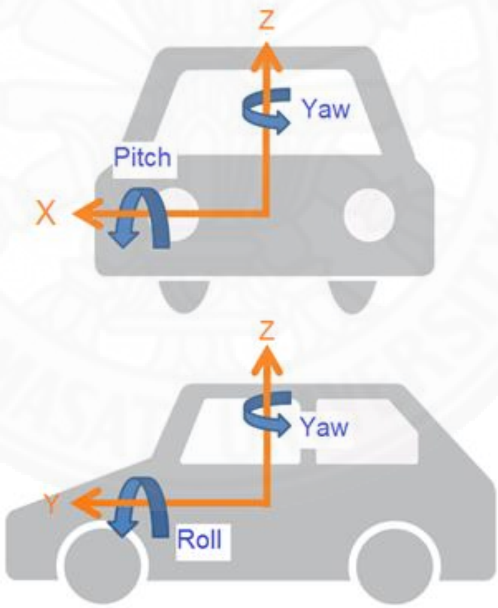


Fig. 4.2 Accelerometer and rotation axis setting

4.3 Signal processing

The acceleration and orientation signals, collected at 50Hz as previously described, were separated into windows and the index parameter was calculated for each axis of the sensor's data. Then, every index parameter was matched to the position from the GPS data.

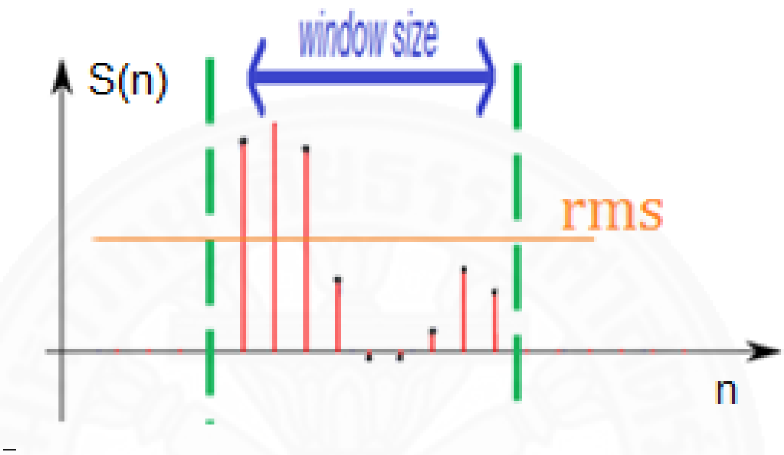


Fig. 4.3 Root mean square of moving window

$$RMS\{S(n)\} = \sqrt{\frac{1}{N}\sum_{n} S^2(n)} \qquad \text{Eq. 4.1}$$

$$Parameter = RMS\{S(n)\} - mean\{S(n)\} \qquad \text{Eq. 4.2}$$

Research has been carried out on many approaches to calculate index parameters, such as peak impulse signal (Eriksson, Girod, Hull, et al. 2008; Gunawan 2015), difference between the maximum and minimum impulse signals (Vittorio et al. 2014) and signal cleaning using a filter (Astarita et al. 2012). In this paper, the root mean square of the one second window size Eq. 4.1 was used with the zero frequency component removed Eq. 4.2 for more precision. After the calculation, the parameters will be matched with the position based on the timestamp.

4.4 Classification and features selection

The linear kernel support vector machine was used to classify the road conditions which were defined in section 4.1. In this section, experiments to select the training data and set of features are described.

Training data were selected by the nearest location from manually recorded road conditions as shown in Fig. 4.4. The test road was repeatedly driven on and the sensor's data and location were compared to ensure exactness. Finally, there was a total of 145 samples of good road, 118 samples of bad road and 113 samples of road bump respectively.

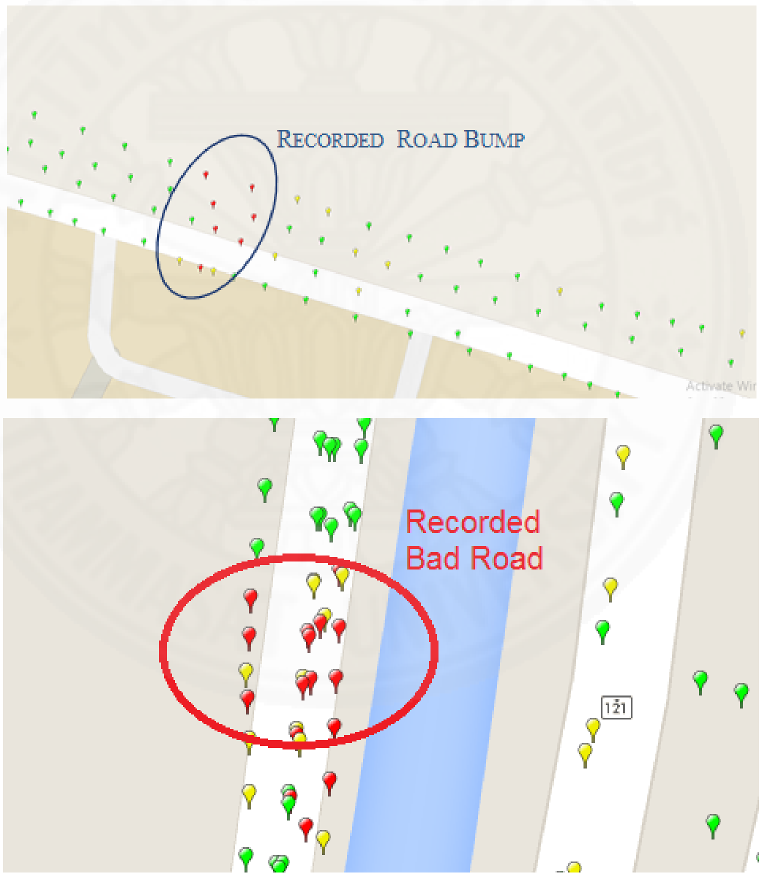


Fig. 4.4 Sample of hand-labeled (circle) and system reported (mark inside circle) road bump location (blue) and bad road location (red).

According to the signal processing section, the six parameters (from 3-axis acceleration and 3-axis orientation) were considered as features and the three road conditions were considered as a class. First, the two most relevant features to the characteristic road conditions (as defined in section III.A) were selected and the features which were not relevant were ignored. This step was repeated by adding up to four more features. To score the sets of features, cross validation was performed at 75 and 90 percent of the training set and the results are shown in Table 4.1.

