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Design of Driving Behavior Pattern Measurements Using Smartphone Global Positioning System Data

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ABSTRACT

The emergence of new technologies such as GPS, cellphone, Bluetooth device, etc. offers opportunities for collecting high-fidelity temporal-spatial travel data in a cost-effective manner. With the vehicle trajectory data achieved from a smartphone app Metropia, this study targets on exploring the trajectory data and designing the measurements of the driving pattern. Metropia is a recently available mobile traffic app that uses prediction and coordinating technology combined with user rewards to incentivize drivers to cooperate, balance traffic load on the network, and reduce traffic congestion. Speed and celeration (acceleration and deceleration) are obtained from the Metropia platform directly and parameterized as individual and system measurements related to traffic, spatial and temporal conditions. A case study is provided in this paper to demonstrate the feasibility of this approach utilizing the trajectory data from the actual app usage. The driving behaviors at both individual and system levels are quantified from the microscopic speed and celeration records. The results from this study reveal distinct driving behavior pattern and shed lights for further opportunities to identify behavior characteristics beyond safety and environmental considerations.

Key Words: Information communication and technology (ICT), Driving pattern, At-risk behavior, Trajectory data

1. INTRODUCTION

The emergence of new information and communication technologies (ICT) such as GPS devices, cellphone, Bluetooth, etc. offers the capability to collecting high-fidelity high-resolution travel data in a cost effective manner. These technologies also permit continuous data collection so long as the vehicle/device is in operation. Given the ever growing cellular phone market - 90% among adults in the United States, of which one third owns a smartphone (Rainie 2013) – it has become much easier to track and understand traveler activity and travel patterns through smartphones.

Current ICT technology, such as smartphones and "apps", opens a new way to data collection and travel survey. The data collected with build-in GPS modules in a smartphone usually include not only the vehicle spatial-temporal dimension location, which could be used to correlate the network geography attributes and/or real-time traffic condition, but also the detailed information about the vehicle dynamics including speed, acceleration, and deceleration, whereby a driver's control and maneuver of a vehicle can be analyzed in detail.

Individual driving behavior has long been a major topic in transportation safety research, and the data collected from ICT offers promising future for the driver behavior analysis at microscopically, yet the relevant research is limited.

The crux of this paper is to explore driving performance utilizing the trajectory data retrieved from the information and communication technology. The paper begins with a discussion about the previous and current studies about driving behavior, followed by the descriptions of the methods to measuring the driving performance utilizing the trajectory data. Case studies based on example Metropia data are elaborated in detail in Sections 4. Remarks regarding future research opportunities are offered in the final section.

2. LITERATURE REVIEW

2.1. Driving Pattern Research

Individual driving behavior, such as speeding and distraction and aggressive driving has long been a major topic in transportation safety research. At-risk driving behaviors related to crash causation have been well researched. Some studies focus on acceleration pattern and their relations with fuel consumption and emissions. On the other hand, driving patterns or habits such as celeration and braking behavior under various conditions have not been extensively studied due to the limitation in data collection. These previous studies are mostly based on crash reports, self-reported crash and behavior, driving simulation, instrumented vehicle or GPS devices.

A recent effort in the individual driving behavior is the 100-car naturalistic driving study. (Klauer *et al*. 2009) Drivers are monitored and recognized as unsafe, moderate safe and safe according to frequencies of crashes/near-crashes. The results indicate that hard braking, inattention, and tailgating are the top three at-risk behaviors among drivers. Unsafe drivers are more likely to engage in the at-risk behaviors and decelerate/swerve greater than the safe drivers. The results also imply that improper braking and inappropriate speeds are positively related to crash/near-crashes. Different traffic and weather conditions are also studied separately for the driving behavior and crash risk. The unsafe drivers drive more aggressively regardless of traffic conditions.

Af Wåhlberg (2008) stated that behavior of the driver can be measured as function of speed changes and the celeration (acceleration/deceleration) behavior. Also, potential or actual risk of an incident is strongly indicated by the change in speed of a vehicle and proportional to the size of the change and the speed from which it starts. The researcher's conclusions are based on GPS tracking on bus drivers in Sweden and history accidents records of the drivers. Measurements associated with the road accidents are suggested as the combination of celeration and the driving speed. Af Wåhlberg also stated that celeration research is still in its infancy.

A study by Ellison, Greaves *et al*. (2012) proposes a framework for profiling drivers by at-risk behavior using driving pattern, spatial and temporal characteristics and driver characteristics. Second-by-second GPS data observations are collected from 106 drivers in Sydney over several weeks. Behavioral measures are summarized as maximum, average, minimum and standard deviation of speed, acceleration and deceleration, distance at 75% of speed limit or over speed, number of sharp celeration $\geq 4\frac{m}{s^2}$), etc.

Studies in driving pattern regarding fuel consumption and emission can also be found in the literatures. Both safe and green driving style drivers are observed to have less stop and hard braking, smooth acceleration and deceleration and moderate engine speed. Young *et al*. (2011) and Ericsson (2000) matched the driving pattern data to the transportation network and examined the variation of the driving patterns as a function of external conditions. Five cars were used in daily driving by 30 families for two weeks. The driving patterns are measured by aggregated speed, acceleration/deceleration, oscillation of speed and celeration, power use, engine speed and gear changing behavior for different street types. The parameters are defined as percent of time speed < 2 km/h, frequency of local max/min values of speed curve, percent of time at acceleration over 2.5m/s^2, speed celeration ($v \cdot a$) distribution. A linear regression model is proposed to examine the relations between a certain driving pattern with street characteristics, traffic flow conditions, weather and drivers. The impact of these driving behaviors on emissions and fuel-use is further investigated (Ericsson 2001). This study suggests strategy for eco-driving to avoid heavy acceleration, large power demands and high engine speeds.

