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GPS-based Driving Observations of Personal Vehicles In Bangkok

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ABSTRACT

GPS receivers/loggers were installed in personal vehicles to collect driving information around Bangkok areas, Thailand, during 2015-2016. During the experiment, there are 30-32 operational GPS satellites with visible 3-13 satellites were in the sky over the observed point. This study took five degrees GPS elevation mask angle. Total sample of 267 vehicles, 1869 days 3965 trips, data were transferred into a GIS database for visualization and analysis. Participants and vehicles basic information were also collected, including driver gender, vehicle fuel type, size of total volume of all engine cylinders, driver age, and driving experience. Collected data were statistically explored with the SPSS (MANOVA) with fuel types, all cylinder volumes, driving experiences, and driver age as independent variables and distance, average speed, and time as dependent variables. This study found that fuel types, driver experiences, car engine cylinder volumes, and driver age have statistically significant influence on driving behaviors that were related to distance, average speed and driving time. Multiple regression models were produced to predict driving behaviors pertinent to distance, average speed and driving time.

1. Introduction

There are many factors that affect driving behaviors/habits/characteristics, in which notify what drivers do or choose to do on the road, with their knowledge, skill, perceptual and cognitive abilities (Evans, 2004). First of all, it should come to a question of how to characterize driving behaviors/ habits/characteristics? To begin, it needs to observe how driver drive the vehicle. Global

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Positioning System (GPS) technology makes it possible to track all the movements. With current state of GPS constellation, it has enough number of satellites over the observed sky to track the vehicle even in urban canyon of high-rise buildings in city like Bangkok, Thailand. GPS data can be imported to Geographic Information System (GIS) database for further analysis and visualization the driving. Therefore, this study uses the state of technology to get the real driving data and statistical analysis can be made to find the significant of the factors that influent the driving. This work is in particular more interested in factors like vehicle fuel type, vehicle specification, driver age, and driving experience and how these factors related to driving distance, average driving speed and time. The schematic of data collection and analysis is given in Figure 1.

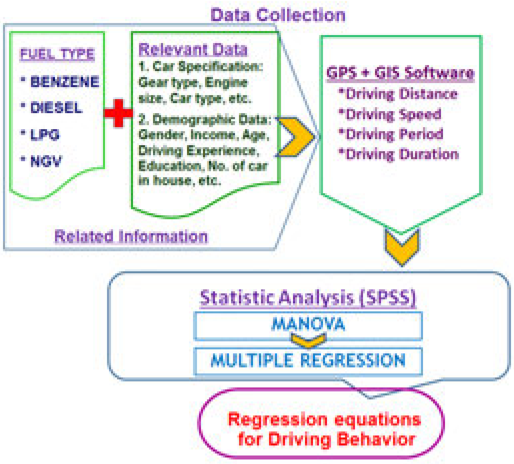

Figure 1: Schematic of data collection and analysis

2. Literature Review

There are several works that applied GPS to traffic and transportation studies. Barth et al. (1996) applied GPS to relate macroscopic and microscopic traffic parameters. Gonder et al. (2007) used GPS travel data to assess real-world energy use of plug-in hybrid electric vehicles. Grengs et al. (2008) used GPS data to understand driving behaviors.

Jensen et al. (2010) studied effects of using GPS navigation systems on driving behaviors and performance, due to output configurations (audio, visual and audio-visual) of a GPS navigator. The results illustrated that visual output causes a substantial amount of eye glances, as well as decreasing driving performance. Herrera et al. (2010) evaluated traffic data obtained via GPS-enabled mobile phones. Wang et al. (2013) used GPS to provide driving range and patterns of private passenger vehicle in Beijing. With GPS technology evolution, it is possible to find centimeters accuracy with the so called "Precise Point Positioning (PPP)" technique, even in kinematic mode with sub-meter accuracy (Witchayangkoon, 2000).

In order to get local driving observation in Bangkok, this work uses GPS receiver/data logger to track real driving of personal vehicles. This work focuses on multi-factors such as vehicle fuel type, vehicle specification, driver age, and driving experience and analyzes these factors in relation to driving distance, driving speed and time.