Table 4.1 Accuracy of Cross Validation

Features (axis)				Training size	
Roll	Pitch	Z	X	75%	90%
☑	☑	-	-	86.9 %	87.0 %
-	-	☑	☑	92.0 %	92.2 %
☑	-	☑	-	92.8 %	93.1 %
-	☑	☑	☑	91.7 %	93.1 %
☑	☑	☑	-	91.8 %	93.4 %
☑	☑	☑	☑	92.6 %	93.1 %

The left side of Table 4.1 (Features axis), presents the 4 most relevant features. The right side of Table 4.1(Training size), presents the results of cross validation which 75 percent and 90 percent is the size of the training data.

The results in Table 4.1, show that all the sets of features have almost the same accuracy. The results explain that using only two features, it is enough to classify the road surface condition for this experiment. Therefore, we consider only the set of Roll and Pitch, Z and X, and Roll and Z. The set of Roll and Pitch was discarded because the results were less accurate than the other sets. Comparing the sets of Roll and Z and the set of Z and X, the later set has 0.8% lower, however only the accelerometer was used and it was considered a better choice in terms of power consumption and CPU resource usage of the smartphone. For this reason, the set of Z and X was selected for this experiment. The classification result of the selected feature set is shown in Fig. 4.5 Linear Support Vector Machine Classification. Selecting a set of features and optimizing the model, a drive test was performed to validate our proposed algorithm which is discussed in the next section.

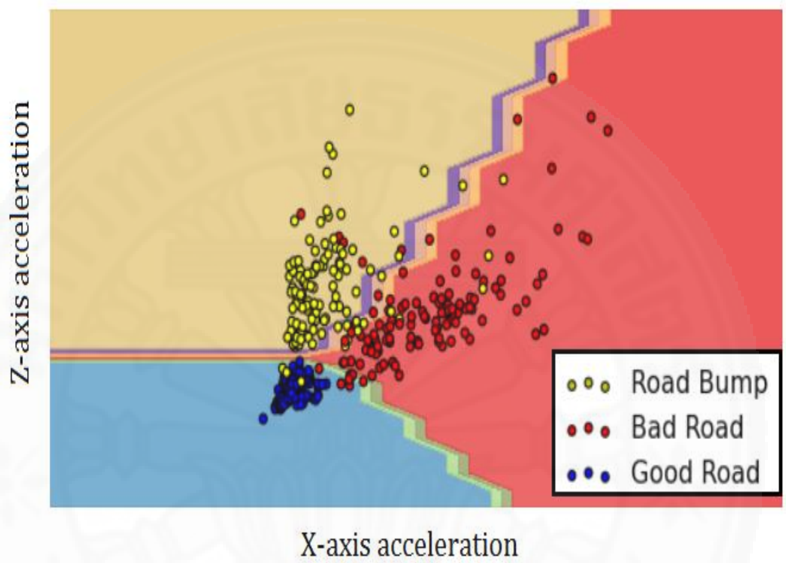


Fig. 4.5 Linear Support Vector Machine Classification

4.5 Results

To evaluate the model, the smartphone was placed in the same conditions as the data collection process and the three road conditions that exist on the testing road were examined. This evaluation focusses on the detection of bad road and road bump events and the results are shown in Fig. 4.6.

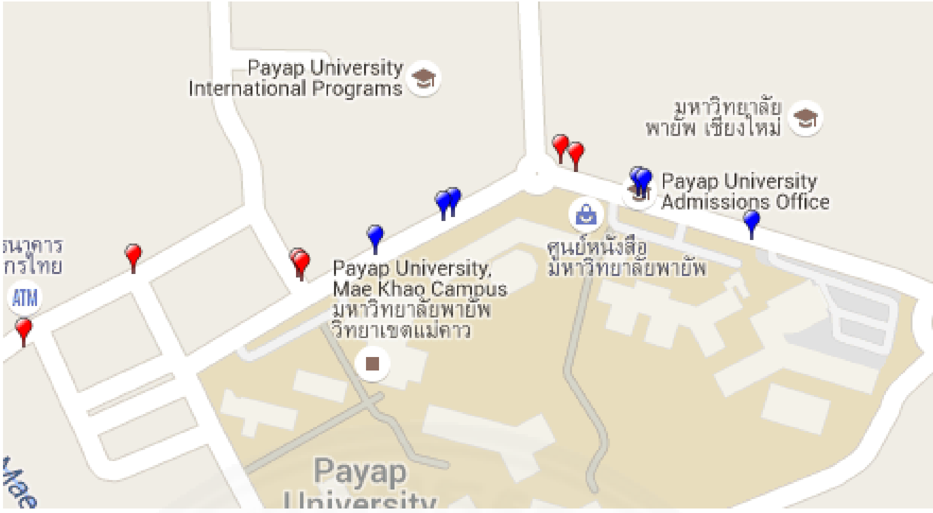


Fig. 4.6 Detected data was reported on the map (Blue mark represent road bump and the red mark represent bad road).

4.6 False detection analysis

The detected results were compared with the hand labeling data that was observed in detail at every point shown in Table 4.2. The detection error is quite high especially the false negative of bad road. To address this problem, we re-analyzed false detected data and found two main issues which are the driving event and the road characteristic.

Table 4.2 Validation Result

	Bad road	Road bump	Overall
FP	8 %	10.6 %	9.3 %
FN	25 %	16 %	19.75 %

FP: False Positive, FN: False Negative

Some events that could cause false detection such as turning, abrupt lane changing or hard braking were observed during this experiment. It was confirmed that turning the car caused a false positive detection. While the problem that caused the most of false negative detection was the characteristic of the bad road. The assumption previously defined about bad road (section 4.1) did not cover all cases and a large broken road section that affected the vehicle similar to a road bump was found.

4.7 Loosely hand-labeling data

Although data was carefully collected, there could be errors in the process of hand-labeled data collection. For example, in term of bad road, there are several ambiguous roads that are difficult to judge whether it is normal or bad. When the system reported a bad road while hand-labeled as a good road, it was found that there were some points where the road was not smooth or had some small collapses.

4.8 Conclusions

In this research, a road condition detection and classification system was proposed based on a smartphone's sensors. The sensor's data was collected by third party application and sent directly to a laptop for analysis. Three classes of road condition were defined in this experiment including good road, bad road and road bump. To prepare the data for classification, the stream data was calculated in a one second window size by the root mean square. A linear support vector machine was used in classification process and the set of z-axis and x-axis acceleration was selected to use as features of training data. Finally, the result of tests from this model give overall system false negative of 19.75 percent and a false positive of 9.3 percent.