It can be seen that most studies on driving pattern analysis are based on the historical accident reports or driving simulators, missing the detailed driving behavior data collection makes the microscopic driving pattern analysis impossible. The research framework proposed in some recent literatures start to study the driving pattern with certain assumptions, but limited model validation using the real data have been observed. In the last decade the Data Acquisition System (DAS) or In-Vehicle Data Recorders (IVDR) have been introduced to collect detailed driving behavior data, but the usage was limited due to the high hardware cost, and the research sample size are usually insufficient (Toledo and Lotan 2006; Toledo *et al*. 2008). Furthermore, with those devices, drivers may not act exactly in the same way as they normally do during the experiment period; in other words, these methods may introduce certain biases to the experiment.

2.2. Information and Communication Technology Application in Transportation

The rapid adoption of the internet and mobile phone allows for feasible and convenient applications of information and communication technology (ICT). Most of the studies prove that the real time information and communication can encourage the travel behaviors changes. In San Francisco area, real-time freeway and Caltrans travel time information are provided, such as the MITTENS (Messaging Infrastructure for Travel Time Estimates to a Network of Signs) (Sharafsaleh *et al*. 2011) and Predict-a-Trip^{SM} (Goodwin 2007). For example, the SmartRide is developed by the Georgia Power for internal employees during 1996 Olympic Games. This software enables users to track carpool, vanpool and transit information, further to encouraging people to share rides and drive less (FHWA 2006).

Increasing applications based on the Smartphone platform emerge with the advances in wireless communication and computer technology. In 2006, a 13-week field study with 340 participants was conducted in Netherlands in the Spitmsijden project. Smartphones are provided to track participants' travel behaviour and rewards are offered if they can avoid driving during morning rush hours. Substantial evidences are obtained that commuters are willing to shift departure time or commuting mode in order to gain rewards (Ben-Elia *et al*. 2011; Ben-Elia and Ettema 2011). This easy-access information encourages motorists to consider taking public transit instead of driving, or prospective carpools. Sustainable social networking services for transport (SUNSET) project in Europe aims to use incentives and social network to improve person mobility and reduce traffic congestion (Broll *et al*. 2012; Bie *et al*. 2012; SUNSET 2012). A few iOS applications are also designed for ridesharing. The dynamic ride-matching system extends the public transport using private automobiles, by matching available seats in-route and integration of pricing mechanism (Transportation for America 2010). Also, transit service can be provided based on demand, such as TELE-Bus in Krakow Poland. A 600% increase of transit passengers is observed after this dynamic dispatch and routing platform being implemented after six months (AENEAS 2010).

Overall, it is generally agreed that ICT applications with advanced technology will continue to be developed in the foreseeable future. With the upcoming data achieve from ICT, more research ideas become feasible besides the travel behavior. This study proposes a research approach to explore the design of the driving pattern/habit utilizing the data obtained from a Smartphone platform. This analysis is highly related to safe driving behavior and driver education, reducing fuel consumption and flexible vehicle insurance.

3. ANALYSIS METHODOLOGY AND FRAMEWORK

3.1. Metropia Technology and Data

Metropia is a recently available mobile traffic app that uses prediction and coordinating technology combined with user rewards to incentivize drivers to cooperate, balance traffic load on the network, and reduce traffic congestion. Metropia uses advanced algorithms to determine which departure times and routes have available capacity, and offers varying levels of incentives for using less congested departure times and routes. Drivers use the app to reserve these faster routes, and when the recommended departure time gets close, the app reminds drivers when it's time to leave.

The Metropia system keeps track of the number of drivers using alternative routes and times, and automatically adjusts incentive levels for recommended trips if too many Metropia drivers are attempting to use the same alternate routes. As shown in Figure 1, Metropia servers use both real-time and historical data to analyze (in space and time) where available capacity exists, whereby moving additional demand that will lead to overall reduction of travel time and congestion (Step 1).

The Metropia server system then utilizes such information to estimate the amount of "mPoints" to be awarded for each departure time and route. If a departure and route is found be more beneficial to the entire system, then a higher amount of mPoints are allocated to that departure time-route option. Metropia also provides predicted experienced travel time for future departure times. The accurate prediction[1] empowers a driver to decide to leave now or depart later, considering the onset of congestion. The mPoint incentive and travel time prediction is a combination to motivate drivers to use a less congested route and time. A driver will then make a reservation for a specific route and time (Step 2).

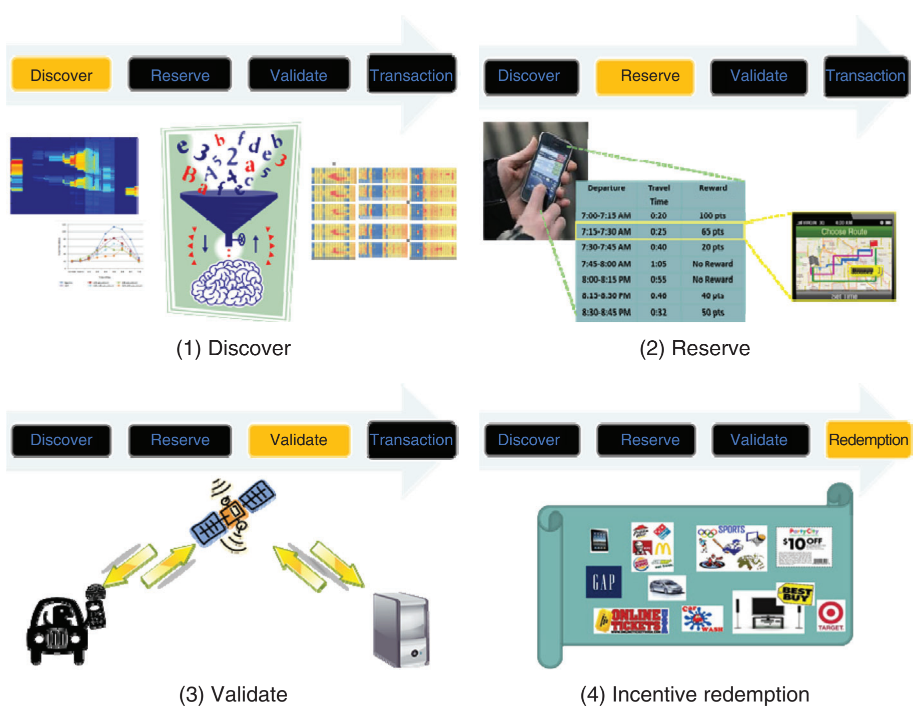

Figure 1. Metropia user experience

[1] Extensive field testing shows that the prediction error for Metropia is merely at 15%, much less compared to two other major navigation tools at 30% and 40% respectively.