3. Equipment and Data Collection

3.1 GPS Receiver/Data Logger

This study utilizes total 40 GPS receivers, each to be installed in each personal car. The GPS receiver model is Qstarz Travel Mate BT-Q1000XT Bluetooth Data Logger GPS Receiver, see Figure 2. This receiver tracks L1 (C/A-code, 1575.42MHz) signal of GPS. The receiver has ability to take 66 channels with 1-5Hz update rate. It can record up to 400,000 waypoints (capable of recording up to 40 days with ultra-low power consumption up to 42 hours operation). Number of recorded waypoints would be decreased when the more options are selected. Note that for this receiver, Time to First Fix (TTFF) to GPS signals for hot start is 1second and cold start is 35seconds. In case of lost the lock to signals, reacquisition to signal is possibly less than 1second. The recorded information within the GPS receivers includes time, the vehicle coordinates (standard UTM, Latitude, Longitude), altitude, speed, distance. The recorded data in each receiver is later downloaded into a computer/GIS database through USB for further analysis. Each GPS receiver is set to record GPS signal every 15seconds, with pre-set of auto logging after ignition of the vehicle. GPS receiver has dimensions72.2 (L) X 46.5 (W) X 20 (H) mm with weight 64.7g (including battery).

Figure 2: GPS receiver unit (Qstarz Travel Mate BT-Q1000XT)

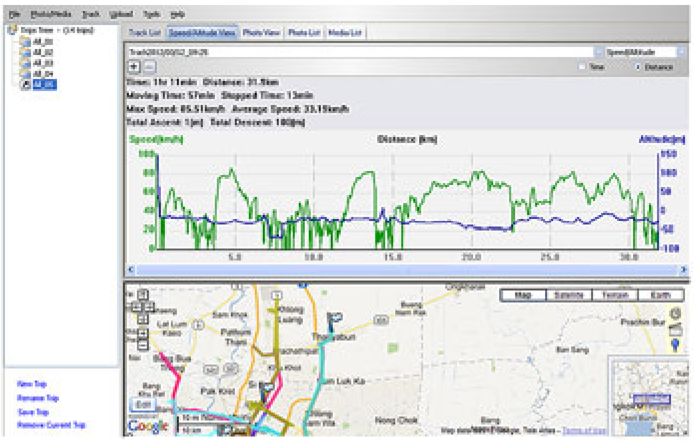

Figure 3: Weekly driving information from a vehicle with 14 trips to show speed, distance, and altitude.

After install GPS equipped on vehicle the logger will collect data and visualize in the Figure 3 to show the route and trips of driving of each particular vehicle. The data will be used in combination with vehicle specification and driver information for statistical analysis.

3.2 Participants

As stated that this study utilizes 40 GPS receivers, thus it need 10 rounds, 40 personal vehicles for each round, therefore this study 400 personal vehicles are randomly chosen and asked to take part of this study. All of these participants' cars run in the Bangkok areas of Thailand. However, after collecting and processing the data, only data from 267 personal vehicles are usable for this study. Data has been collected during March 2013 to September 2014. GPS data from each vehicle is taken for seven days long period.

Table 1: Participants and vehicles basic information.

Nominal variable	Driver Gender (persons)	
	Male	221
	Female	46
	Vehicle Fuel Type (number of vehicles)	
	NGV/CNG (US$0.38 per kg)	11
	LPG (US$0.38 per kg)	105
	Diesel (US$0.74 per liter)	101
	Gasoline (US$0.82 per lite)	50
Interval variable	Size of car engine total cylinder volumes (number of vehicles)	
	≤1,500cc	62
	1501-1999cc	53
	2000-2499cc	108
	≥2500cc	43
Scale variable	Driver's age (years)	
	Max	64
	Min	18
	Average	37.8
	SD	7.9
	Driving experiences (years)	
	Max	46
	Min	0.5
	Average	13.9
	SD	7.9

Note: Price of each fuel type is the average local prices.

3.3 GIS Database

Collected GPS data (coordinates of each epoch) can be imported to Pythagoras GIS® database software. The data are compiled to get distance, speed, direction, and time information of the driving. These data are combined with relevant data (fuel type, vehicle specification, and driver information). Temporal visualization can be made to see the driving for each selected vehicle.

