Final Report

Research Grant 2012

ATRANS

ASIAN TRANSPORTATION RESEARCH

Driving Styles Evaluation using Smartphones

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1. Introduction

In a fast paced and competitive environment in our society today, commuting from place to place in the shortest possible time seems to be a necessity. As a result, safety issues when traveling on the road are not always our first priority. Hence, aggressive driving behaviours such as fast lane change, tailgating and sudden braking which often lead to accidents are likely to occur. According to statistics, the number of casualties from road traffic accident in Thailand in 2013 is 585,324. Out of that total, there are 6,834 deaths [1]. At present, Thailand has the second most dangerous roads in the world with 44 road deaths per 100,000 people [2]. Hence, this is one major issue that needs to be solved quickly.

It has been found that when a driver is monitored and driving events are recorded the chances of aggressive and dangerous driving behaviour are reduced [3]. There are a number of commercial products available in the market using in-vehicle data recorders equipped with a wide variety of sensory devices such as GPS receiver and often a video camera [4]. Examples of these products are used in fleet management systems and taxi operators where every driver can be traced to ensure that they follow designated routes and do not violate the speed limit.

Many application domains such as logistics and intelligent transport systems benefit from this network of sensory devices [5]. Examples of these can be found in [6] where real-time driving data from controlled test crashes is stored and analyzed in order to detect possible collisions and also assess the level of damage of the potential crash. Car manufacturers have taken this idea and developed an advanced driver-assistance systems (ADAS) such as collision prevention and avoidance systems [7]. At present, this can only be found in high-end models as the sensors required for ADAS system are expensive making it very unlikely to be included in lower priced vehicles.

Human error is one of the three key contributing factors to road traffic accidents, the other two being vehicles capabilities and road infrastructures. The fundamental elements leading up to aggressive driving behaviours are from different driving maneuvers or events that occur during a journey such as harsh braking and acceleration, rapid turning and rapid lane change. Therefore, it is essential to be able to detect these fundamental driving events and classify whether or not they are aggressive in order to recognize potential crashes.

All of the driver monitoring systems discussed so far make use of in-vehicle data recorders which possess the ability to store relevant driving data [4,6,7]. However, these recorders are attached to one vehicle only and are not removable to be taken off and used in other vehicles. An alternative is to replace in-vehicle data recorder with a smartphone since it is easily accessible, widely available and low cost. In addition, modern smartphone models at present are embedded with multi-sensors on-board which enables the capability similar to in-vehicle data recorders. Considering all these options, it is clear to see that smartphones are a good candidate to be deployed as a tool to be used to collect, process and analyze driving data as well as detect and classify aggressive driving behaviours in order to alert drivers when they are being reckless.

The multi-sensing capabilities of smartphones available in the market enable us to collect a rich vein of raw data. Accelerometer data provides an insight into the longitudinal and lateral movement of the phone while the on-board GPS receiver provides us with location data in terms of latitude and longitude. In the literature, smartphones have already been deployed as a tool to collect data for the analysis of driver's behaviour and external road conditions in [8] and [9]. With all the data and sensors we are able to detect vehicle's movement when a smartphone is placed inside the vehicle of interest. As a result, typical driving events such as turning left and right, braking and accelerating can be detected. It is important to detect these typical driving events as they are fundamental to the evaluation of driver behaviour. This would be highly beneficial to many application domains in the road safety perspective such as an automated advanced warning system.

The objective of this research is two-fold. Firstly, the aim is to detect and classify driving behaviours using different sensors available on modern smartphones. Data collected from smartphones sensors will be analyzed so that different driving events such as turning left, right, braking and acceleration can be identified. Furthermore, these events will be further assessed in order to determine if they are classified as aggressive. At present there is no measure to evaluate driving styles amongst drivers in Thailand. The second objective of this research is to implement the detection algorithm on a smartphone platform as an application with a tool to produce appropriate driving score. It is aimed that the application should be available on iOS and Android, the major two operating systems in today’s marke

2. Background

In this project, three sensors from a smartphone are considered. Firstly, the 3-axis accelerometer measures the force of acceleration whether caused by the phone's movement or gravity. The three axes correspond to lateral, longitudinal and vertical accelerations. In this project we are only interested in movements along the lateral and longitudinal axes which refers to side to side movement and forward and backward movement respectively. In real-world scenarios lateral acceleration or side-to-side movements represent driving events such as turning left and right and lane change while longitudinal acceleration corresponds to vehicle braking and accelerating.

The second sensor, magnetometer, measures the strength of magnetic field which can provide us a sense of direction at which the smartphone is pointing towards with respect to the magnetic north. It is a sensor usually found in a compass. Raw data from magnetometer will be utilised as an indicator for the detection of driving events in lateral domain. Finally, a GPS receiver which provides positioning and speed data of the vehicle that the smartphone is attached to. Overall, accelerometer and magnetometer data are sampled at a rate of 5Hz where one sample is recorded every 200ms. Data from GPS receiver is sampled at 1Hz.

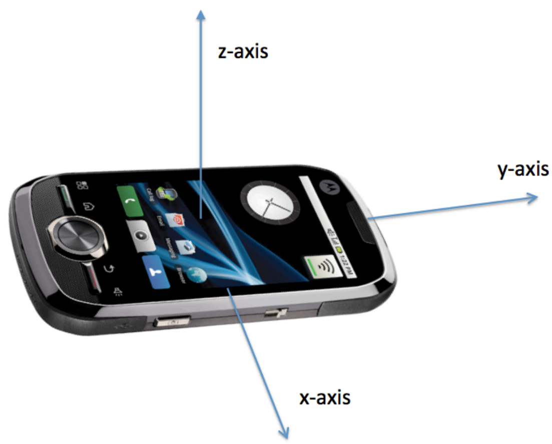


Figure 1: 3-axis Accelerometer

Figure 1 shows a typical smartphone with relevant axes in accordance with the measurement from accelerometer. The lateral movement is denoted by the x-axis while the longitudinal movement is denoted by the y-axis.

Based on the measurement of raw data in the previous section, fundamental driving events can be established and is summarized in Table 1. It can be seen from the table that 13 driving events are considered in total, 10 in the lateral movement domain and 4 in the longitudinal domain. These include standard and aggressive events.

Table 1: Driving Events.

Lateral	Longitudinal
Right/Left Turn (normal and aggressive)	Braking (normal and aggressive)
Right/Left Lane Change (normal and aggressive)	Acceleration (normal and aggressive)
U-turn	

2.1 Literature Review

Recent technological advancements in smartphones capabilities coupled with an increasing smartphone adoption rates worldwide has initiated the development of many new ITS related applications. The work in [10] proposed a low cost lane departure warning system implemented on a smartphone in order to bring advanced technology to a device which is widely available. The main idea of the work in [10] is to apply image processing techniques to the images captured from smartphone camera. In addition, their proposed algorithm is optimized such that it can tolerate low quality images and is robust to run on smartphones with lower processing power.

Mohan et al. proposed a system where smartphones are utilized as a means to monitor road and traffic conditions [11]. This was achieved by using sensors onboard smartphones such as accelerometer and GPS sensor to detect potholes, bumps as well as vehicles braking and honking. The system has been implemented and tested where promising results in terms of the effectiveness of sensing functions have been reported. Similar to [11], the approach proposed in [12] deploys a smartphone app which collects data from multi-sensors onboard to analyze road conditions obtaining at the same time high accuracy results in classifying different road defects.

Johnson and Trivedi proposed an approach in order to classify different driving styles based on data collected from smartphones [9]. In their approach, driving styles can be in the form of normal, aggressive and very aggressive. The results from their work reveal that various sensors on smartphones can provide good source of information for an accurate measure and classification of different driving styles. Furthermore, the work presented in [12] discusses about the use of smartphones to report and detect car accidents in real-time. Similar to [11], the approach in [12] also utilizes GPS receiver and accelerometer data in order to detect car accidents.

3. Research Methodology

3.1 Driving Event Detection Algorithm

One of the advantages of the use of accelerometer sensor on the smartphone is that it is independent of external factors such as obstacles blocking line of sight of signal and weather conditions. An example of this is that the lost of GPS signals due to no line-of-sight will result in data loss. The accelerometer provides measurements of acceleration of the vehicle that the smartphone is attached to in 3-axis domain, vertical, longitudinal and lateral as shown previously in Figure 1. Data from accelerometer sensor is recorded at a rate of 5Hz in this work in order to form a time series of acceleration of the smartphone.