Ten minutes prior to the reserved departure time and route, the GPS will turn on and a reminder will pop up to remind the driver that it's time to leave. A certain time buffer is allowed so that the driver can leave within a certain time window. Once the trip is started, Metropia becomes a navigation app that provides audio turn-by-turn navigation guidance to help the user follow the reserved route until reaching the final destination (Step 3).

A user can continue Steps 2 and 3 in order to continue accumulating mPoints. The earned trekpoints can then be redeemed for various discounted products and services, freebies, lotteries, or even donated to charities (Step 4).

3.2. Metropia Collected Data

Besides the traveler's response to the incentives, detailed trajectory data and driving behavior data for each trip are collected during the trip validation process. When a Metropia user starts a trip, the internal GPS module is activated and starts to record the second-by-second latitude/longitude data location and instantaneous moving speed. These data allow detailed position, velocity, acceleration and deceleration data to be stored and analyzed online or offline. Further, what's unique about Metropia data is its backend server also estimates traffic speed and volume for each link that the vehicle traverses.

Such type of dataset combining both user trajectory and link speed/volume information is rarely seen in prior research, permitting a unique opportunity to link critical traffic congestion factors leading to driving behavior and crash potential. For example, if a driver exhibits stop-and-go or abrupt accelerate/decelerate behavior, it is usually difficult to tell if this is simply due to the driver's behavior or because of heavy traffic conditions. With both data linked together, one can discern hazards caused by driving behavior and/or congestion levels.

3.3. Measurements Design

To fully explore the performance metrics, such as at-risk and fuel consumption, a systematic data management and processing platform integrating GIS technique and additional traffic volume data was built. In this study, we focus on designing the measurements base on the trajectory data exclusively.

Location and time are the two direct values extracted from the GPS data. What's more, driving speed and acceleration/deceleration can also be calculated from the second-by-second detailed GPS trajectory. Various measures can be defined for individual and system driving pattern, and the process of defining the behavior, such as at-risk score, requires the comparison of the individual to the system across spatial-temporal and traffic conditions.

3.3.1 Individual driving performance

The continuous speed and celeration GPS data points observed for the same driver along his/her journey include thee followings:

- Distribution of the speed/ acceleration/ deceleration, including average, maximum, minimum, variance;

- Percentage of time over speed limit by 5 mph/ 10 mph or more; and
- Percentage of time or number of high acceleration and deceleration (limit = 4 m/s^2)

Furthermore, variability of speed could be regarded an indicator of at-risk driving. A person driving at a relatively low average speed may still be at-risk if the drive is not "going with flow". A smooth driving pattern is preferred from both safety and environment aspect. Therefore, the additional measurements can be:

- Average frequencies of change from acceleration to deceleration and vice versa;
- Max/min speed distribution (The crest speed/ previous trough speed, representing acceleration strength); and
- Frequency of stops, as speed < 2 mph

Moreover, speed and acceleration should be considered simultaneously. A higher acceleration at a lower speed is more reasonable comparing to a high acceleration at a speed over 60 mph. The hard break at a cursing speed over 30 mph may imply a hazardous situation, such as avoiding another vehicles, stopping at a traffic signal, etc. Combining the speed and celeration behavior together, it is important to jointly consider:

- Instantaneous speed when acceleration is triggered, and
- $v{\cdot}a$ distribution, (*speed* × *celeration* celeration performance at each speed point).

To further correlate with other external conditions, the records for the same driver can be initially classified by time, road type, and traffic conditions. The above measures can be calculated for different external conditions.

3.3.2. System driving performance

The general driving performance of drivers depends on both roadway and traffic conditions. Freeways and arterials have significantly different traffic flow characteristics and drivers may behavior differently in terms of car-following and lane-changing behavior. Using the speed and celeration data to measure a traveler's performance on each segment enables us to identify the dangerous locations. The measurements can be defined through the following approaches:

- Average and variance of speed/ acceleration/ deceleration
- Average over drivers' over speed pattern
- Average over drivers' sharp acceleration and deceleration pattern
- Average over drivers' frequency of stops per unit distance

With a large amount of records covering most of the network and time of day, the above measures can be calculated by time of day to identify the at-risk period. These measurements can be further analyzed together with traffic and roadway class and geometry design, to achieve the system wide driving pattern under various spatial-temporal conditions.

3.4. Driving Pattern Exploration

With the measurements discussed in Section 3.3, a driver's behavior can be examined. Various criteria can be defined to answer questions such as if the driver is an aggressive drive or not. In this section, we propose several approaches to identify the linkage between the measurements and various performance metrics, such as at-risk index, emission, etc. We propose the exploration from the following two aspects.

3.4.1. Inter-driver comparison

The first approach is to quantify the value and distribution of the measurements among the whole samples. For example, the drivers can be clustered to 5 at-risk levels according to multiple measures. This can be achieved using various cluster methods, such as K-mean cluster. In addition, a risk index can be defined by locating the individual behavior among all drivers by multiple measurements. As an example, if these measurements are assigned with an equal weight in the index reference, and the full score for each measurement as 10 points, then if a driver's average speed is higher than 60% of all drivers' average speed, 6 points is received. Similarly, if his acceleration and deceleration performance are among the top 10% good drivers, 1 point will be given for each measurement; so consequently, a total of 8 points are assigned to this driver as the risk index. Such an index can include other measures and be adjusted with external conditions if needed. Drivers with a certain risk index can be categorized to be one of the five levels of at-risk driving performance.