4. Results and Discussion

Having gained GPS data collected from 267 personal vehicles, Table 2 shows basic information. Data from GPS receiver/logger is used to track vehicle, as displayed with 10seconds interval in Figures 3 and 4. Driving speeds can also be observed as the traces are put with different colors. With Pythagoras GIS software, it is possible to import GPS data to the database as shown in Figure 3. Figure 4 exhibits GPS tracked vehicle data overlaid on Google Earth®.

Table 2: GPS-based driving observation data of all vehicles.

GPS-based Observation	Mean	SD	SE
Distance (km/day)	74.69	61.55	3.77
Average Speed (km/hr)	38.91	11.63	0.71
Max Speed (km/hr)	86.94	17.63	1.08
Daily Driving Time (min)	176.75	131.34	8.05

Figure 4: Example of Driving Observation from 50 personal vehicles, in Pythagoras GIS software.

Figure 5: Tracked positions of personal vehicles with varied speed from GPS overlaid on Google Earth® over center of Bangkok (Courtesy of Google Earth®)

When going into detail classified according to different fuel types, vehicles driving attributes are given in Table 3. The highest mean for daily driving distance is vehicles with NGV, followed by LPG, while mean travel time for each fuel type shows the same trend. Mean speeds for all types of fuel are very close due mainly to traffic congestion conditions.

Table 3: Daily driving attributes classified according to different fuel types collected from GPS.

Fuel Type	Number of vehicles	Distance (km)		Speed (km/hr)		Time (min)	
		Mean	SD.	Mean	SD.	Mean	SD.
NGV	11	105.3	64.7	35.7	8.2	272.7	152.6
Benzene	50	71.7	64.2	39.1	12.4	159.6	81.4
LPG	105	83.4	70.2	40.1	12.8	188.1	114.3
Diesel	101	63.8	46.9	37.9	10.2	159.1	86.4
Total	267	74.7	61.5	38.9	11.6	175.4	103.1

To further statistically analyze the GPS data, Multivariate Analysis of Variance (MANOVA), an ANOVA with multiple dependent variables, is conducted to determine if the dependent variables are significantly affected by changes of independent variables. Table 4 gives two-way MANOVA analysis results of collected GPS data, with fuel type and all cylinders volume as independent variables and having distance, average speed, and time as dependent variables. In addition, a p-value is generated, to determine whether or not the null hypothesis can be rejected. P-value is considered significant when the p-value < 0.05. Therefore, it can readily be seen that all independent variables is significantly related to all dependent variables, i.e., fuel type, all cylinders volume, and fuel type * all cylinders volume affecting on all three – distance , average speed, and time.

Table 4: MANOVA analysis of collected GPS data
with fuel type and cylinders volume as independent variables

Independent variable	Dependent variable	Type III Sum of squares	df	Mean Square	F	p-value
Fuel Type	Distance	30164.014	3	10054.671	5.914	.009*.
	Avg Speed	313.329	3	104.443	3.775	.034*
	Time	36.709	3	12.236	2.796	.041*
All cylinders volume	Distance	19170.288	3	6390.096	3.867	.013*
	Avg Speed	53.096	3	17.699	2.716	.045*
	Time	35.653	3	11.884	4.131	.031*
Fuel Type * all cylinders volume	Distance	109166.860	9	12129.651	3.203	.023*
	Avg Speed	1572.422	9	174.714	3.296	.000*
	Time	90.148	9	10.016	2.289	.017*

Note: * is marked for significant level 0.05

With fuel type and driving experience as independent variables and having same dependent variables, and with the same manner of MANOVA analysis and get result Table 5, it is found that all independent variables is significantly related to all dependent variables i.e., fuel type, driving experience, and fuel type * driving experience affecting on all three – distance, average speed, and time. When analyzing fuel type and driver age as independent variables, see MANOVA result in Table 6, it is also found that fuel type and driver age affect driving distance, average speed, and time.

Fuel type is considered as nominal variable. From this finding, it is possible to use cylinders volume of car engine, and driver experience and driver age as factors into multiples regression, to generate the equation model to predict driving behavior. The regression result is given in Table 7.

Table 5: MANOVA analysis of collected GPS data with fuel type and driving experience as independent variables.