The proposed algorithm to be used in this project is a pattern matching algorithm. It is based on the Dynamic Time Warping (DTW) technique. Dynamic Time Warping was originally implemented in order to perform speech recognition by Sakoe and Chiba [13]. It has then been utilized extensively in the field of computer sciences such as the approach in [14] where DTW was used to find patterns in time series. In general, Dynamic Time Warping provides a similarity measure between two signals, namely the incoming and the reference signals. The main feature of DTW is that it allows for stretched and compressed portions of the two signals to be compared by compensating for length differences in the two signals while taking into account of the non-linearity of the length differences between the incoming signal and the reference signal. This feature is not possible with a traditional pairwise comparison between the two signals using the Euclidean distance. In this project, the concept of Dynamic Time Warping will be used for the detection of driving events. Raw data from various sensors from a smartphone will be collected to form strings of time series. A brief description of the DTW algorithm is given below.

Consider two time series X and Y with length n and m respectively, where each time series is represented by $X = \{x_1, x_2, ..., x_i, ..., x_n\}$ and $Y = \{y_1, y_2, ..., y_j, ..., y_m\}$. An n x m matrix is constructed with time series X and Y on the top and left sides of the grid respectively as shown in Figure 2. Each element (i,j) of the matrix contains the Euclidean distance between the points x_i and y_j on the two corresponding time series, where

$$d(x_i,y_j)=(x_i - y_j)^2.$$

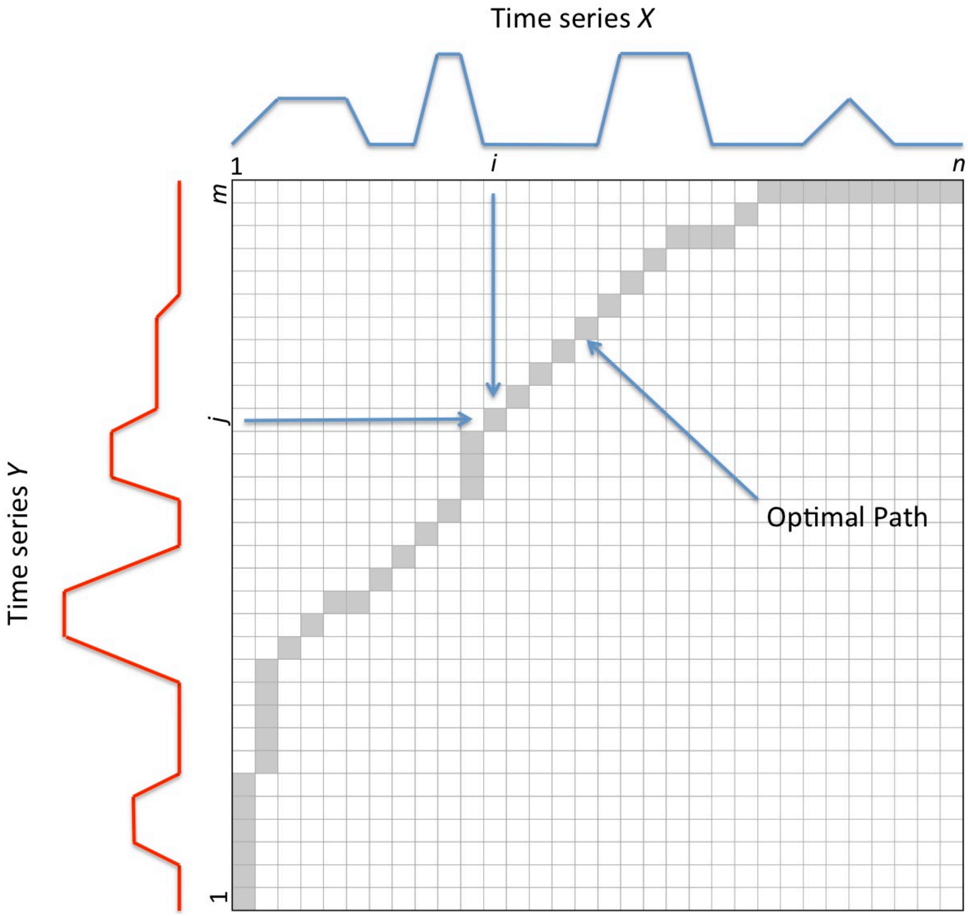


Figure 2: Dynamic Time Warping Grid

The lower the value of *d* the closer the two points are to each other. Essentially, DTW tries to find an optimal alignment of the two time series. This idea is applied in this work where the time series of the pre-recorded template is aligned with the raw data. The next step of DTW is to identify a warping path *W* which consists of the minimum distances between the two points on the time series where the k^{th} element of *W* is denoted by $w_k = (i, j)_k$ [15]. The next stage is to sum these minimum distances along the warping path *W* in order to obtain the cost function *C* as described below:

$$C(X, Y) = \sum_{k=1}^{K} w_k(x_{nk} y_{mk})$$

Finally, the reference signal with the lowest total cost *C* is the best match to the given incoming signal.

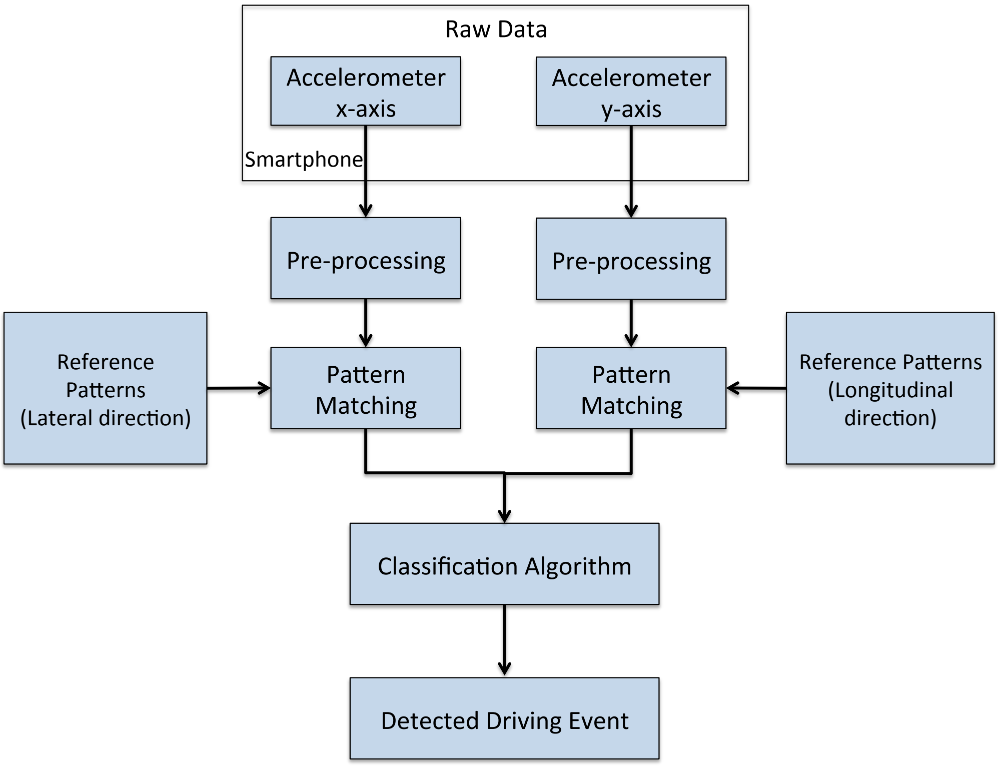


Figure 3: Overall of the Algorithm

Figure 3 illustrates the proposed the pattern matching algorithm to detect driving events based on the use of DTW algorithm. The algorithm is divided into three main stages.

1) Pre-Processing:

Data pre-processing is an initial stage of the pattern matching algorithm. Raw data collected from the accelerometer sensor is pre-processed in order to smooth out the effect of unwanted noise in the signals. In this paper a simple moving average is utilized to achieve that goal.

2) Pattern Matching:

This is the stage where DTW algorithm is deployed to find the best match using a given reference pattern for all driving events in Table I. Some of the reference driving patterns are illustrated in Figure 5. It can be seen that there is an apparent dissimilarity in the shape of the waveforms of an ordinary driving event, in a green line, and an aggressive driving event, in a red line. Aggressive or sudden driving events tend to possess a large change in acceleration values. The essential goal in this stage of the algorithm is to use the reference driving patterns to find the best match for the incoming driving data. In order to generate appropriate reference patterns for each driving event, a training data set is obtained through a real- world experiment for our pattern matching algorithm. These reference patterns are then used as a template to match the incoming signals from accelerometer sensor in the test data set. In this paper, 70% of data samples are utilized as training data, resulting in 30% to be used as test data set. At the completion of the algorithm, a total cost of the alignment path C is obtained for all of the templates selected to cover all 12 events.