3.4.2. Comparing with system performance

Drivers' behavior captured from the platform is not the only factor that represents the driving patterns. Given two different drivers, with one driver mostly travels on the highway and the other uses more local roads. Then, the comparison result in Section 3.4.1 using their speed and celeration may indicate a higher risk index for the highway driver. However, it is unreasonable to compare these two drivers that are exposed to different external conditions. Incorporating the system driving performance in 3.4.2, a driver's behavior on certain roads can be quantified by comparing with the average performance of all the drivers using the same road. With sufficient users in the platform and most segments traveled repeatedly, this approach becomes feasible and reasonable in capturing a person's performance level.

4. CASE STUDY

In this section, the analysis based on data collected by Metropia app from Los Angeles area in April-July 2013 is presented. For each of the 12 test drivers, at least one set of trajectory data of traverse history is available, and the test last for multi-days. Due to the limited number of test users and lower spatial-temporal coverage, the goal of the case study is to demonstrate the feasibility and result of applying the above quantifying methodology in the driving pattern analysis and to reveal future research directions. Examples of individual and system measurements are presented in Sections 4.1 and 4.2. Section 4.3 explains the approaches to exploring the safety related at-risk driving pattern utilizing the proposed measures.

4.1. Individual Driving Performance Measures

Driver (#9212) is selected as an example and the data of this driver covers both freeway and local road. A list of measurement values is presented in Table 1 following the discussion in 3.3.1.

Table 1. Measurements for Driver #9212

		all		Freeway exclude ramp			local		
		mean	Std	mean	Std	max	mean	Std	max
1	Speed (mph)	57.64	11.22	61.54	7.93	77.00	44.13	8.08	61.00
	Acceleration ($\frac{m}{s^2}$)	0.39	0.69	0.26	0.21	1.50	0.54	0.84	7.20
	Deceleration (m/s^2)	–0.30	0.71	–0.26	0.20	–1.20	–0.48	1.82	–19.30
2	Percentage of time speed over 65 mph for freeway and 50 for local				8.04%			14.35%	
3	Percentage of time |celeration| > 4 m/s2	0.34%			0.52%			0.29%	
4	Frequency of celeration change (#/100s)	0.61			0.61			1.01	
5	Max/min speed distribution	1.36	0.30	1.36	0.27		1.37	0.31	
6	Frequency of stops <2 mph/hard brake<–4 (#/100s)	0.04							
7	Point speed when acceleration starts	56.81	11.68	60.71	8.55	75.00	43.27	7.90	58.00
8	v.a	3.40	23.82	1.22	16.27	82.50	7.55	33.44	280.80

Based on the statistic description of speed, acceleration and deceleration, significant difference between the performance on freeway and local roads can be observed. The overall average speed is 57.64 mph, with 61.54 mph on freeways and 44.13 mph on local roads. The speeds on local road exhibit a large standard deviation than those on freeways, because the driving speed and behavior on freeways are more stable, and speeds on local roads fluctuate considerably due to more varying traffic conditions. Acceleration/deceleration behavior of this driver is moderate with 0.39 (m/s^2) and –0.30 (m/s^2) average celeration rate. Records on local streets still claim a higher celeration rate compared with that on freeway segments (excluding ramp). The variation of celeration rates on local roads are higher with maximum values of 7.2 (m/s^2) and –19.3 (m/s^2), which are not realistic and reveals issues in missing data to be addressed. Currently, the trajectory points with over 5 (m/s^2) acceleration and –11 (m/s^2) deceleration are removed from the sample.

With these values, we examine the over speed and sharp celeration by measure 2 and 3. This driver's speed exceeds 65 mph for around 8% of the driving duration on freeways. On local roads, the duration of speed exceeding 50 mph accounts for over 14%. The road type of each link is identified from the GIS system, and this measurement can be further linked to speed limit on the corresponding segment in the future as designed in 3.3.1. The celeration behavior analysis also reveals that among all the acceleration period, sharp acceleration is observed in 0.52% duration and the number is 0.29% for the sharp deceleration among all deceleration period.

The variability of speed change from the above measurement items 4, 5 and 6 is also observed. Measurement is identified as the total numbers of crests and troughs in the speed wave. Minor fluctuations in the speed such as maintaining around a certain speed are ignored. This measurement can be considered a habitual behavior in speed control; with high value means driver tends to change from acceleration to brake frequently instead of maintaining a stable speed. This value depends on the traffic condition and some external situations. For example, the signals and intersections on local roads force the driver to change celeration direction frequently, as proved with 1.01/100s on local streets vs. 0.61/100s on freeway. Then the value of the crest divided by the previous trough is calculated as measurement 5. This value represents amplitude of the speed wave and strength of consecutive accelerations. This value is similar in freeway and local streets. The number of stops is also an important indicator. For this driver, only five stops are observed during the total of 3.2 hours after removing the records at signals. It should be noted that with more records on the local roadway segments in future, this measurement can be improved in the following studies.

Next, we explore the driving pattern with the speed and celeration jointly. First, at each timestamp when the speed starts to increase, the average point speed is calculated as a measure. On average, the point speed at acceleration is 56.81 mph in the moving period. The value is high (60 mph) for freeway and lower for local at about 15 mph. Another measurement is the value of ($speed * celeration$). The average value of this measurement is around zero as the acceleration and deceleration are almost evenly. The high value indicates the situation with both sharp acceleration and high speed. Figure 2 shows the histogram plot of this measurement. It can be observed that most of the observed trajectory points are close to zero representing a stable speed when celeration is close to zero. And the acceleration and deceleration on each side mostly centered around ±10 indicating moderate speed during celeration. The records beyond ±100 show the scenario of sharp celeration when users are driving at high speed.