Independent variable	Dependent variable	Type III Sum of squares	df	Mean Square	F	p-value
Fuel Type	Distance	27103.047	3	7444.478	3.065	.005*
	Avg Speed	409.382	3	282.669	4.124	.018*
	Time	46.396	3	7.674	4.795	.019*
Driving Experience	Distance	8532.892	4	3.375	3.401	.009*
	Avg Speed	57.895	4	97.817	2.735	.048*
	Time	9.433	4	2.306	3.539	.043*
Fuel Type * all Driving Experience	Distance	56431.865	11	8812.449	2.445	.026*
	Avg Speed	1212.716	11	210.638	2.833	.011*
	Time	57.955	11	17.335	4.055	.001*

Table 6: MANOVA analysis of collected GPS data with fuel type and driver age as independent variables.

Independent variable	Dependent variable	Type III Sum of squares	df	Mean Square	F	p-value
Fuel Type	Distance	156971.9	22	7135.088	1.311	.000*
	Avg Speed	3147.57	22	143.071	1.063	.005*
	Time	191.468	22	8.703	3.963	.007*
Driver Age	Distance	212841.2	1	212841.2	61.055	.000*
	Avg Speed	53287.49	1	53287.49	396.004	.000*
	Time	313.557	1	313.557	70.714	.000*
Fuel Type * Driver Age	Distance	18586.32	3	6195.439	2.213	.022*
	Avg Speed	150.729	3	50.243	4.025	.008*
	Time	25.796	3	8.599	2.451	.025*

Table 7: Regression result

	Distance					Average Speed					Time				
	B	S.E.b	Beta	t	p-value	B	S.E.b	Beta	t	p-value	B	S.E.b	Beta	t	p-value
x_1	0.430	0.028	0.451	15.097	.000*	0.456	0.033	0.459	13.883	.000*	0.444	0.035	0.405	12.528	.000*
x_2	0.238	0.03	0.233	8.043	.000*	0.185	0.039	0.175	4.766	.000*	0.24	0.032	0.218	7.587	.000*
x_3	0.132	0.025	0.139	5.208	.000*	0.135	0.035	0.136	3.797	.000*	0.132	0.041	0.118	3.207	.001*
intercept	0.675	0.092		7.322	.000*	0.77	0.105		7.344	.000*	0.247	0.115		2.148	.032*

From regression result in Table 7, it is possible to write the following predictions:

Distance: $$y_1 = 0.430x_1 + 0.238x_2 + 0.132x_3 + 0.675 \text{ with } R^2 = 0.633 \quad (1)$$

Average Speed $$y_2 = 0.456x_1 + 0.185x_2 + 0.135x_3 + 0.770 \text{ with } R^2 = 0.562 \quad (2)$$

Driving Time $$y_3 = 0.444x_1 + 0.240x_2 + 0.132x_3 + 0.247 \text{ with } R^2 = 0.562 \quad (3),$$

where parameters

x_1 = Driver experience

x_2 = Cylinders volume of car engine

x_3 = Driver age.

These three parameters (driving experience, cylinders volume of car engine and driver age) can be used to predict of driving distance behavior, average speed behavior and driving time behavior as given in regression Equations (1)-(3). When notice coefficients of these Equations (1)-(3), the highest coefficient is associated with driver experience, having the most influence to all driving behaviors in distance, average speed and driving time. The lesser coefficients are related to cylinders volume of car engine and driver age, respectively. These mathematic regression models might be used to confirm that driver experience is the most important and followed by cylinders volume of car engine and driver age. This driving behavior information is useful for launching and serving essential public administration and policy on transportation.

5. Conclusion

This study collected GPS data from GPS receivers/loggers, each installed in 267 personal vehicles driving around Bangkok areas, Thailand. GIS and SPSS (MANOVA) were used as research tools to analyze driving data collected from GPS. This study found that fuel types, driver experiences, car engine cylinder volumes, and driver age have influence on driving behaviors that were related to distance, average speed and driving time. Multiple regression models were produced and presented, to predict driving behaviors pertinent to distance, average speed and driving time.

6. Acknowledgement

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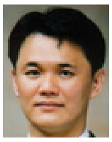

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