CHAPTER 5
SMARTPHONE VIRTUAL REORIENTATION

5.1 Coordinate system and rotation Axes

3 coordinate system used in this paper were defined that is Earth coordinate system (N, E, -G) is referred to the North(N), East(E) and Earth's Gravity(-G). Car's coordination system (F, S, -G) is defined to car side(S), car forward direction(F). For the Earth's Gravity Axis(-G) is sheared with Earth's coordinate. Phone's coordination system is referred to local sensor's coordinate system (X, Y, Z). Phone's rotation angles (β, α, γ) relative to Earth's coordinate is defined to pitch (β), roll (α) and yaw (γ) measured counter-clockwise about corresponding axis X, Y and Z respectively. Since Earth's gravity axis was shared between car coordinate and Earth coordinate, the F-E plane of car coordinate and N-E plane of earth coordinate are in the same plane with different angle called Azimuth. Azimuth or car heading angle (ψ) relative to North is defined to rotation of gravity axis (-G) of car coordinate.

5.2 Rotation matrix

Rotation matrix used to transform a vector under a rotation of coordinate system. Equation (5.1 - 5.3) show the rotation matrices by angles pitch (β), roll (α) and yaw (γ) about X, Y and Z axes respectively.

$$R_x(\beta) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & cos(\beta) & sin(\beta) \\ 0 & -sin(\beta) & cos(\beta) \end{bmatrix} \quad \text{Eq. 5.1}$$

$$R_y(\alpha) = \begin{bmatrix} cos(\alpha) & 0 & -sin(\alpha) \\ 0 & 1 & 0 \\ sin(\alpha) & 0 & cos(\alpha) \end{bmatrix} \quad \text{Eq. 5.2}$$

$$R_z(\gamma) = \begin{bmatrix} cos(\gamma) & sin(\gamma) & 0 \\ -sin(\gamma) & cos(\gamma) & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad \text{Eq. 5.3}$$

The rotation matrix based on x-y-z rotation sequence (R_{xyz}) can calculate by multiplication of $R_x(\beta)$, $R_y(\alpha)$ and $R_z(\gamma)$ by equation 5.4.

$$R_{xyz}(\beta, \alpha, \gamma) = R_x(\beta)R_y(\alpha)R_z(\gamma) \quad \text{Eq. 5.4}$$

5.3 Smartphone Orientation Estimation

Earth's gravitational field is used to estimated phone orientation angles in term of pitch (β) and roll (α). To simplify the equation, 2 assumptions are defined below. these assumptions and estimation method are applied from AN3461 (Pedley 2013). Initialization of orientation: X-Y plane of phone's coordinate is perpendicular to Earth's gravitational field (-G) and Y-axis is referenced by North. No linear acceleration component: the summation of acceleration is equal to gravitational field. Other source of acceleration such as phone movement, turning or vibrating will cause errors of estimation.

Defined G_p is a unit acceleration vector reading from smartphone's accelerometer rotated from initial orientation and $[0\ 0\ g]^T$ is normalized gravitational field vector. G_p can be written as:

$$G_p = \frac{1}{|G_p|}\begin{bmatrix} G_{px} \\ G_{py} \\ G_{pz} \end{bmatrix} = R_{xyz}\begin{bmatrix} 0 \\ 0 \\ g = 1 \end{bmatrix} \quad \text{Eq. 5.5}$$

Substituting equations (5.1 - 5.4), the solution can be written as:

$$\frac{1}{|G_p|}\begin{bmatrix} G_{px} \\ G_{py} \\ G_{pz} \end{bmatrix} = \begin{bmatrix} -\sin(\alpha) \\ \cos(\alpha)\sin(\beta) \\ \cos(\alpha)\cos(\beta) \end{bmatrix} \quad \text{Eq. 5.6}$$

Solving pitch (β) and roll (α) angles from Eq. 5.6, the solutions are:

$$\beta = \tan^{-1}\left(\frac{G_{py}}{G_{pz}}\right) \qquad \text{Eq. 5.7}$$

$$\alpha = \tan^{-1}\left(\frac{G_{px}}{\sqrt{G_{py}^2 + G_{pz}^2}}\right) \qquad \text{Eq. 5.8}$$

To estimated yaw angle (γ), phone's magnetometer used to measure 3-axis magnetic field represented by $[m_x \quad m_y \quad m_z]^T$. Since yaw angle (γ) is initiated by North, the x-y plane of phone's magnetometer need to be transformed to lying flat with N-E plane of the Earth's coordinate. The Transformed magnetic field $[m'_x \quad m'_y \quad m'_z]^T$ can be written as:

$$\begin{bmatrix} m'_x \\ m'_y \\ m'_z \end{bmatrix} = R_{xyz}(\beta, \alpha, 0) \begin{bmatrix} m_x \\ m_y \\ m_z \end{bmatrix} \qquad \text{Eq. 5.9}$$

Therefore, yaw angle (γ) can be estimated by:

$$\gamma = \tan^{-1}\left(\frac{m'_x}{m'_y}\right) \qquad \text{Eq. 5.10}$$

5.4 Vehicle orientation estimation

In this research, Orientation of car are assumed to lying flat to Earth surface. Therefore, only car heading (ψ) is considered for car orientation other angles are assumed to be zero. To obtain direction of car heading(ψ) relative to North, 2 difference GPS data of moving car represented in term of latitudes (φ_1, φ_2) and longitudes (Λ_1, Λ_2) can be used to determine by the following formula below.

$$d\Lambda = \Lambda_2 - \Lambda_1$$

$$\Delta X = \sin(d\Lambda) - \cos\varphi_2$$

$$\Delta Y = \cos\varphi_1 \sin\varphi_2 - \sin\varphi_1 \cos\varphi_2 \cos(d\Lambda)$$

$$\psi = \tan^{-1}\left(\frac{\Delta X}{\Delta Y}\right) \qquad \text{Eq. 5.11}$$

5.5 Relative orientation angles

Orientation angles mentioned previously are relative to Earth coordinate system. Since objective of this paper is to transform sensor's data from phone coordinate to car coordinate which data of X, Y, Z axes belong in the F, S, -G axes respectively, the phone orientations angles need to be transformed to relative orientation angles (β', α', γ'). In this paper, relative orientation angles (β', α', γ') are defined as the orientation angles of phone relative to car coordinate system. Relative yaw angle can be calculated by subtraction of phone yaw angle (γ) and car heading angle (ψ) shows in equation 12. According to previous assumption that car lying flat to Earth surface, the relative roll and pitch angles will be equal to roll and pitch angles.

