MobiDriveScore – A System for Mobile Sensor Based Driving Analysis

A Risk Assessment Model for Improving One's Driving

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Abstract— **Assessment of driving behavior and estimation of risk therein is an important use case for telematics and vehicular networking technology domain, which has gained interest in the fleet management and consumer verticals, but above all with the car insurance firms. These firms have started incorporating the results of such analysis to provide their customers with "pay as you drive" insurance plans, which decide the initial premium based on the driver's past history of crashes and violations. Then the parties enter into an evaluation period of about two months (say), at the end of which premium is recalculated based on analysis of accelerometer, GPS and on-board diagnostic (OBD II) data. However, the consumer has no knowledge of the progress of his or her evaluation due to lack of access to device data from insurance provider. One major criterion of such evaluation is based on the detection and aggregation of high-risk maneuvers by the driver, which typically constitutes of hard bump, sharp cornering, hard stop and speed limit violations. In this paper, we propose a novel method named MobiDriveScore for routine ventures using which the consumer can assess his/her own driving pattern. Thus the consumer can consciously reduce the risk associated with his/her driving by using MobiDriveScore. For MobiDriveScore, detection of maneuvers is done using accelerometer and GPS sensors only, which are integral part of modern day smartphones. Using MobiDriveScore, the user can choose an alternate route or choose to travel a little early to improve upon the premium rates and stay safe. It will also help aggressive drivers to become more passive. Experiments have been conducted and the initial results of MobiDriveScore are found to be encouraging.**

Keywords- Smartphone Sensors; Analysis; Modelling; Telematics; Jerk-Energy

I. Introduction

With the advent of telematics and architectures for vehicular networks, one of the most appealing use-case that has appeared is the analysis and reporting of driving patterns. The reporting can be in real-time in the form of feedback and alerts or in the form of aggregated off-line reports in the form of visualization. Categorization of drivers is an important information for auto insurance firms, who intend to provide "pay as you drive (P.A.Y.D.)" dynamic insurance policies. Again, fleet management companies are also concerned about how their drivers are featuring in the scale of safety both for safety compliance regulations and rating and also from a customer satisfaction standpoint. Also fewer crashes would mean lower maintenance and insurance premium for these companies. Finally consumers also want to get real-time and aggregated feedback on their driving to improve upon their skills and stay safe on the road.

However, insurance firms remain the largest consumer for such solutions. A standard practice to provide P.A.Y.D. insurance plans is to decide on a premium for the customer based on the past driving records, and enter into an evaluation period of about two months (say). At the end of this period the premium is revised based on driving analysis, using sensors deployed within the vehicle. Toledo [1] provides the details of an in-vehicle data recorder (IVDR) which uses 3-axes accelerometer signals from within a vehicle to arrive at risk indexes which are weighted mean of high risk maneuvers. Maneuvers typically considered include hard-bump, sharp-cornering, sudden stop and speed-limit violation. The problem at the consumer end is that the user usually does not receive any report or feedback as to how the evaluation is going and what the scores are. If the driver receives such feedback and analysis, it is possible to correct some of the aspects in-time to settle for a lower premium and also drive safer. For example if it is found that the driving scores are bad due to a rough route then an alternate route can be chosen by the driver, again if rogue traffic is the reason for some risky maneuvers, the driver may choose to leave home early to escape traffic.

The sensors used to analyze driving patterns are mostly 3-axes accelerometer and GPS (Global Positioning System), which are present in modern day smartphones and also allow installation of applications (apps). So, in this paper, we present MobiDriveScore, a novel method for driver behavior analysis using sensors available in smartphones. Some work has been done on road condition monitoring using smartphone sensors [2], and we propose to use the same sensors in MobiDriveScore for driver analysis as well. The driver categorization problem can be attacked using smartphone sensors and historic data stored on a back-end server, which might be a stand-alone server or a cloud based infrastructure.

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MobiDriveScore consists of a driving analysis model, which is built through capturing accelerometer and GPS sensor signals to detect events. The events are high risk maneuvers as discussed above with a confidence score. The scores are then aggregated either locally (short term) or on a server (long term) to provide risk indexes for a driver. For such classification of driving pattern, MobiDriveScore supplies a "severity" index to each maneuver. Subsequently the anomalous region is deciphered using histogram plots. The aggregated anomaly for each trip is normalized with respect to severity index and a risk score is calculated. MobiDriveScore uses this risk score to categorize the driver as aggressive, passive etc.

The rest of the paper is organized as follows: section two contains an overview of the prior works and how it led us to our current work. The next section describes the system with respect to the hardware components and the software modules involved. Section four describes our method in detail, thereby elucidating the algorithms involved and how they fit together to provide an end-to-end solution. Section five details our experimental set-up and provides a detailed analysis of our results. The final section contains our concluding remarks including any known limitations and scope for future work.