3) Classification Algorithm:

At this point the algorithm will decide which of the reference patterns is the best match to the incoming signal. Specific constraints are set in accordance to each of the 13 different driving events. One of the constraints is the similarity score produced by the DTW algorithm, where a score of zero would indicate two patterns being exactly alike. The fact that driving events are categorized into two domains, lateral and longitudinal movements as described in Table I means that there are two pools of events to select depending on the source of incoming signals.

3.1.1 Validation of Driving Event Detection Algorithm

As a starting platform to the project the driving event detection algorithm was evaluated in terms in order to assess its accuracy. A real world experiment was set up for data collection. In this experiment raw data was collected using a single driver in one vehicle, 2010 Toyota Vigo pick-up truck. The reason that this was selected as a test vehicle is that pick-up trucks are the second most accident prone on the road in Thailand behind motorcycles. This makes it the most risky amongst vehicles with four wheels. Overall, approximately 120 driving events in urban and rural road environments were recorded. The route chosen was approximately 40km long, from central Bangkok to the outskirt on the north west of the city. Data was collected using Android-based smartphone with a tailored made application which allowed a team of traffic engineering researchers to record driving events in real-time where corresponding timestamps were noted in order to label our ground truth data.

Figure 4 A Smartphone collecting data

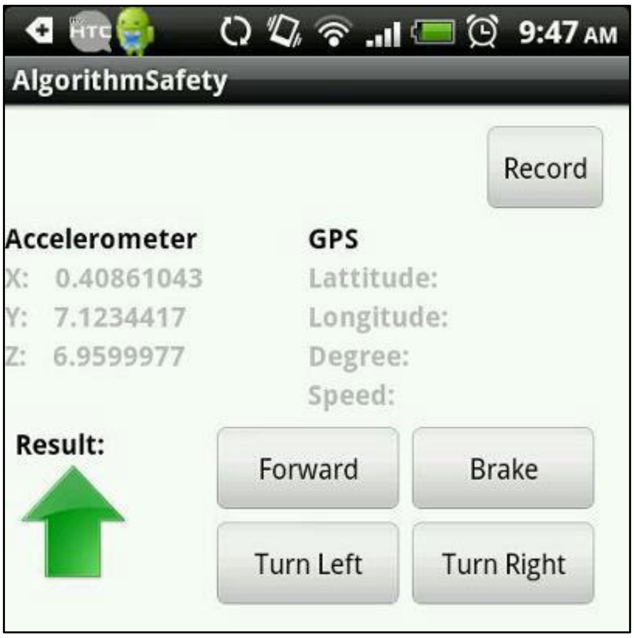


Figure 5 Screenshot of data collector application

Figure 4 shows a smartphone being used to collect driving data with our mobile application while Figure 5 shows a screen shot of data collector application.

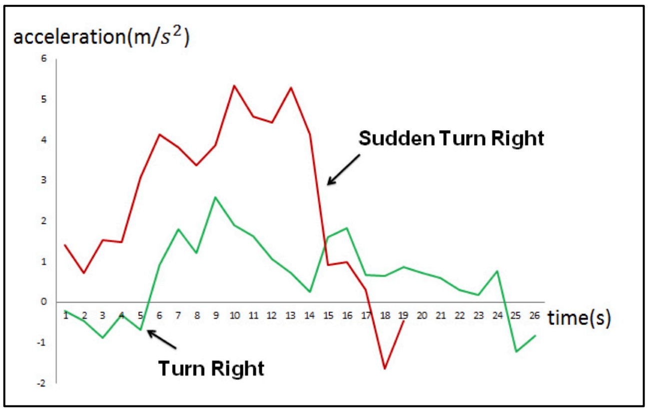
Two metrics will be used in order to assess the effect of varying the threshold of standard deviation on the performance of driving event detection. These are the detection rate (DR) and the false alarm rate (FAR) which are defined in the following equations.

$$DR = \frac{Number\ of\ Driving\ Events\ Detected}{Total\ Number\ of\ Driving\ Events} \times 100,$$

where the numerator is the number of driving events detected by the algorithm and the denominator is the total number of driving events indicated by a team of traffic engineering researchers.

$$FAR = \frac{Number\ of\ Alarms\ not\ in\ Specified\ Duration}{Total\ Number\ of\ Alarms} \times 100,$$

where FAR is expressed as false alarm rate per second in %. At the time of writing, no other work in the literature has reported FAR for the detection of driving events using sensory data from smartphone.



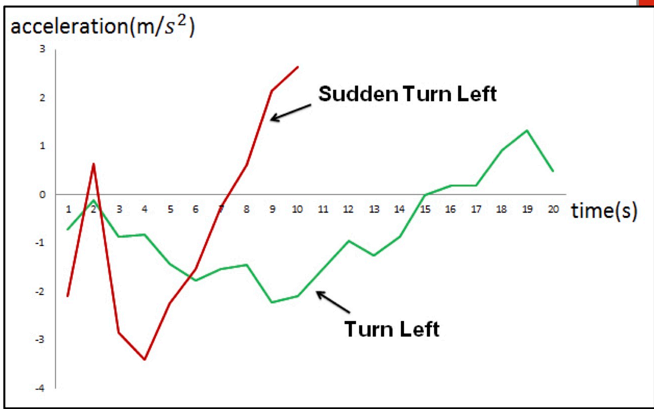


Figure 6 Example of raw data collected from accelerometer sensors illustrating turning events

A selection of raw data from accelerometer is show in Figure 6. Four types of driving events are shown. These are right turn, sudden right turn, left turn and sudden left turn.

After data collection, our algorithm is applied to raw data in order to obtain driving events detected by the proposed algorithm. The result of that is compared with the ground truth as indicated by a team of researchers sitting in the vehicle during the journey.

Table 2 illustrates the confusion matrix of the pattern matching algorithm for driving events detection. The diagonal entries highlighted in green are the number of events that have been correctly detected by the algorithms according to ground truth data. The numbers in each entry in the table denotes the number of occurrence of each event detected while the number inside the parenthesis denotes the detection rate (DR). The cells highlighted in red denote the events which have been incorrectly detected as they are from completely different domains. For example, a brake event has been detected instead of an acceleration event. The parts that are highlighted in dark grey represent a scenario which should not occur theoretically as the algorithm should not detect longitudinal events when the vehicle is moving in the lateral direction and vice versa. For example, a right turn event was detected by the algorithm when the actual event was a sudden acceleration.

It can be seen clearly from the figure that the Pattern Matching Algorithm performs well as most of the detections from the algorithm are in the green diagonal elements. 12 types of driving events have been observed. These are brake (B), sudden brake (SB), accelerate (A), sudden accelerate (SA), left turn (L), sudden left turn (SL), right turn (R), sudden right turn (SR), lane change left (CL), sudden lane change left (SCL), lane change right (CR) and sudden lane change right (SCR). In total there are approximately 83 usable driving events noted by the team of traffic engineering researchers.

Table 2: Confusion Matrix for the Driving Event Detection Algorithm

		Driving Events Detected by Pattern Matcing Algorithm											
	Event	B	SB	A	SA	L	SL	R	SR	CL	SCL	CR	SCR
Ground Truth	B	17 (94.44)	1 (5.56)										
	SB	4 (50.00)	3 (37.50)	1 (12.50)									
	A			28 (100)									
	SA			1 (50.00)	1 (50.00)								
	L					4 (100.00)							
	SL						4 (80.00)				1 (20.00)		
	R							1 (100.00)					
	SR								3 (75.00)				1 (25.00)
	CL									5 (100.00)			
	SCL									1 (50.00)	1 (50.00)		
	CR							2 (50.00)				2 (50.00)	
	SCR											1 (50.00)	1 (50.00)

From Table 2, high percentages of detection rate of events being correctly identified across all driving events in both lateral and longitudinal axes have been reported. The detection rate of the pattern matching algorithm range from 37.5% up to 100% with 11 out of 12 types of driving events achieving above 50% detection rate. The only exception is the sudden brake event with 37.5% detection rate reported. Some of these sudden brake events have been detected as a brake event. One possible reason for this misdetection is the fact that the change in acceleration value might not be high enough for the algorithm to detect it as a sudden brake event. This could be improved by re-training the algorithm to recognize more sudden brake event patterns. In addition, only one detection has been identified in the incorrect driving domain indicated in a cell highlighted in red and no lateral-longitudinal cross detection have been reported. For all driving event types, a small number of events have been incorrectly detected. However, these detections appear within the same driving event domain. For example a sudden lane change left detected instead of a normal lane change left or a lane change right detected instead of a right turn. More details of the driving event detection algorithm and more experimental results can be found in [16].