Table 5.1 Summary of symbol

Symbol	Description
N, E, -G	Earth coordinate system: N points to North, E points to East, and -G is anti-gravity axis.
F, S, -G	Car coordination system: F is car forward axis, S points to car side, and -G is anti-gravity axis.
X, Y, Z	Phone coordination system: X points to right side of phone along the transverse axis, Y points to phone head along the phone body axis, and Z is perpendicular to phone's screen.
M_x, M_y, M_z	Magnetic field vector measured by Smartphone
M_x, M_y, M_z	Reoriented magnetic field vector
β, α, γ	Phone rotation angles relative to Earth coordinate rotate around X, Y, Z respectively
β', α', γ'	Phone rotation angles relative to car coordinate rotate around X, Y, Z respectively
ψ	Car heading Angle relative to North
φ, Λ	GPS positioning in term of latitude and longitude

In this theoretical background, the definition of coordinate systems and formula to determine angles are showed. These definitions and formula will be applied next section. The summary all of symbol is shows in Table 5.1.

5.6 Sensor's data acquisition

In this research, 2 smartphones were used to collect data in May 2016 by driving a 2006 ISUZU mu7 gold series. In this driving, Data was collected in various speed (up to 80 km/Hr.), and the system was tested on the roads with 2 characteristics. the data collection was test on the highway that driving speed are between 40 and 80 km/Hr. Second road segment is local road in lower driving speed. The detail of this collection is described

5.6.1 Smartphone Initialization

two smartphones were place on the vehicle in different orientation. P1 is referred to the smartphone that has a same orientation as vehicle, and the P2 is referred to the smartphone mount on smartphone holder. The relative orientation angles of P1 are equal to zeroes. For the P2, relative orientation angles (β', α', γ') are set to 50, -123, and -110 While test on highway and 25 -118, -120 while test on local road. these smartphones were used to collected acceleration, magnetic field, and GPS positioning. acceleration and magnetic field data were collected in 50 Hz and position from GPS was collected in 1 Hz.

5.6.2 Reference data

2 video cameras were install on vehicle. The first camera installed inside vehicle used to record traffic on forward direction. Second camera was install outside and projected to road surface. These videos are used to analyze sensor's signal and validate the system.

5.6.3 Measurements preparation

The 50 Hz data rate of acceleration and magnetic field data were decimated to10 Hz and GPS data was increased to 10 Hz by repeated primary data, and FIR low pass filter was applied to acceleration and magnetic field data by 0.5 Hz cutoff frequency. With the same data rate, 3 sensors' data were combined to one set of measurement.

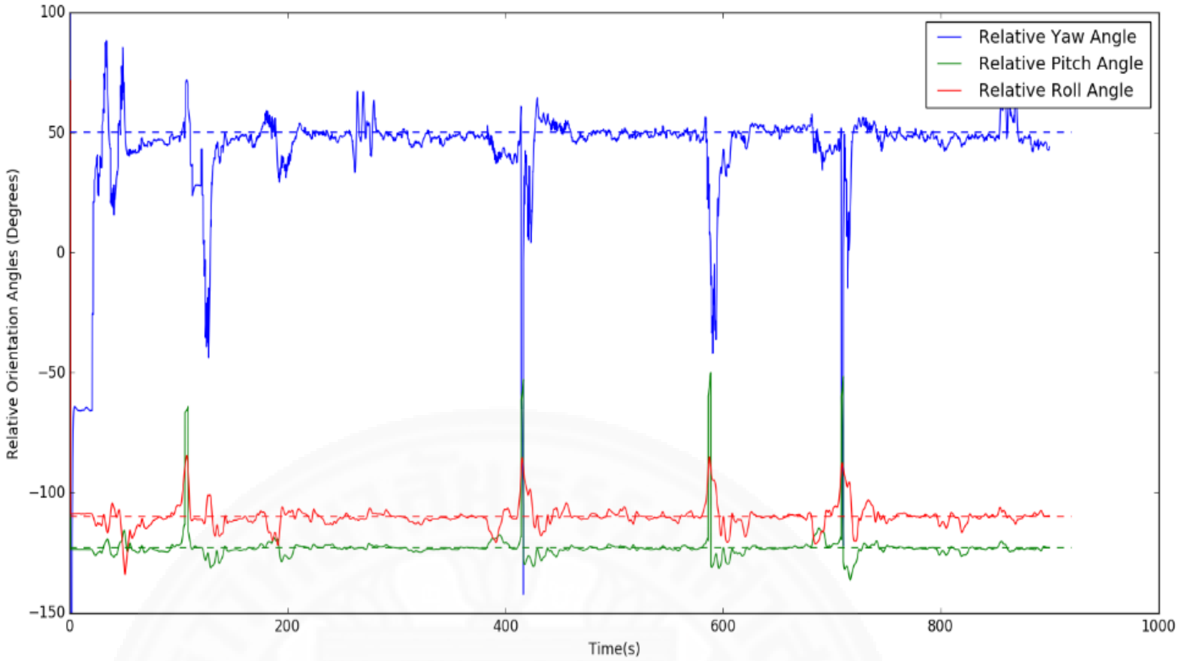


Fig. 5.1 Result of relative orientation angles estimation from collected data, testing on directed road with U-turn event.

5.7 Driving Experiment

Fig. 5.1 shows the whole trip results of estimation on highway driving. the dash lines present the ground truth angles of P2 orientation and solid lines shows the results of estimation. In this experiment, the system was tested in straight road and U-turn event. Result of relative yaw angle present the highest error comparing with pitch and roll angles because of low sampling rate of GPS positioning. Obviously, the results of three angles shows the high error during U-turn at 100, 410, 590 and 700 seconds. The motion during U-turn can cause a high level of linear acceleration that contrary to the assumptions of car orientation and phone orientation.

5.8 Driving state identification

As mentioned previously, the estimation equations of roll and pitch orientation angles were proved under the assumption which is suitable for smartphone in stationary situation. Therefore, applying this estimation method in moving status have a high error caused by certain driving conditions. To categorize the status of smartphone based on change of relative orientation, 3 driving state were defined that is normal state, event state and phone moving state. The normal state is defined to situation when car is lying flat to Earth surface in steady smartphone placement without any linear acceleration component. Generally, driving straight with constant velocity is considered normal state. Event state is referred to situation that car is moving on road conditions such as curve, bridge, pothole, road bump, etc., and smartphone keep the same orientation. In this state, the linear acceleration component is presented and car orientation might not be lying flat. The duration of driving that relative orientation changes whether caused by human or driving motion are considered smartphone moving state.