Overall, the above discussions are about the measurements for individual driver under various roadway conditions. These measurements can be extended according to time of day and traffic condition on the link.

4.2. System-wide Driving Performance Measures

The driving pattern over the whole network is useful to identify the locations with high crash risk and low fuel efficiency. Figure 3 shows the average driving performance of the total 12 users over few days on the whole network. The real speed, acceleration and deceleration performance can be further converted to risk index and emission index. With sufficient driving trajectory data, the average driving pattern on each segment can be obtained by time of day. By comparing acceleration and deceleration during off-peak

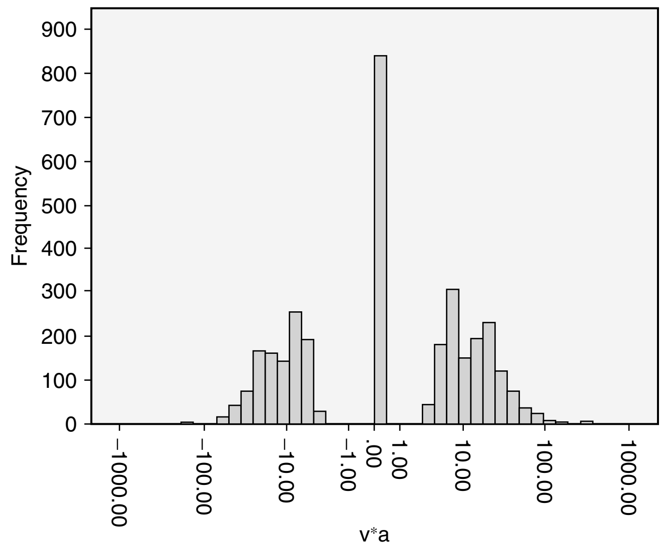

Figure 2. Histogram plot of (speed × celeration)

and peak hours in Figure 3, we observe more locations with rapid celeration (yellow color) during peak hour and more links with slow celeration (green color) during off-peak period. In Figure 4, the average speed values among all the driving records are presented by time of day (every 15 minutes). The speed is low during morning peak from 7 am to 11 am and evening peak from 5 pm to 7 pm. Also it should be pointed out the result can become more accurate for the daytime with more observations available in future, instead of current zig-zag curve.

With a broad overview, two road segments of interest (I-10 and CA-60 as shown in Figure 5) are chosen as targets for the discussion and comparison. These two routes are almost parallel and traversed by several drivers during the test period. These two road segments are similar in function and direction. Both are freeways with ramp access, and I-10 has more accesses in this segment. The user GPS trajectories on these two routes are selected and used in the calculation. The comparison results are shown in Table 2.

It is observed that the traffic speed is faster on CA-60 with a relatively smaller variance. The acceleration and deceleration are similar probably due to the fact that both of them are freeways. As the speed on CA-60 is faster, there are longer durations (18.93%) when the speed is over 65 mph than I-10 (12.89%). The celeration behavior is moderate on CA-60 comparing with I-10 by comparing the percentage of time that the absolute value of acceleration rate is over 2 m/s^2. This implies that the speed fluctuation is higher on I-10, or drivers are forced to modify the speed quickly. This value can be further analyzed combined with the traffic condition. The other measurements such as frequency of stops and point speed at the start of acceleration are not representative in this example. With more records on local segments, it is

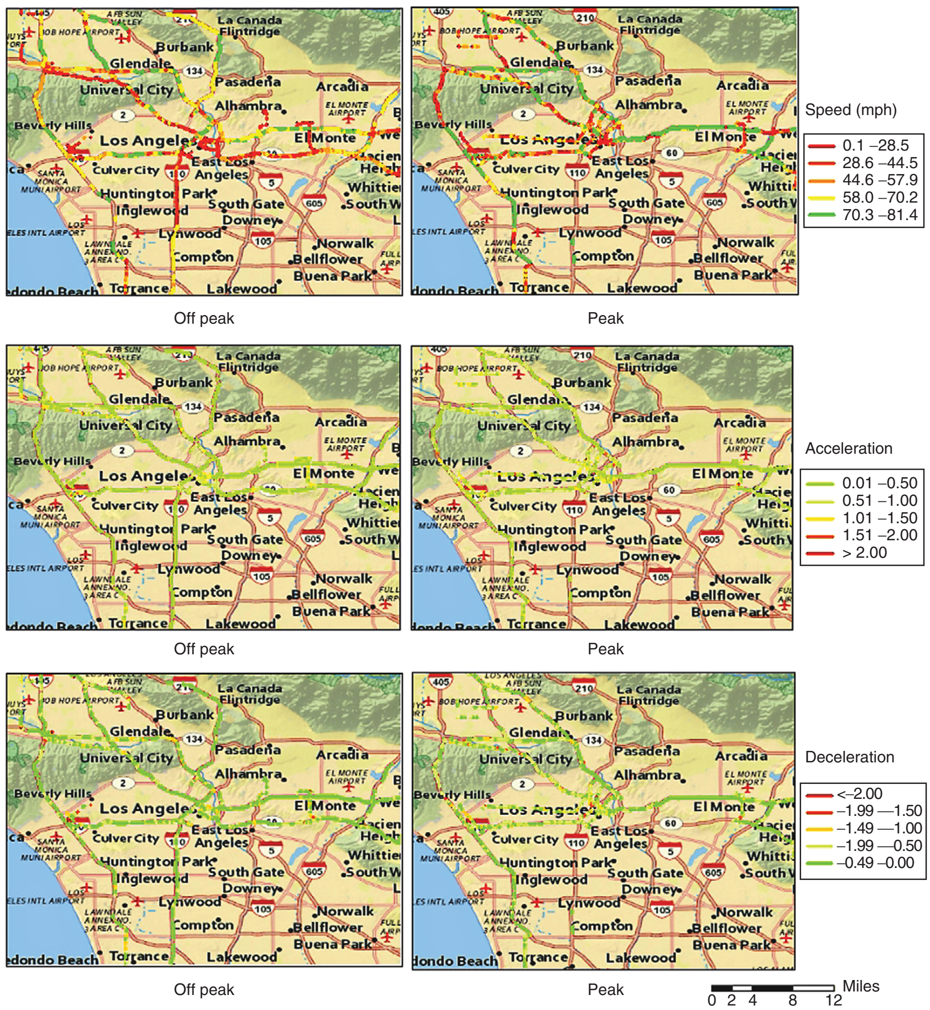

Figure 3. System speed, acceleration and deceleration performance during off peak and peak hour

meaningful to compare among all the freeway segments and local segments, with more distinctive link-level driving pattern.