3.2 Automatic Reorientation of Accelerometer Sensor

In order to measure the appropriate acceleration values to detect the vehicle's movement the smartphone has to be fixed at a known orientation in the same plane and coordinate as the vehicle direction of travel for our current approach. This is one of the practical limitations for our approach as well as the existing approaches as users are not able to place the phone anywhere they desire making it impractical for real life application. In order to overcome this limitation the initial methodology discussed in this chapter proposes a method for automatic reorientation of the accelerometer on the smartphone to be used for driving events detection with no user input. The impact of this is that any ordinary smartphone user can download the application and evaluate their own driving behavior with their phones placed in any orientation, i.e. in their pockets, in their bags or in the vehicle's console.

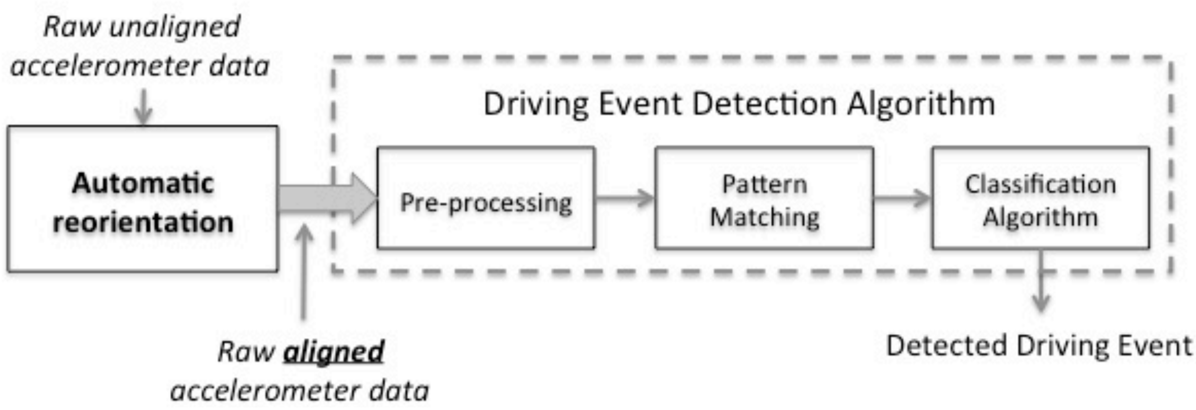


Figure 7: The use of Automatic Smartphone Reorientation in Driving Event Detection

Figure 7 illustrates the use of automatic smartphone reorientation for driving event detection. The main objective is to align the phone coordinate system with the vehicle's coordinate in order to correctly measure the acceleration acting upon the phone.

Let's define the orientation of smartphone by using the (x, y, z) coordinate system, as shown in Figure 8(a), and the vehicle-referenced (x', y', z') coordinate system, as shown in Figure 8(b). Suppose now that the phone-referenced coordinate (x, y, z) is not in alignment with the vehicle's (x', y', z') coordinate system. To measure the vehicle movement from smartphone's accelerometer, it is therefore necessary that the referenced coordinate system needs to be reoriented.

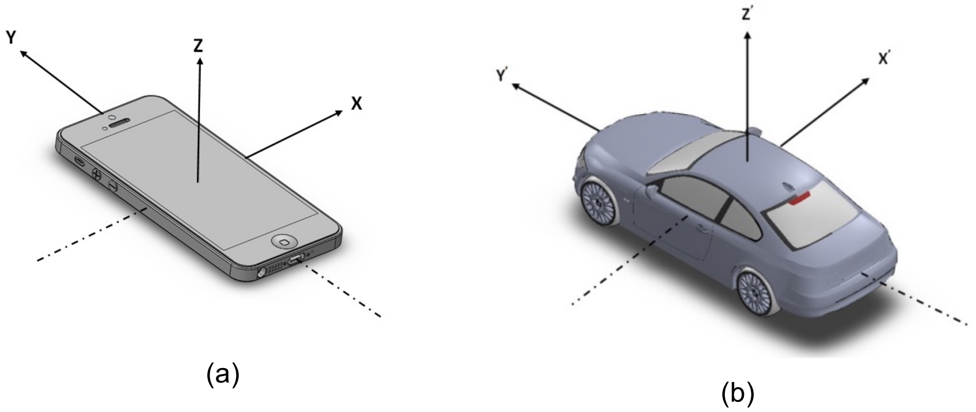


Figure 8 (a) The orientation of a smartphone described by (x, y, z) coordinate system, and (b) the direction of the vehicle movement given by (x', y', z') coordinate system

To specify the device-referenced frame in terms of the vehicle coordinate system, we often describe it in terms of the angular rotations around the three axes. As shown in Figure 9, the parameters $\beta, \alpha,$ and ϕ represent the angular rotations around the $x'-, y'-,$ and $z'-$ axes accordingly.

Once these rotational angle parameters (β, α, ϕ) are obtained, the phone-referenced coordinate system (x, y, z) can be transformed into the vehicle-referenced coordinate system by multiplying with the reorientation matrices, where the rotation matrices corresponding to the angular rotations around $x'-, y'-,$ and $z'-$ axes are given by

$$\mathbf{R}_x = \begin{pmatrix} 1, & 0, & 0 \\ 0, & \cos\beta, & -\sin\beta \\ 0, & \sin\beta, & \cos\beta \end{pmatrix} \mathbf{R}_y = \begin{pmatrix} \cos\alpha, & 0, & -\sin\alpha \\ 0, & 1, & 0 \\ \sin\alpha, & 0, & \cos\alpha \end{pmatrix}, \mathbf{R}_z = \begin{pmatrix} \cos\phi, & \sin\phi, & 0 \\ -\sin\phi, & \cos\phi, & 0 \\ 0, & 0, & 1 \end{pmatrix} \tag{1}$$

The reoriented coordinate system can be found from

$$\begin{pmatrix} x' \\ y' \\ z' \end{pmatrix} = \mathbf{R} \begin{pmatrix} x \\ y \\ z \end{pmatrix}, \tag{2}$$

where $\mathbf{R} = \mathbf{R}_z \mathbf{R}_x \mathbf{R}_y$.

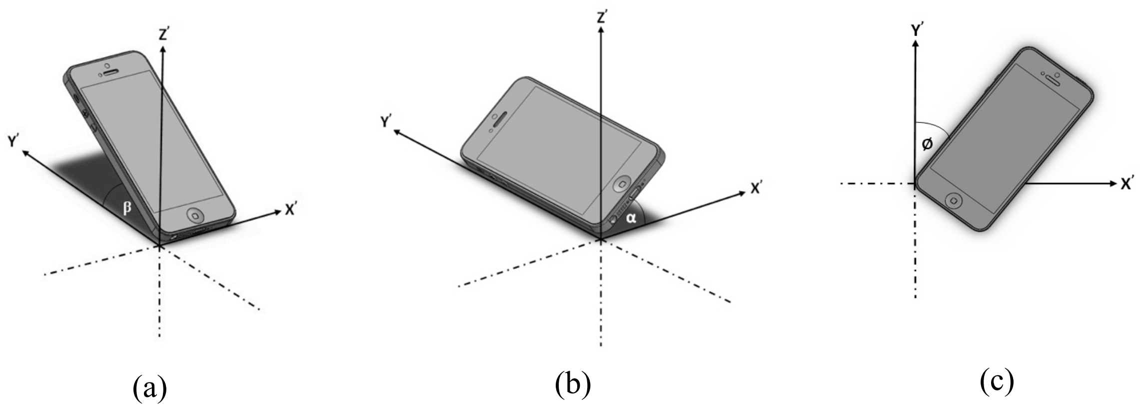


Figure 9 An illustration of angular rotations around (a) the x' axis, (b) y' axis, and (c) z' axis

To estimate the angular rotation parameters (β, α, ϕ), let's separate the analysis into two parts. First, let's assume the angular rotation around the $z'-$ axis is equal to zero ($\phi = 0$). That is, the projected vertical edge of a phone onto the $x'-y'$ plane points in the same direction of the vehicle movement. In this case, the angular parameters α and β can be estimated at the beginning when a vehicle has not moved and the phone is kept idle. Hence, the only force that applies on the smartphone comes from the earth gravity, which is $g = 9.8\ m/s^2$. If the phone is placed on the $x'-y'$ plane, then the readings on the $x-$, and $y-$ accelerations (a_x, and a_y) will be zero. However, when $\alpha \neq 0$ and/or $\beta \neq 0$, the readings will indicate the magnitude of the projected gravity on the phone-referenced frame, where

$$\begin{aligned} a_x &= g\ \sin\alpha \\ a_y &= g\ \sin\beta \end{aligned} \tag{3}$$

Thus, the parameters α and β are found from $\alpha = \sin^{-1}(a_x / g)$, and $\beta = \sin^{-1}(a_y / g)$.