Algorithm 1: Posture Change Detection

```
//Declearaion
    constant SDT
        // SDT is {2.54, 0.47, 1.09} for {yaw,pitch,roll}
        // SDT refer to standard deviation threshold
    function std(narray)
        //return standard diviation of narray

// Posture change detection function
    function Pos_chk(narray SMA_Array,float SDT):
        int N = length(SMA_Array)
        if std(SMA_Array) > SDT*2:
            if std(SMA_Array[N/2: -1]) < SDT:
                // check second half of SMA_Array
                return SMA_Array[N/2: -1]
                    // return only second half of array
        return SMA_Array
            // return original
```

Algorithm 2: Filtering Algorithm

```
//Declearaion
    input Streaming_Input
    output Steaming_Output
        //relative orientation angles
    narray Detection_Array[30]
    narray SMA_Array[70]
    constant Threshold  // slope thresholding
    constant SDT  // standard deviation threshold
    function Slope(narray)
        // return slope of regression line
    function Mean(narray)
        // return mean of narray
    function Pos_chk(narray,float)
        // return collected data array (Algorithm 1)

// process loop
While (1){
    for input in Streaming_Input:
        Detection_Array.append(input)
        if Slope(Detection_Array) > Threshold:
            SMA_Array.append(Detection_Array[0])
            SMA_Array = ReCalib_chk(SMA_Array, SDT)
                // if phone moving, need to clean array
            SMA_Array.pop(0)
        Detection_Array.pop(0)
        Steaming_Output.append(Mean(SMA_Array))
}
```

Fig. 5.2 Pseudocodes of Filtering method with posture change detection. Algorithm 1 shows process of posture change detection system and Algorithm2 shows the full process of filtering algorithm.

5.9 Event filtering

Since previous estimation method is still sensitive to noise either from measurements device or driving state, the results of estimation present high error. To improve the system, linear regression method is applied to detect normal state by slope thresholding. Only normal state data is used to determine relative orientation angles because of least estimation error. After filtering other state out, Simple Moving Average (SMA) is applied to remove noise in normal state data. pseudocode of filtering method is shown in Fig. 5.2 (algorithm 2).

5.10 Smartphone posture change detection

Although filtering method by slope thresholding can detected normal state efficiently, the phone moving state are still affect to the system in case of replacing in a new orientation. After action of phone moving state, the relative orientation angles can be changed that cause error in SMA step because the old angles data remain in array. From experimental data, the average of standard deviation in normal state is 2.54, 0.47, 1.09 for relative yaw, pitch, and roll angles respectively. The standard deviation of SMA array should corresponding to this value. In case of higher standard deviation, it has a high possibility that the relative orientation was changed. To reject the wrong angles, the SMA array was divided into smaller array and re-check standard deviation for each array. In this detection, the standard deviation threshold(SDT) was defined and the Pseudocodes of this detection was shown in Fig. 5.2 (algorithm 1).

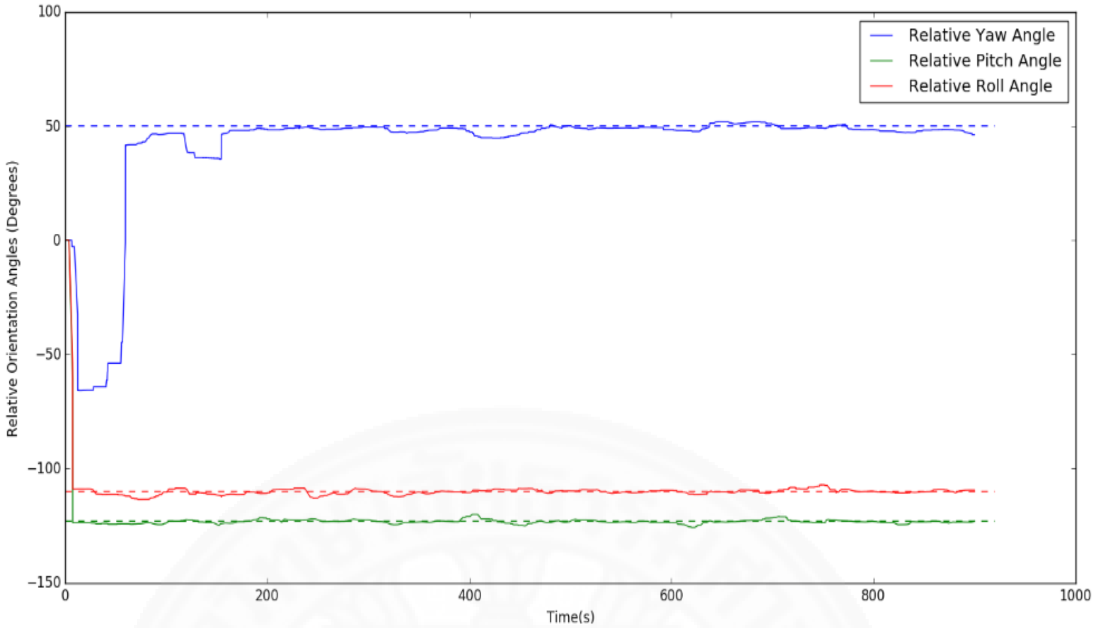


Fig. 5.3 Result of relative orientation angles estimation using filtering algorithm

Fig. 5.3 show result after using event filtering. By using event filtering, the effect of smartphone moving state and event state can be removed efficiently. To provide more extensive testing, the system was tested on local road including bump, pothole, small bridge, curve, and broken road section over a distance of 8 km approximately. The results of highway and local road driving experiments were presented in term of mean and start deviation shown in Table 5.2 and Table 5.3.

Table 5.2 Results of highway testing.

P2				
Relative Orientation angles	No Filtering System		Filtering System	
	Mean	SD	Mean	SD
Yaw = 50	45.64	14.61	48.02	2.84
Pitch = -123	-122.7	7.22	-123.1	0.82
Roll = -110	-109.8	4.65	-110.0	0.96

P1				
Relative Orientation angles	No Filtering System		Filtering System	
	Mean	SD	Mean	SD
Yaw = 0	1.99	15.21	4.05	1.65
Pitch = 0	-0.51	5.60	-0.27	0.93
Roll = 0	-0.52	5.65	-0.71	0.53

Table 5.3 Results of local road testing

P2				
Relative Orientation Angles	No Filtering System		Filtering System	
	Mean	SD	Mean	SD
Yaw = 25	23.96	13.07	25.19	2.21
Pitch = -118	-117.8	2.51	-117.8	0.83
Roll = -120	-120.4	6.42	-120.0	2.08

P1				
Relative Orientation Angles	No Filtering System		Filtering System	
	Mean	SD	Mean	SD
Yaw = 0	-0.90	18.66	0.74	3.33
Pitch = 0	0.16	2.38	0.19	0.75
Roll = 0	-0.53	3.29	-0.57	1.15

5.11 Settling time and steady state error

The event filtering method can be removed the periods of event state and phone moving state efficiently; however, system take time for calibration when system start. Settling time is defined as the time required to reach and stay within a range of 10 degrees' error of relative orientation angles and steady state error is defined as the error of relative orientation angles after the system was calibrated. To find the relations between settling time and steady state error, we selected a direct road segments data to simulated settling time by randomly initialize angles. Fig. 5.4 and Fig. 5.5 shows the comparison between settling time and steady state error of P2 by varying slope thresholds in filtering method.