Considering the traffic condition at peak and off-peak hours, we further examine the average driving behavior on these two links at different time periods. First, we observe most of the record on I-10 during peak hours and CA-60 during off-peak hours. This is because of the Metropia app recommends the routes to the users according to the real time traffic. I-10 is suggested during peak and CA-60 is suggested during off-peak. In

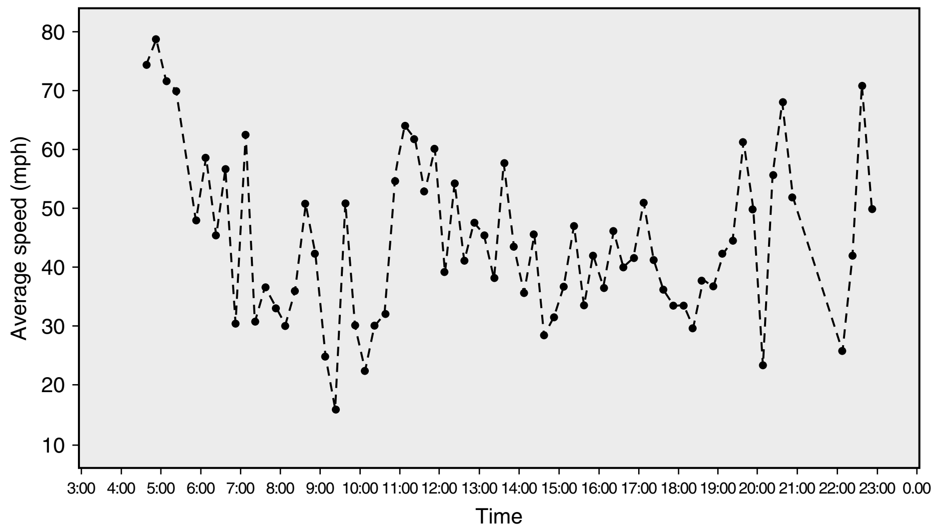

Figure 4. Average speed by time of day

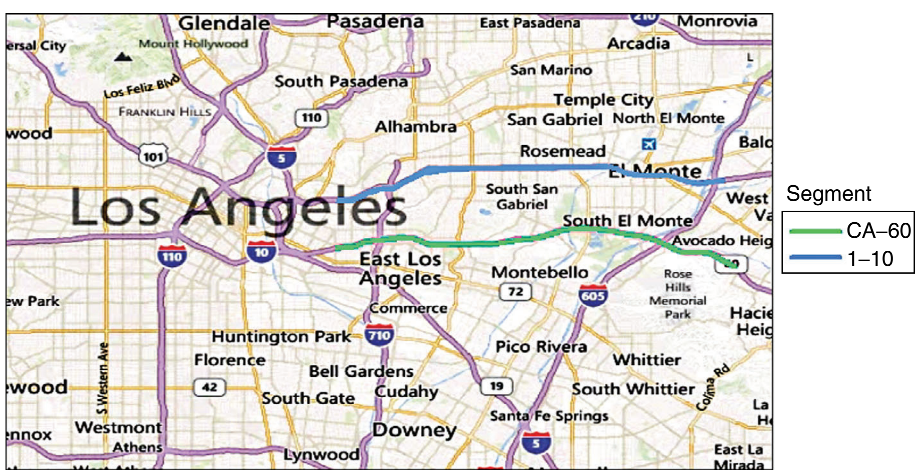

Figure 5. Selected links: I-10 and CA-60 for comparison

fact, the average speed on I-10 is a little bit slower than CA-60, but the variance of the speed is higher on I-10. The celeration rate is also a little steeper on I-10, with sharp acceleration and brakes. It is interesting to observe that there are relatively shorter period when the speed is over 65 mph on CA-60, even the average speed is faster. The limited records on CA-60 during peak hours indicate a stable speed around 40 mph and

Table 2. Measurements for the two links

		I-10 (5786s)			CA-60 (7256s)		
		mean	Std	max	mean	Std	max
1	Speed	41.58	19.93	77.00	47.11	17.06	81.00
	Acceleration	0.42	0.31	2.10	0.37	0.28	2.60
	Deceleration	–0.46	0.44	–3.70	–0.42	0.41	–4.60
2	Percentage of time speed > 65		12.89%			18.93%	
3	Percentage of time |celeration| > 2		0.57%			0.29%	
		I-10 peak (4379s)			CA-60 peak (266s)		
		mean	Std	max	mean	Std	max
1	Speed	37.58	20.66	77.00	40.00	9.36	69.00
	Acceleration	0.43	0.32	2.10	0.36	0.25	1.40
	Deceleration	–0.47	0.48	–3.70	–0.38	0.29	–1.10
2	Percentage of time speed > 65		13.40%			1.88%	
3	Percentage of time |celeration| > 2		0.75%			0.00%	
		I-10 off-peak (1407s)			CA-60 off-peak (6990s)		
		mean	Std	max	mean	Std	max
1	Speed	53.26	11.35	72.00	47.27	17.16	81.00
	Acceleration	0.39	0.28	1.80	0.37	0.29	2.60
	Deceleration	–0.42	0.32	–2.00	–0.42	0.41	–4.60
2	Percentage of time speed > 65		11.30%			19.58%	
3	Percentage of time |celeration| > 2		0.00%			0.30%	