Now, consider the scenario when the angular rotation around $z'-$ axis is non-zero ($\phi \neq 0$). This illustrates the scenario when the phone's heading is different from the vehicle's heading. For the coordinate reorientation, it is therefore necessary to know the headings for both the vehicle and the smartphone. This can be done via exploiting the GPS and magnetometer information. First, the vehicle heading can be estimated from the tracking of vehicle movement by using the GPS. The change on the latitude and longitude of the moving vehicle can precisely indicate the vehicle heading. Meanwhile, a data from a magnetometer helps in finding the direction of a phone with respect to the North. As the vehicle moves, this angle that points to the North will change. By comparing the vehicle movement measured from the GPS with the change detected from the device magnetometer, the rotational angle ϕ around the $z-$ axis can be found.

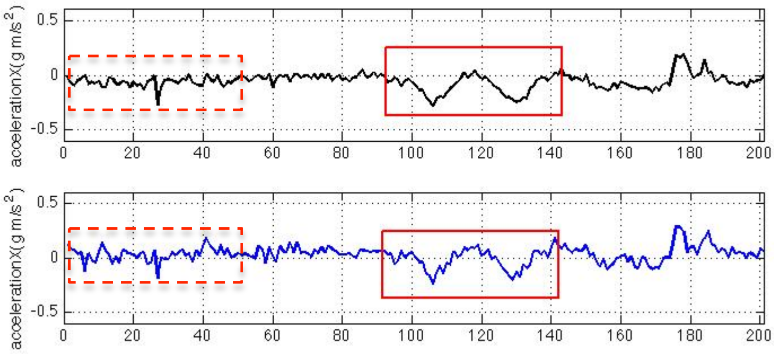
3.2.1 Evaluation of Automatic Accelerometer Reorientation

Reorientation Algorithm

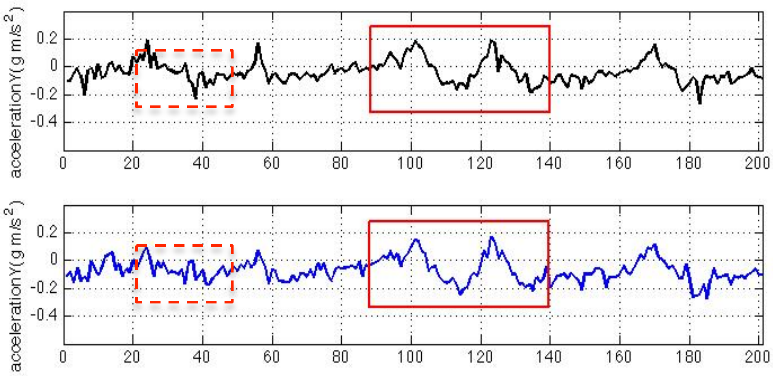
The objective of this Section is to examine the accuracy of the presented automatic accelerometer reorientation, together with the analysis on the use of reoriented accelerations to detect driving events in real-world scenario. In this experiment, two smartphones of the same model (iPhone 4s) were used. The first handset was placed on the floor in the back of the driver seat, where its orientation was in alignment to the vehicle movement. Meanwhile, the second handset was placed close to the first handset, but it was fixed on a device holder, where its orientation was described by the angular rotation of $(\beta, \alpha, \phi) = (15^\circ, 23^\circ, 30^\circ)$. The sampling period is $500\,ms$. The route that we used in this study is a freeway segment of the main route that links

Bangkok to the Northern provinces of Thailand. The overall distance is approximately $24.1\ km$. To perform an accelerometer reorientation, we need to know the rotational angle parameters (β,α,ϕ). The parameters (β,α) are obtained first before the vehicle started moving. Meanwhile, the parameter θ is estimated from the GPS and magnetometer when the vehicle is in motion. In this work, we assume the parameters (β,α,ϕ) are fixed and do not change during the experiment. In the case of varying angular rotation, however, the information from gyroscope which measures the change of angle over time may be employed to update the correct orientation of the phone in each cycle.

Figure 10 compares the lateral and longitudinal accelerations between the referenced accelerometer and the automatic reoriented accelerometer. It is noted that the waveform of reoriented accelerometer looks very similar to the referenced accelerations indicating a good accuracy of the coordinate reorientation. This is shown in the red boxes with solid line. On the other hand, red boxes with dashed line refer to waveforms which are slightly dissimilar but proved to be insignificant as they are not the waveforms representing driving events but background noise. The acceleration error in terms of the root mean squared was found to be 0.102 and $0.065 m/s^2$ for the $x-$ and $y-$ accelerations respectively.



(a)



(b)

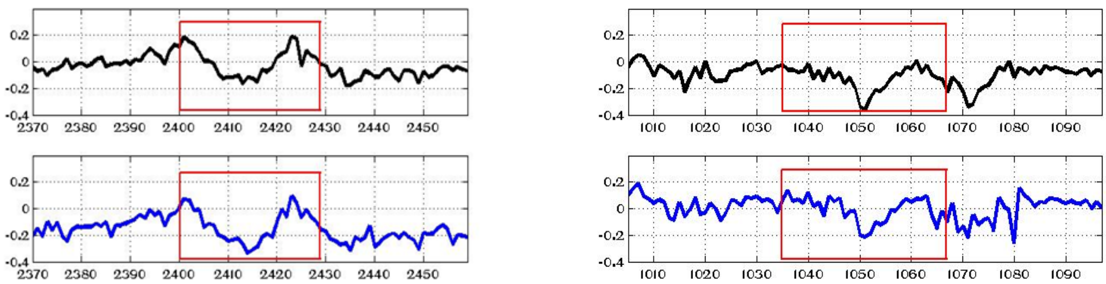
Figure 10 Comparisons of (a) $x-$ acceleration and (b) $y-$ acceleration between the referenced accelerometer (in black), and the automatic reoriented accelerometer (in blue).

Performance of Driving Event Detection

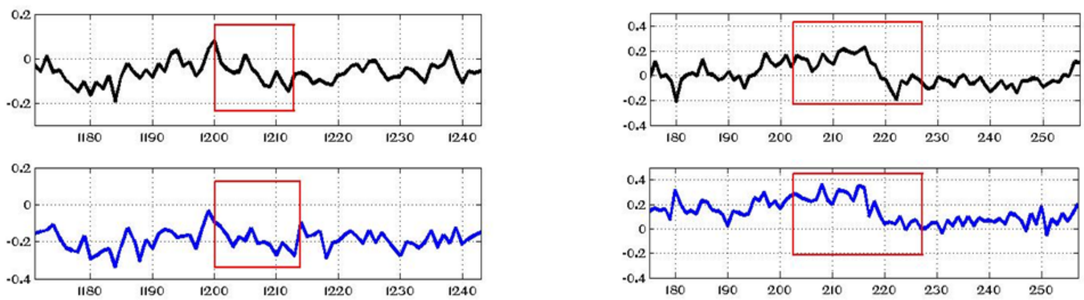
Two driving events, namely vehicle braking, and left lane-changing were examined in this experiment. Table 3 illustrates the total number of detected events after the reoriented accelerations were passed on to the driving event detection algorithm to evaluate drivers accordingly.

Table 3 Comparison of the number of detected events between the referenced accelerations and the automatic reoriented accelerations

Events	Referenced (Handset 1)	Reoriented Accelerations (Handset 2)
Braking	20	24
Left lane-changing	26	29



(a)



(b)

Figure 11 Comparisons of (a) a scenario when both the referenced and the reoriented accelerometers were correctly detected the events, and (b) a scenario when the reoriented accelerometer detected the event, but the referenced acceleration did not. The y – accelerations are shown on the left, and x – accelerations are shown on the right

According to the results shown in Table 3, the numbers of detected events due to the reoriented accelerometers are slightly higher than those from the referenced accelerations in both events. This is mainly due to the unintended fluctuation of rotational angles when a vehicle was in motion. When this happens, the measured accelerations tend to fluctuate more, up to a certain degree, that sometimes cause a false alarm in event detection. Figure 11(a) illustrates a scenario when both the referenced and the reoriented accelerometers were correctly detected the events. The red boxes represent the part where driving events take place. Meanwhile, Figure 11(b) illustrates the case when the reoriented accelerometer detected the event, but the referenced acceleration did not.

4. Data Collection with The Transport Co Ltd.

In collaboration with the Transport Co Ltd, we have selected two routes for our data collection, Bangkok to Korat and Bangkok to Chiang Rai which are the two major routes out of Bangkok to the north eastern and northern regions of Thailand respectively. These two routes have different characteristics in that the route to Chiang Rai consists of many twists and turns along the way while the Korat route is more straight.