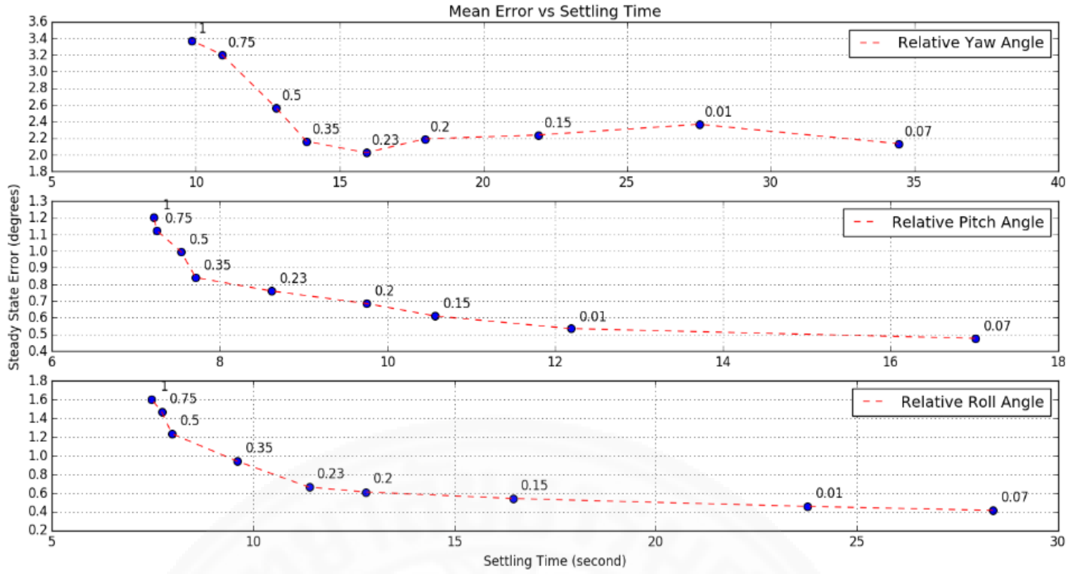


Fig. 5.4 comparison between average of steady state error and average of settling time for each slope thresholding.

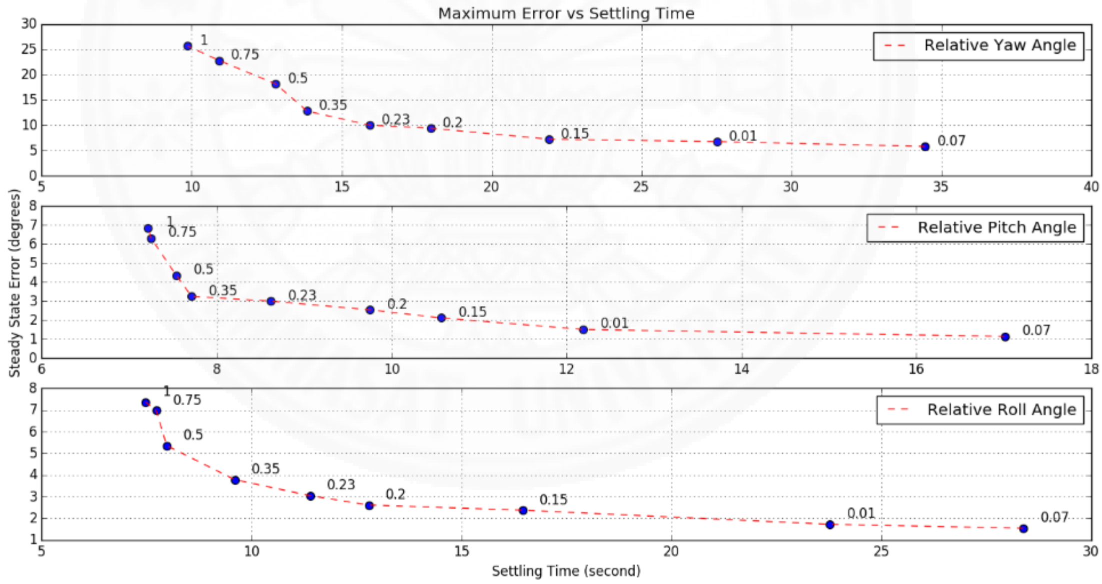


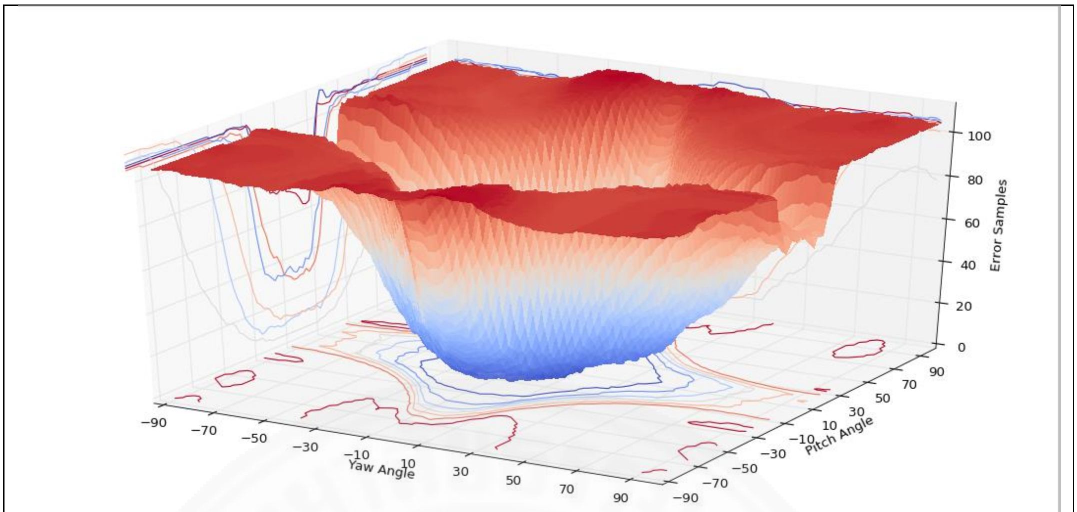
Fig. 5.5 comparison between maximum of steady state error and average of settling time for each slope thresholding.