with minor fluctuations. In contrast, drivers on I-10 need to adjust the speed in a wider range with quicker reaction. The estimation for off-peak hours shows a result opposite to peak hours. CA-60 is more likely to be suggested with a lower average speed but larger variance. Celeration is similar on the two links, but sharp celeration is only observed on CA-60. Drivers can drive with a speed higher than 65 mph on CA-60 longer than I-10. The above calculations are based on data from three test users traversing the two routes repeatedly. Therefore, the results could be constrained by the individual's behavior strongly. This step can be further improved by: (1) collecting and analyzing more traversing data from more users; and (2) joining the traffic condition on each segment. With plenty of segments as the sample, regression analysis can be conducted to examine the system performance given spatial-temporal traffic conditions.

4.3. Identifying Potential At-risk Drivers

To identify a driver's at-risk index or classify a driver's risky level, a huge sample is required to build up the standard criterion. Due to the limited test users at the current stage, an example is provided to support the feasibility of identifying at-risk drivers using the individual and system measurements. For the comparison purpose, we calculate the individual driving pattern measurements for driver # 9197 and # 9204 on the freeway. The individual measurements are listed in in Table 3. The measurements for both persons are calculated from their travel records on the links shown in Figure 5. Two-step approaches are discussed in this section: (1) comparing with other drivers in the sample (2) comparing with other drivers sharing the links.

First, the driving behaviors of two test drivers are compared as an example of comparison among all the individuals. Comparing the value of speed, acceleration and deceleration, the average speed of driver 9197 is slower than # 9204. A density plot of the driving speed of these two persons demonstrating the analysis results is shown in Figure 6. The speed of #9204 is more concentrated around 60 mph, and the speed of #9197 spread out mainly from 20 mph to 70 mph. The acceleration and deceleration are similar for these two persons close to 0.4 m/s^2. The percentage of time with a traveling speed over 65 mph and sharp celeration are highly correlated with the traffic condition.

Table 3. Measurements of driver 9197 and 9204 on selected freeway

		#9197			#9204		
		mean	Std	max	mean	Std	max
1	Speed (mph)	42.01	18.45	73.00	51.72	16.73	81.00
	Acceleration ($\frac{m}{s^2}$)	0.39	0.30	2.60	0.40	0.31	2.10
	Deceleration (m/s^2)	–0.44	0.45	–4.60	–0.43	0.37	–3.70
2	Percentage of time speed over 65 mph for freeway and 50 for local		8.13%			29.82%	
3	Percentage of time |celeration| > 4 m/s2		0.07%			0.00%	
4	Frequency of celeration change (#/100s)		1.08			0.77	
5	Max/min speed distribution	1.97	1.04		1.80	1.08	
6	Frequency of stops < 2mph/hard brake < –4 (#/100s)		0.07				
7	Point speed when acceleration starts	42.01	18.45	73.00	51.72	16.73	81.00
8	v.a	0.42	25.95		0.58	18.76	

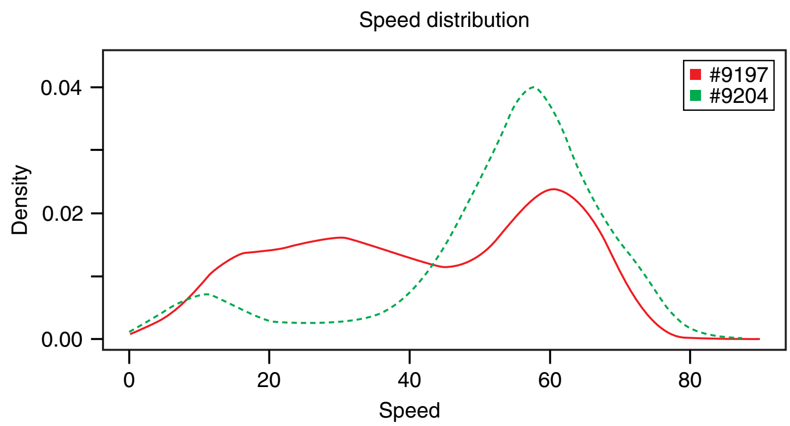

Figure 6. Density plot of speed distribution for #9197 and #9204

For driver 9204, his/her performance is more stable with no rapid acceleration and braking over the total period and higher speed. This can be proved jointly with measurement 4, 5, and 6. Higher vibration frequency and amplitude of the speed wave are calculated for #9197, indicating that the driver keeps accelerating and decelerating within a wide speed range. Limited hard brakes and stops are observed, as the data are collected from the freeway segments. The point speed at the start of acceleration is lower for #9197 than #9204. This is because the latter maintains a higher traveling speed and the former experiences more severe traffic congestion. The distribution of $v \cdot a$ also shows that driver 9204 experiences more stable traveling condition with more records with minor acceleration rate (as shown in Figure 7).

It should be pointed out that a driver is not necessary safer with a relatively slower speed. As in this example, #9197 drives slower, but keeps shifting from accelerating to braking frequently with huge difference in the consecutive minimum and maximum speed. The instability also causes at-risk issues and requires more concentrations in vehicle control. Therefore, it is difficult to identify which of the two drivers is at-risk due to the differences in traffic and external conditions. This step will be further extended to all the trips from a large sample of drivers. Combined with traffic condition, we can design a at-risk index based on the individual measurements comparing with the distribution of the sample measurements.