Table 4 Summary of data collection routes

Route	Start Date	End Date	Number of trips	Distance (km)	Duration (hours)
Bkk – Korat	26 Aug	15 Sep	30	270 (approx.)	4
Bkk – Chiang Rai	16 Sep	31 Oct	30	800 (approx.)	10

Figure 12 Map of data collection routes

4.1 Experimental Setup

Data collection is carried out on a commercial coach operating on the two routes with 30 trips planned for each route. As a result, high number of samples can be obtained. We have set up a team of researchers to carry out data collection on these coaches. Three researchers are deployed for each coach. During the trip, a tester would place the smartphones in a specially made bag with carved out polystyrene as seen in Figure 13. This is to stop the phone from sliding out of position which would interfere with data collection process. The bag is placed so that the phones lie flat and pointing towards the same direction as the coach's heading. On each smartphone we have installed our tailor made application which has the ability to record raw data from various sensors on board, i.e. accelerometer, magnetometer, GPS. Figure 14 shows the screenshots of data recorder application. It is designed to maximize ease of use with minimum number of buttons to be pressed. It is required that a record button is pressed once at the start of the trip. After that the phones are left untouched for the duration of the journey to collect raw driving data. The data recorder app is fully automatic, once a record button is pressed you can leave it running without requiring users input until the end of the trip. Raw data can be exported via email and/or SD card.

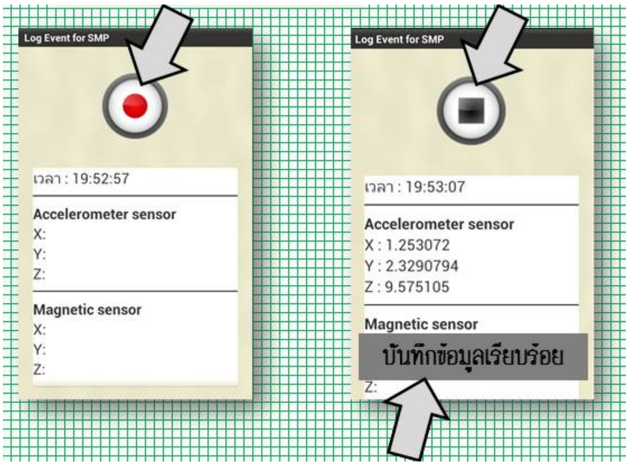


Figure 13 Driving data collection equipment **Figure 14 Sensory data collector application**

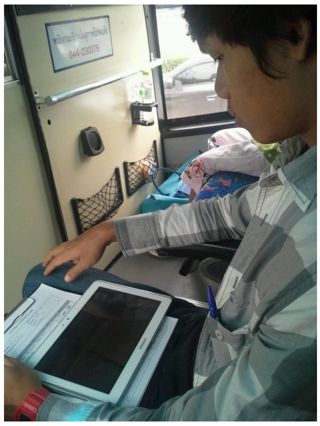


Figure 15 A Bag with Smartphones inside **Figure 16 A Researcher recording driving data**

A second equipment, a tablet, is used for manual recording of driving events which occur during the trip. A team of traffic engineering researchers will manually input any driving events during the trip for example, a left lane change or a sudden brake. This is achieved through our second application which is the driving event data collector. Events logged from this application will be used as a baseline to evaluate our driving event detection algorithm. Figure 16 shows a researcher operating on a tablet with our driving data collector application installed while figure 17 shows a screenshot of the application. Similar to the sensory data collector application, the driving data collector application user interface is optimized so that a researcher can easily indicate driving events which occur during a journey in real time.

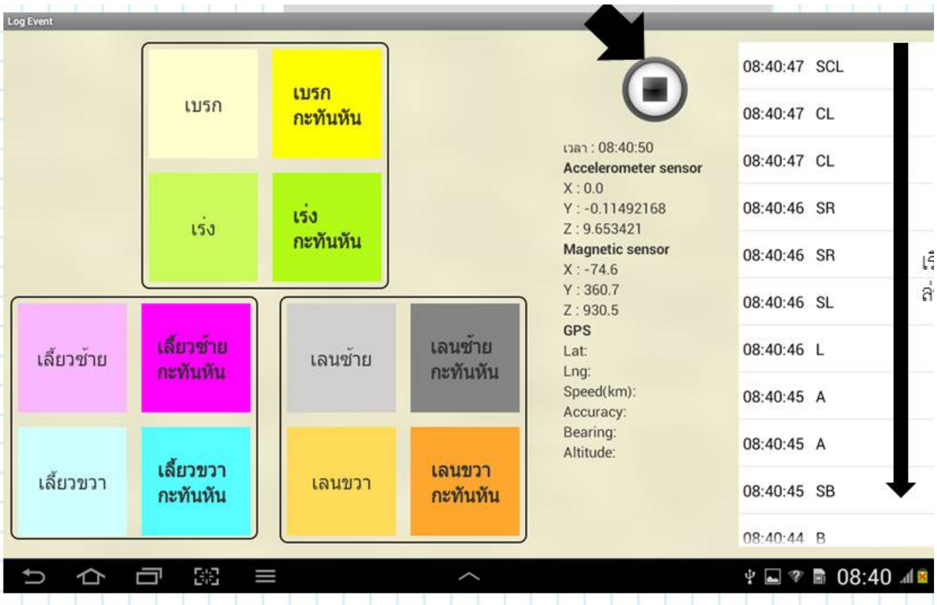


Figure 17 Driving data collector application

4.2 Results

Selected results from real world data collection with the Transport Co Ltd buses are shown in this section. Note that only sudden events are of interest here as they have higher risk of causing road accidents.

Table 5: Number of Sudden Driving Events for Bangkok – Korat route

		Number of Sudden Driving Events Only						
		Brake	**Accelerate**	**Left**	**Right**	**Change Left**	**Change Right**	**Total**
BKK - Korat	Human	37	6	0	0	10	19	72
	Algorithm	23	1	0	3	13	11	51
Korat - BKK	Human	25	1	1	0	4	17	48
	Algorithm	22	8	5	1	7	17	60

Table 5 shows the number of sudden driving events of Bangkok – Korat route. The table has been divided into two sections where the top part represents outward journey and bottom part represents return journey. In total 30 trips of this route has been carried out. From the table it can be seen that the number of detected sudden events from the algorithm is fairly close to the number indicated by our team of traffic engineering researchers. In addition it can be seen that the driving event detection algorithm is more sensitive in picking up sudden driving events on the return journey than the outward journey. Table 6 shows the Detection Rate and False Alarm Rate for detecting sudden driving events. It can be seen that we have a much higher detection rate for the return journey while the false alarm rate per second is very low for all cases.

Table 6: Detection and False Alarm Rates for Sudden Events of Bangkok – Korat Route

	BKK – Korat (Outward)		Korat – BKK (Return)	
	Detection Rate (%)	**False Alarm Rate (%)**	**Detection Rate (%)**	**False Alarm Rate (%)**
Brake	62.16	0	88	0
Accelerate	16.67	0	100	8.7
Left Turn	N/A	N/A	100	8
Right Turn	N/A	10	N/A	10
Lane Change Left	100	2.3	100	4.3
Lane Change Right	57.89	0	100	0

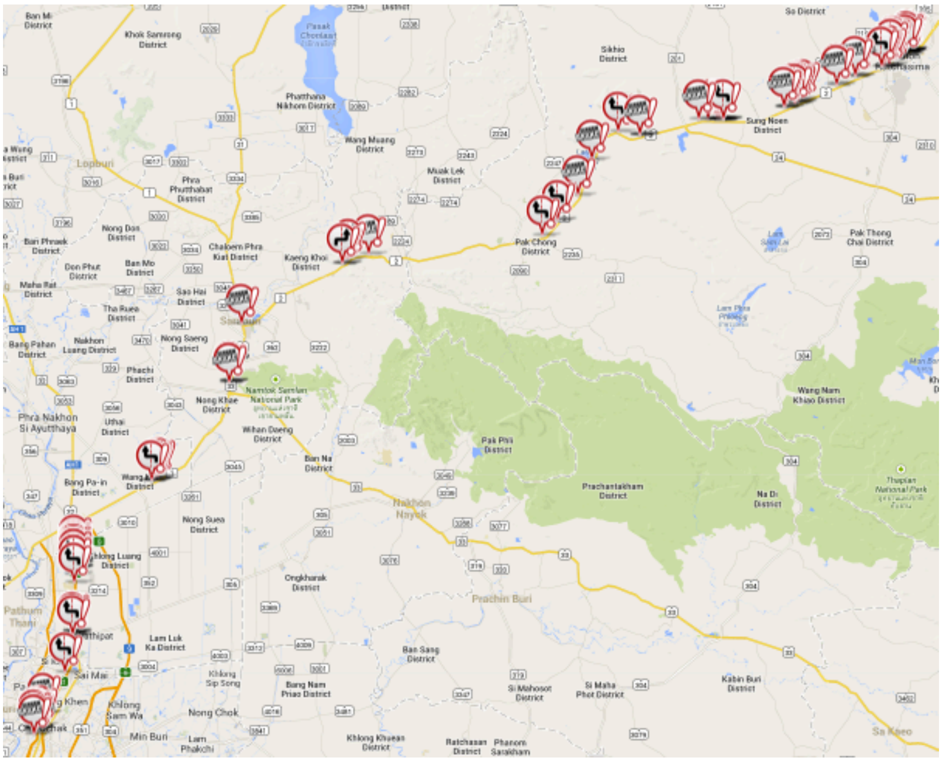


Figure 18 Dangerous driving events plot on a map of Bangkok – Korat Route

Figure 18 illustrates a map of Bangkok – Korat route marked with aggressive driving events according to location of detection. This particular map is the summary of the return journey (Korat – Bangkok) consisting of 15 trips. Visually, it can be seen that driving events seem to cluster in certain areas of the route which indicates that these areas might potentially be accident prone. The mapping of sudden driving events to a geo-location map will definitely be useful for road surveyors and traffic engineers as they can integrate this data to analyze potential road hazards and hence might be used for black spot identification.