Considering Fig. 5.4 and Fig. 5.5, the inverse relations between settling time and steady state error can be applied to optimize the event filtering method depends on application that need accuracy or responding time. To comply with our classification model which will be described in the next section, the slope thresholds are set to 0.23 for all relative orientation angles. at this slop thresholds, the average settling time tested on direct road is around 16, 9 and 11 seconds for yaw pitch and roll angles respectively, but the settling time of local road including many of road conditions and discontinuous direct road segment is up to 60, 26, 22 seconds respectively. In case of the smartphone on driver pocket is more difficult for calibration that system take 100 to 300 seconds for relative yaw angle to reach a steady state. The main factor that could explain the increasing of setting time, Event filtering is directly affected to settling time. When Event state or smartphone moving state are detected, output angles of event filter will keep a last value of normal state that can cause a high waiting time.

5.12 Effect of Reorientation Error

To applied a virtual reorientation system with classification system, we studied the effect of tolerance in virtual reorientation process that directly affect to accuracy of classification. the training data that can be classified correctly were selected for simulation. Selected data were reoriented by gradually increasing of angles, and observed the classification errors in each angle. In this simulation, there are 100 training data for each class of classification.

Table 5.4 simulation the effect of virtual reorientation error



Error			Range of Rotation Angles	
Good Road (%)	**Bad Road (%)**	**Road Bump (%)**	**Pitch Angle (degrees)**	**Yaw Angle (degrees)**
0	0.92	0	(-5, 5)	(-5, 5)
0	1.85	1.01	(-10, 10)	(-10, 10)
0	3.70	4.04	(-15, 15)	(-15, 15)
0	4.63	10.10	(-20, 20)	(-20, 20)
0	6.48	34.34	(-25, 25)	(-25,25)
0	6.48	75.75	(-30, 30)	(-30, 30)
0.68	23.15	100	(-50, 50)	(-50, 50)
3.45	55.56	100	(-90, 90)	(-90, 90)

The number of testing data of good road, bad road, and road bump is 145, 108, and 99 respectively

Table 5.4 show the result of simulation by rotation of pitch and yaw angles. In vertical axis of 3d graph, shows the number of error occurred when rotate in each angle pairs. On the table below the graph show a range of angles that cause error in a various number o This simulation can apply to setup threshold in event filtering.

5.13 Detection System in Unfixed Installation

In the end of experiment, the virtual reorientation system and classification model were combined. This system was tested to detect pothole and road bump by installing 3 smartphones in different orientation. The ground truth data was manually counted using video camera and assigned the area of each road condition. when the system report road condition in the correct area at least 1 times, we will consider 1 correct detection. And wrong detection is count when the system report outside the area. The detection results of 3 smartphones were shown in Table 5.5.

Table 5.5 Results of road condition detection system.

<table>
<tr><th colspan="7">Ground Truth</th></tr>
<tr><td colspan="4">Road Bump = 41</td><td colspan="3">Bad Road = 19</td></tr>
<tr><th colspan="7">Number of System Detection Report</th></tr>
<tr><td colspan="3">smartphone</td><td colspan="2">Road Bump</td><td colspan="2">Bad Road</td></tr>
<tr><td colspan="3">P2</td><td colspan="2">39</td><td colspan="2">24</td></tr>
<tr><td colspan="3">P1</td><td colspan="2">36</td><td colspan="2">20</td></tr>
<tr><td colspan="3">P3</td><td colspan="2">36</td><td colspan="2">29</td></tr>
<tr><th colspan="7">Smartphone Detection Result</th></tr>
<tr><td rowspan="2">Smartphone</td><td colspan="3">Road Bump</td><td colspan="3">Bad Road</td></tr>
<tr><td>Detected (%)</td><td>Undetected (%)</td><td>Wrong detection (%)</td><td>Detected (%)</td><td>Undetected (%)</td><td>Wrong detection (%)</td></tr>
<tr><td>P2</td><td>87.80</td><td>12.20</td><td>7.69</td><td>94.74</td><td>5.26</td><td>25</td></tr>
<tr><td>P1</td><td>82.93</td><td>17.07</td><td>5.56</td><td>84.21</td><td>15.78</td><td>20</td></tr>
<tr><td>P3</td><td>70.73</td><td>29.27</td><td>19.44</td><td>84.21</td><td>15.78</td><td>44.83</td></tr>
</table>

Detected and undetected are based on ground truth value
Wrong detection is based on total system detection report

The result shown on table 5.5 present the number of correct and incorrect system report of 3 smartphones. In this experiment, the ground truth data was manually counted using video camera and assigned the area of each road condition. when the system report road condition in the correct area at least 1 times, we will consider 1 correct detection. And wrong detection is count when the system report outside the area.

CHAPTER 6
DISCUSSIONS AND CONCLUSIONS

6.1 Highway and local road

In experiment to estimate relative orientation angles on the highway and local road, we found that estimation during driving on highway is much more accurate than local road considering standard deviation from table 5.2, 5.3. Mostly of driving on highway is a long straight road that result in less effect of linear acceleration. In term of driving speed, highway is also higher than local road resulted in higher precision when use GPS to estimate car heading (ψ). Considering table 5.4 that shows the effect of estimation error, since result from local road driving presents a higher standard deviation, the result is still acceptable for this classification model.

6.2 Unfixed smartphone installation effect

In this research, the detection system was operated in 3 placing conditions of smartphone that affect to the performance of system in different ways. Since P2 was mounted on the vehicle and support vector machine was constructed under this placing conditions that the detection result should be the most effective, but the experiment result (table 5.5) show that the correct detection of P2 are less than P1. Smartphone holder affect the sensitivity of vibration that made P1 are more sensitive for road conditions. In contrast, recall of P1 is less than P2. In case of P3, smartphone on the driver's pant pocket is often shifting sporadic that can change an orientation of smartphone and produce acceleration component, result in many wrong detections occurred. This system can work properly only in stationary smartphone placement conditions.

6.3 Effect of other road conditions

The purpose of this experiment was to detect the damaged road in term of bumpy road. The characteristic of vertical vibration of damaged road is like road bump, which is not considered as damaged road. Therefore, we aim to distinguish this two road conditions by adding lateral vibration in classification as Fig. 4.5. In term of practical use, there are many road conditions included that can cause error in detection. Turn the vehicle is the one conditions that produce mistake in detection due to centrifugal acceleration that system decide as pothole. Driving through the road bump while turning is decide pothole as well. While driving on the ramp Resulting in a change in the vertical acceleration, depending on the slope, which be reported as road bump.