The next step is to compare the individual driving behavior with the system pattern by link. For any trip completed by a driver, the route can be divided into several links and segments. For each segment, we can calculate the system performance defined as the average performance of all the records on that link with respect to traffic/time attributes. Then a driver's driving performance is composed of the comparison results between individual and system on all the links. In Table 4, system performance (average from 7 users traverse the links) and two of the drivers' driving patterns are displayed for

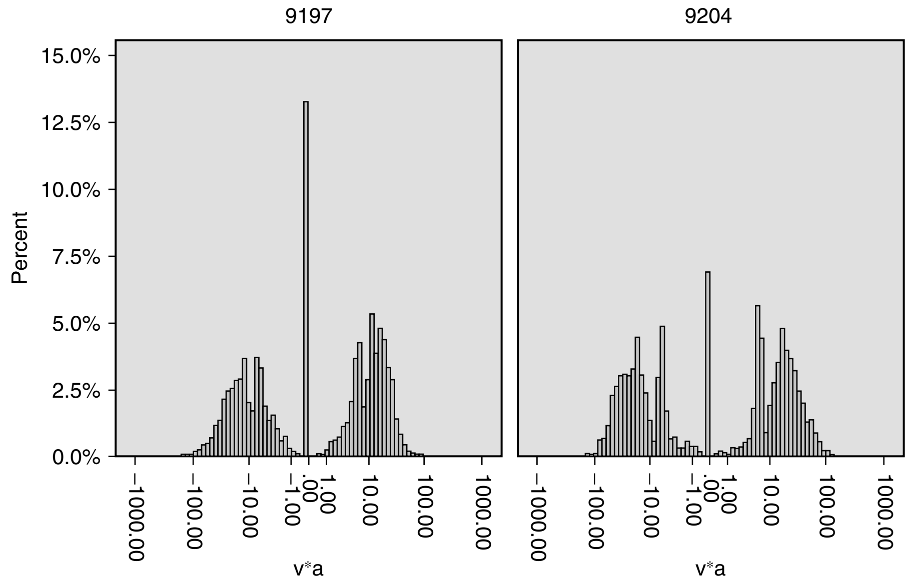

Figure 7. Histogram plot of $v \cdot a$ distribution for #9197 and #9204

I-10 and CA-60 regardless of the time of day. These two links are not the only links covered by these two drivers. Just for the comparison purpose between individual and system, the trajectory data on the two links are selected for the example.

Driver 9197 reports an average speed 10 mph lower than that on I-10, and a similar speed as the system average on CA-60. The acceleration and deceleration are close to the system measurements. The percentages of travel time with speed over 65 mph are around half of the system average on both I-10 and CA-60. The percentages sharp celeration period is slightly higher than the average performance. Therefore, this driver is relatively safer on both links comparing to all the users on the same links and performs better on I-10 than CA-60. Then we compare the results of driver 9204 with the system. This driver travels over 10 mph faster than the average speed on the two links. His/her acceleration behavior is close to the system average. The deceleration behavior is similar to the system on I-10, but more moderate on CA-60. This driver's speeds exceed 65 mph more often than the other users on the two links and celeration is smoother. Overall, this driver is traveling faster than other users, experiencing less congestions and smooth speed.

The system average performance is calculated from the trajectory of only three drivers currently. So the differences between the system and individual pattern are not significant in this example. This step can be further expanded with at-risk score designed as the average of the at-risk level over all the links in a route. And the at-risk level is calculated from the comparison results of the measurements between individual and system performance. In addition, time of day and traffic should be identified and

Table 4. System and individual driving pattern example

			I-10			CA-60		
			mean	Std	max	mean	Std	max
system	1	Speed	41.58	19.93	77.00	47.11	17.06	81.00
		Acceleration	0.42	0.31	2.10	0.37	0.28	2.60
		Deceleration	–0.46	0.44	–3.70	–0.42	0.41	–4.60
	2	Percentage of tim speed > 65		12.89%			18.93%	
	3	Percentage of time |celeration| > 2		0.57%			0.29%	
#9197	1	Speed	32.55	18.62	71.00	46.11	16.79	73.00
		Acceleration	0.43	0.32	2.10	0.37	0.28	2.60
		Deceleration	–0.49	0.50	–3.40	–0.42	0.42	–4.60
	2	Percentage of time speed > 65		4.98%			9.47%	
	3	Percentage of time |celeration| > 2		0.86%			0.34%	
#9204	1	Speed	50.91	16.52	77.00	69.76	9.70	81.00
		Acceleration	0.41	0.32	2.10	0.31	0.27	1.40
		Deceleration	–0.44	0.37	–3.70	–0.25	0.14	–0.60
	2	Percentage of time speed > 65		17.82%			96.58%	
	3	Percentage of time |celeration| > 2		0.49%			0.00%	

system performance should vary hour by hour due to the traffic condition difference.

Overall, the above two steps should be considered simultaneously. From Step 1, driver #9197 does not have as stable driving behavior as #9204, but better than the other users sharing the same links in Step 2. Driver #9204 performs better from Step 1, but faster than other drivers in Step 2. This may be a situation that driver 9204 may keep changing lanes to maintain a faster speed and avoid braking, or the driver faces less traffic. The at-risk performance should combine the results from both of the steps and will be examined with more data.

5. CONCLUSIONS

With the trajectory data collected from the information and communication technology particularly a smartphone app "Metropia", a list of measurements are defined and calculated for individual and system level analysis. Speed and celeration (acceleration and deceleration) are obtained from the Metropia platform directly and parameterized related to traffic, spatial and temporal conditions. These measurements are designed to further reveal the driving performance. Feasible approaches are proposed to explore the driving behaviors, such as aggressive, fuel efficiency, at-risk index. A case study demonstrates the driving pattern of the test users at individual and system level and identifies the at-risk driver in the examined drivers.

By analyzing the trajectory data from the platform, driving behavior at a microscopic level is revealed. The system level performance measurements relate risky location to various time periods and traffic situations. The results from this study lead to further approaches to identifying behaviors not limited to safety and environment considerations. For example, the measurements can be designed to support usage-based insurance premium calculation. Various mechanisms can be devised to provide feedback to users for behavior intervention.

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