5. Comparison of Different Smartphone Models

In the experiment with the Transport Co Ltd, 4 smartphones were used to collect driving data for each journey. These were Samsung Galaxy S4, Samsung Galaxy Y, Sony Xperia E and HTC Desire C. Samsung Galaxy Y is the cheapest handset costing approximately 3,000 Baht while the most expensive handset is the top Samsung model which is Galaxy S4 costing approximately 21,000 Baht. The Sony Xperia E and HTC Desire C cost 4,990 and 6,990 respectively. The detailed comparison of specifications of these 4 smartphones can be found in Table 7.

Table 7 Comparison of smartphone specifications to be used for data collection

Phone	Price	OS	Accelerometer	Compass	GPS	3G	CPU	RAM
Samsung Galaxy Y	3,290	2.3	Yes	Yes	Yes	900/2100	830MHz	290MB
Sony Xperia E	4,990	4.1	Yes	Yes	Yes	900/2100	1 GHz	512MB
HTC Desire C	6,990	4.0	Yes	Yes	Yes	900/2100	600 MHz	512MB
Samsung Galaxy S4	21,900	4.2	Yes	Yes	Yes	850/900/ 2100	1.6GHz quad core	2GB

An analysis is performed on the raw data from the four smartphones in order to assess the difference and similarity between accelerometer data collected from each phone. The metric of mean and standard deviation are utilized for this analysis.

In general, it was found that all of the selected phones are able to pick up accelerometer sensor and GPS signals without any problem. An instance of raw accelerometer data is shown in Figure 19. An occurrence of a driving event is indicated in the pink circle where a noticeable change of waveforms shape can be observed. Out of the 4 smartphones, the Galaxy Y and Sony Xperia E appear to be in sync in terms of the occurrence of the driving event while there is a shift for HTC Desire C and Galaxy S4. In addition it was found that the signal coming from accelerometer of the Sony Xperia E has an offset as the signal of the accelerometer while idle is higher than the other 3 smartphones.

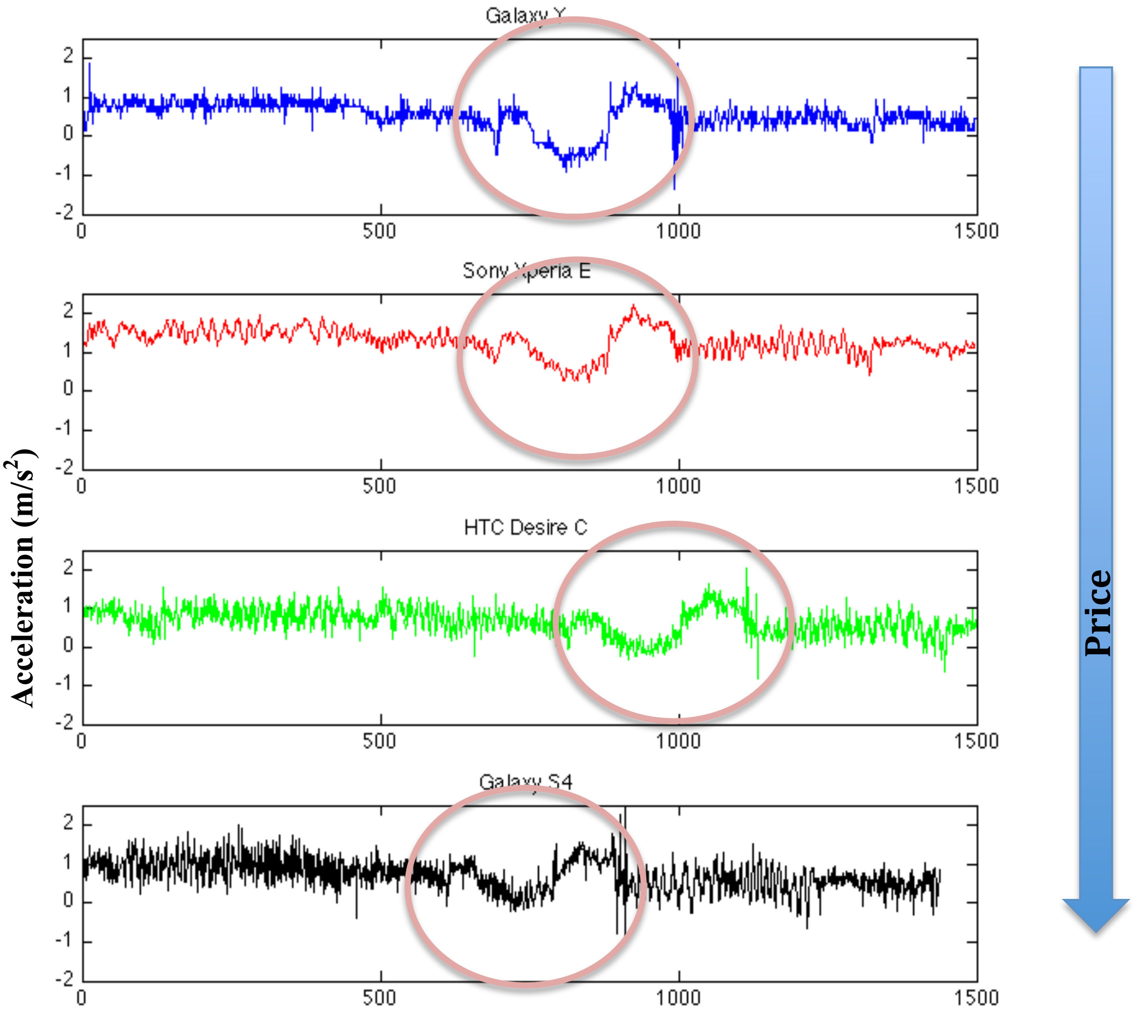


Figure 19 Raw Accelerometer Data of 4 Smartphones

Table 8 Mean and Standard Deviation of Accelerometer Data

Phone	Mean	SD
Samsung Galaxy Y	0.515	0.381
Sony Xperia E	1.287	0.332
HTC Desire C	0.653	0.352
Samsung Galaxy S4	0.721	0.402

Table 8 shows the mean and standard deviation of the raw accelerometer data of the 4 smartphones. The mean value of the accelerometer data of Sony Xperia E is higher than the other 3 due to the offset that was already discussed earlier. The table also indicates that Samsung Galaxy S4, is the most expensive handset, has the highest standard deviation which suggests that it is the most sensitive handset out of the four.

A comparison is made between the four smartphones of interest to see the number of detected sudden driving events. Figure 20 illustrates the number of detected sudden driving events for all of the 30 Bangkok – Korat trips. It can be seen that the number of detected driving events are slightly different for each of the smartphone model with a slight discrepancies between them. However, the difference in number of detected driving events is not significantly high as they seem to cluster in the same range. The reason for the discrepancy is due to slight difference in the raw data from each of the phones accelerometer sensor. Similar findings are reported for Bangkok Chiang Rai trips with higher the number of events due to longer distances travelled. This can be seen in Figure 21.