6.4 The Issue of vibration in different vehicles

Vibrancy for Each model of the vehicle, whether car, truck or SUV is certainly different. It also includes options such as tire and shock absorber which affects as well. Therefore, each vehicle requires a specific classification model. To make system applicable to all types of vehicle, learning capability (mention on section 3.4) is need to adjust classification model accordingly.

6.5 Conclusion

In this research, we have designed a tool used to gather sensor's data and monitor road conditions Which can support in term of crowdsourced data. In this paper, we focus on study a virtual reorientation of smartphone's accelerometer. We applied a traditional method with event filtering system to estimate relative orientation between smartphone and vehicle. This system was tested on local road and highway that have a difference in the pattern of road and range of speed. The results reveal that this system can works successfully under conditions of flat road and stationary smartphone placement. The reorientation system was combined with road detection system that use to detected road distress in term of pothole and road bump. The result show that the system can successfully detect this two road conditions on straight road. In future work, we plan to deploy smartphone application to collect sensor's data in larger scale that we can design an analysis function of crowdsourced data and we also intend to develop the learning capability of system.

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Appendices

Appendix A
Sensor's Data Description

In this research, sensor’s data was collected 2 times in different format. At the first times, data was collected for experiment on chapter 4 road conditions classification. And the second times was collected for experiment on chapter 5 smartphone virtual reorientation.

A.1 Sensor’s data in road conditions classification experiment

Data was record in folder name “First_Experiment”

```
A,9, 1442647054833,0.344765,-0.296881,-8.9734678
O,9, 1442647054831,97.0000076,-2.0,2.0
A,10, 1442647054819,0.3351882,-0.3639187,-8.9734678
O,10, 1442647054807,96.9999847,-2.0,2.0
A,11, 1442647054801,0.3351882,-0.3639187,-9.2128878
O,11, 1442647054788,97.0,-1.0,-1.0
A,12, 1442647054774,-0.248997,-0.1628057,-9.107543
O,12, 1442647054770,97.0,-3.0,0.0
A,13, 1442647054754,0.0766145,-0.593762,-9.6342678
O,13, 1442647054750,97.0000076,-2.0,0.0
G,0, 1442647055020, 268.8991625, 018.7666231, 098.9872742, 1442647055000, 024.0000000, 015.2947798
A,14, 1442647055999,0.593762,-0.0957681,-9.3373871
O,14, 1442647056016,96.1015015,0.0,3.0
A,15, 1442647055982,0.9002199,-0.0957681,-9.203311
```

Fig. A.1 data format in “First_Experiment.txt”

Data was written in comma separated value format. The first column of lines is a header which describe below:

“A” represent acceleration data which format is

A, Index, timestamp, x-axis acceleration, y-axis acceleration, z-axis acceleration

“O” represent orientation angles in degree which format is

O, Index, timestamp, yaw angle, pitch angle, roll angle

"G" represent GPS data which format is

G, index, timestamp1, altitude, latitude, longitude, timestamp2, speed, nan

Training data that use to construct linear support vector machine in Fig 4.5 located at folder "Training Data". In this folder has 2 text file ("Features.txt", "Classes.txt")

```
2.000000000000000000e+00
2.000000000000000000e+00
0.000000000000000000e+00
0.000000000000000000e+00
0.000000000000000000e+00
0.000000000000000000e+00
1.000000000000000000e+00
1.000000000000000000e+00
```

Fig A.2 show data in "Classes.txt"

The list of classes is showed in Fig A2 that use to supervise support vector machine of each feature set (Fig A.3).

```
1.108020207965838777e+00 2.669006603798928623e+00
6.284961437716271027e-01 1.113556695400607532e+00
1.583854464791583094e-01 8.324762654707894560e-01
3.988888490164290146e-01 3.447377076377349248e+00
3.845158373730594992e-01 1.665534267119638701e+00
3.517087508760344261e-01 1.746018096847168799e+00
3.005469933867197518e-01 2.262973422523741895e+00
3.447463649927687834e-01 1.024304937275605454e+00
```

Fig. A.3 show data in "Features.txt"

A.2 Sensor's data in smartphone reorientation experiment

Data was record in folder name "Second_Experiment". This folder contain 3 sub folder that record data from 3 smartphones (P1:, P2, P3).

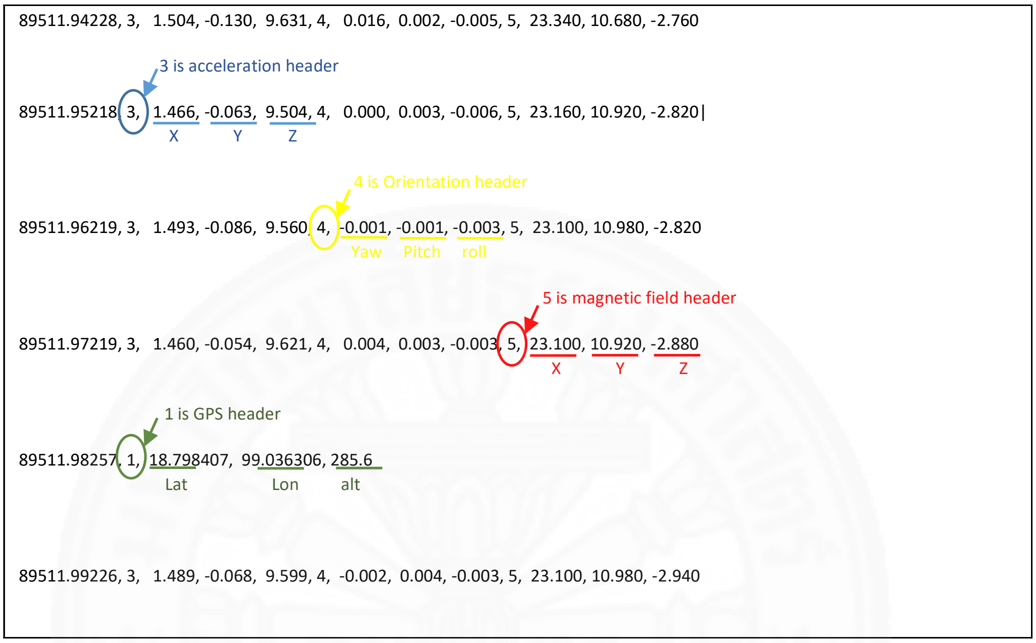

Fig A.4 show description of data format of smartphone virtual reorientation experiment