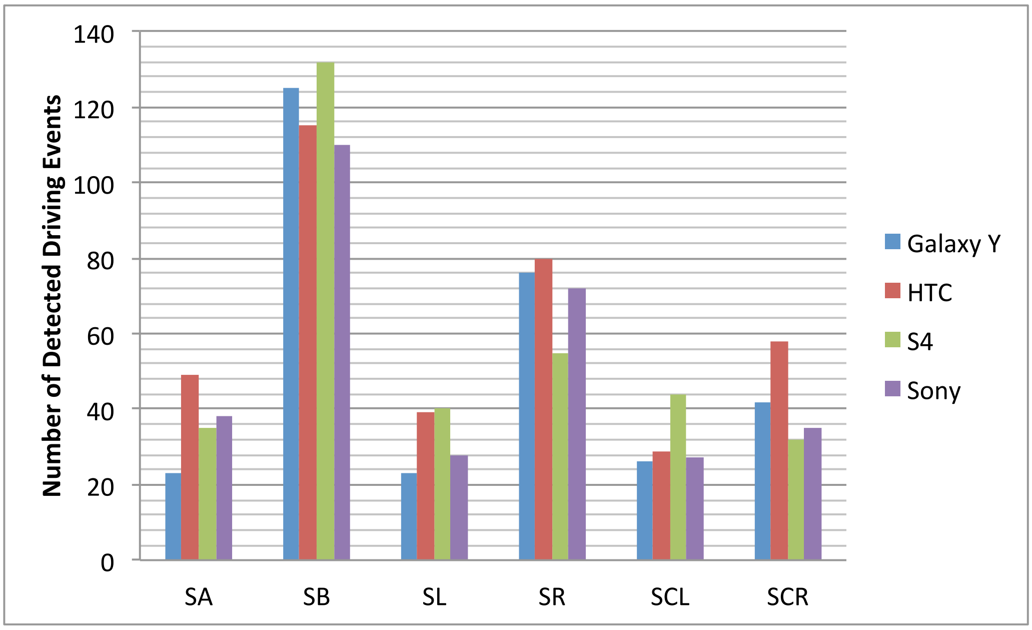


Figure 20 Number of Detected Sudden Driving Events for all 30 Bangkok – Korat Trips

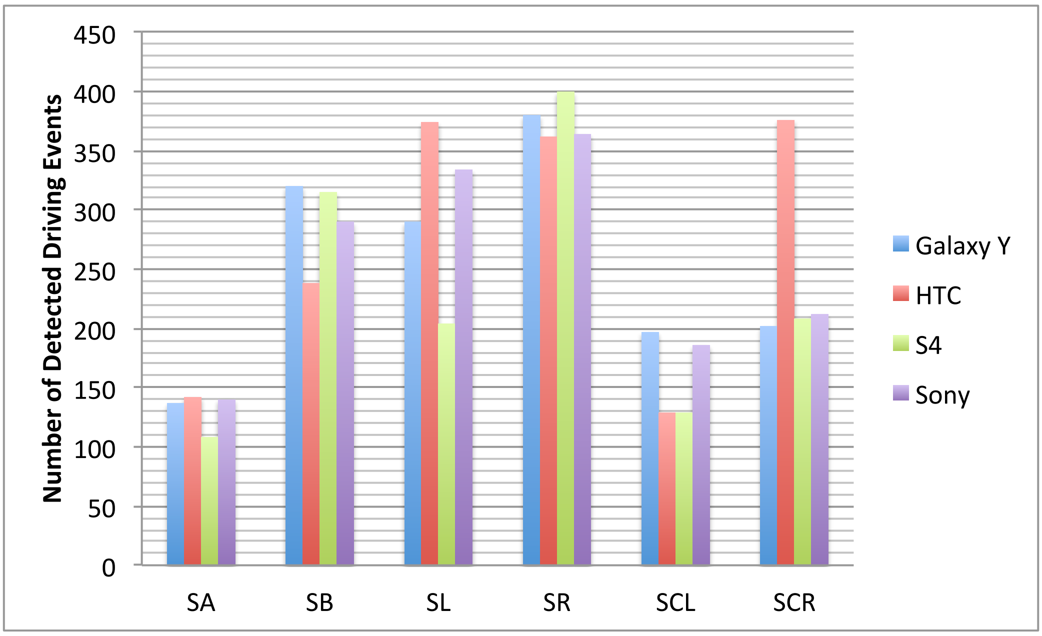


Figure 21 Number of Detected Sudden Driving Events for all 30 Bangkok – Chiang Rai Trips

6. Mobile Application

A mobile application has been created for the use of the proposed method of the detection of driving events. It is available on Android platform ready to download and will be ready for iOS by the end of April. Application features include:

- Detect dangerous driving events
- Warn drivers in real time
- Historical data log
- Provide a drive score at the end of the trip
- Provide suggestions for the trip
- Share driver’s score on Facebook

Figure 22 shows screenshots of mobile application.

Figure 22 Screenshots of Application

7. Publications

The work carried out in this project has been published in the following publications:

- C. Saiprasert, T. Pholprasit, W. Pattara-atikom, "Detecting Driving Events Using Smartphone" in *Proceedings of the 20th ITS World Congress*, Japan, 2013 ** **This paper has been invited for journal publication**
- P. Chaovalit, C. Saiprasert, T. Pholprasit, "A Method for Driving Event Detection Using SAX on Smartphone Sensors" in *Proceedings of 13th IEEE International Conference on ITS Telecommunications (ITST)*, Finland, 2013 ** **This paper has been invited for journal publication**
- N. Promwongsa, P. Chaisatsilp, S. Supakwong, C. Saiprasert, T. Pholprasit, P. Prathombutr, "Automatic Accelerometer Reorientation for Driving Event Detection Using Smartphone" in *Poceedings of the 13th ITS Asia Pacific Forum*, New Zealand, 2014 (to appear)

8. Conclusion

This report presents a study of driving style evaluation using smartphones as a platform. In this report a novel algorithm to detect driving events such as braking, acceleration and lane change has been proposed based on the use of accelerometer sensor on a smartphone. The proposed approach is based on Dynamic Time Warping algorithm which is a pattern matching method. After identifying appropriate driving events for the incoming raw accelerometer data, these events are classified whether they are aggressive or not. It is essential to detect these aggressive driving events as they are the root cause of dangerous driving which causes road accidents. Therefore, the aim of this method is to warn drivers in real-time when these aggressive events are detected. In order to achieve that goal a mobile application to be run on iOS and Android smartphones has been created with many useful features for drivers for a safer drive.

Further studies have been conducted to apply the law of forces in physics with the use of smartphone reorientation. A method of automatic reorientation of accelerometer sensor has been proposed in this report. With this proposed technique, smartphone users will be able to use our application with the phones placed in any orientation with respect to the vehicle that they are travelling in.

Extensive data collection has been carried out in collaboration with the Transport Co Ltd for the driving behaviour of their coach drivers in two main routes connecting Bangkok with the north and north eastern parts of Thailand. In addition, a visualization mapping of potential black spot has been created.

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Appendix

Sample of Raw Accelerometer Data

	A	B	C	D
1	Time Stamp	Acceleration x	Acceleration Y	Acceleration Z
2	15:20:21	2.6048915	0.45968673	10.266336
3	15:20:21	1.8387469	1.0726024	8.274361
4	15:20:21	2.1452048	-0.15322891	8.734048
5	15:20:22	1.0726024	-0.15322891	9.040505
6	15:20:22	2.7581203	0.61291564	9.80665
7	15:20:22	1.532289	1.2258313	9.040505
8	15:20:22	1.685518	0.61291564	8.887277
9	15:20:22	1.8387469	0.15322891	9.959879
10	15:20:23	1.9919758	0.61291564	8.887277
11	15:20:23	1.9919758	0.45968673	7.0485296
12	15:20:23	1.3790601	0.61291564	8.121132
13	15:20:23	1.8387469	-0.15322891	8.734048
14	15:20:23	2.6048915	-0.7661445	11.33894
15	15:20:24	1.685518	0.91937345	9.193734
16	15:20:24	1.532289	0.91937345	8.121132
17	15:20:24	1.685518	0.15322891	9.653421
18	15:20:24	1.3790601	0.15322891	9.80665
19	15:20:24	2.2984335	0.15322891	9.80665
20	15:20:25	1.3790601	0.15322891	8.42759
21	15:20:25	1.685518	0.61291564	8.887277
22	15:20:25	2.1452048	0.61291564	11.33894
23	15:20:25	1.685518	0.30645782	6.129156
24	15:20:25	3.217807	0.7661445	10.572795
25	15:20:26	1.3790601	1.3790601	7.6614456
26	15:20:26	1.685518	0.45968673	9.80665
27	15:20:26	1.685518	0.45968673	9.80665
28	15:20:26	2.2984335	0.91937345	11.032481
29	15:20:26	2.1452048	1.2258313	9.500193
30	15:20:27	1.8387469	0.61291564	8.274361
31	15:20:27	2.9113493	0.91937345	9.653421
32	15:20:27	1.532289	0.7661445	8.580819
33	15:20:27	1.9919758	0.91937345	7.6614456
34	15:20:27	2.1452048	0.45968673	8.580819

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