II. Previous Work

Our work in MobiDriveScore is stemmed from [1], which provides details of a dedicated device for capturing signals from a vehicle using 3-axes accelerometer, GPS and an on-board diagnostics (OBD II) port. Based on these observations, one can provide analysis of driving patterns. Whereby the method in [1] uses a dedicated device, we assume that the accelerometer and GPS sensors on an OTS (off-the-shelf) smartphone can perform similar action if we do not consider the fuel efficiency part mentioned in the paper. Further, Ghose et al. [2] describes a method for monitoring road conditions based on accelerometer present in a smartphone, which implies that smartphone sensors inside a vehicle can be used to model the road and vehicle interaction which forms the basis of physical systems modeling as described by Chakravarty et al. [3]. Also Irmscher et. al. [4] describes a method whereby driver categorization can be done using signals received within a vehicle. The method uses vehicle side-slip angle, which can actually be derived from x/y acceleration captured from a smartphone. Further [4] and [5] provide insights into modeling of day-to-day driving patterns and also identify a few valuable parameters that can be used for such modeling. Ian Law [6] provides a fuzzy logic based approach to driving pattern analysis, which provides a hint that signals generated from motion sensing from within the car might follow a pattern, which can be used for machine learning. Finally [7] provides a brief account on how computer science has featured in the space of modeling driving behavior and patterns therein.

Based on the above research works, we have formulated ModiDriveScore, our own model for driving pattern and risk analysis, which we present in subsequent sections.

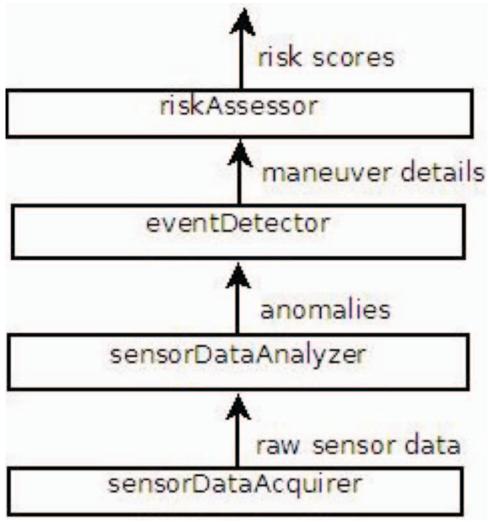

Figure 1. Interaction between software modules in MobiDriveScore

III. System Overview

First we dwell into the software modules involved in MobiDriveScore as illustrated in Fig. 1. The raw sensor data is captured using a sensor data acquisition layer, which interrupts the analysis layer on advent of new data. The analysis layer does window-based analysis of the data and arrives at anomalies. The anomalies are then passed on to an event detection layer, which tries to identify the maneuver involved. Once the maneuver has been identified, it is passed on to the risk-assessment module in MobiDriveScore, which calculates the instantaneous risk index and also runs an aggregation function to calculate the risk index for the entire trip till current point in time. MobiDriveScore also has a logger module in place to log sensor data as well as events and risk scores along with timestamps, into comma-separated-values (CSV) format. These files are uploaded to the server as an off-line process for more detailed analysis along with diagnosis of the application itself.

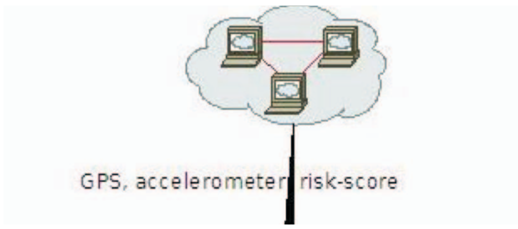

Figure 2. Deployment Scenario

Now we consider the hardware components involved in MobiDriveScore. The hardware system consists of a smartphone and a server, which may be a connected PC (Personal Computer) installed at the user's home to record personal driving straits or a cloud based infrastructure for a fleet or company level solution.

The smartphone is used to capture accelerometer and GPS signals from within the vehicle and run the event detection algorithm to detect high-risk maneuvers. The risk scores are then used to calculate the overall aggregated risk factor for the trip. The risk scores are also uploaded to the back-end server for aggregation and the individual data is logged into the phone storage. In an off-line operation, the log files are uploaded over Wi-Fi to the back-end server for more detailed analysis. Fig. 2 shows the deployment scenario and also illustrates the hardware components involved in MobiDriveScore.

IV. DETAILS OF THE METHOD

We derive our method in MobiDriveScore on the signal processing techniques presented in [9]. Using the smartphone, the raw acceleration data for the three axes are collected inside a moving vehicle. The axis definition for a smartphone is shown in Fig. 3. The feature that we have extensively used in MobiDriveScore for the purpose of analysis is computation of jerk; where jerk is defined as the rate of change of acceleration. For data acquisition, the sampling rate used is $f_s = 20Hz$ giving thereby $\Delta t = 1/f_s = 50msec$.

Let us assume that a_1, a_2, a_3......a_n be the consecutive discrete acceleration samples at time t_1, t_2, t_3......t_n where $\Delta t = t_n - t_{n-1}$ for uniform sampling rate.

Then jerk (m/sec^3) is defined as:

$$J_i = \frac{a_{i+1} - a_i}{\Delta t} \forall 1 \le i \le n-1 \quad - (1)$$

Here, n represents the total number of sample. Using (1), we further define 'jerk energy' as:

$$JE_s = J_{s1}^2 + J_{s2}^2 + J_{s2}^2 + ... + J_{s19}^2 \quad - (2)$$

where, s represents the time-window of 1 sec (therefore 20 samples of acceleration). We also use a sliding window with a shift of 5 samples. For sake of brevity, we have not mentioned explicitly the relevant unit for jerk energy in the following sections.

Using the jerk energy, some maneuvers can be detected in MobiDriveScore using steps illustrated in Fig. 4, which describes the process involved in detecting a hard bump using jerk energy values.

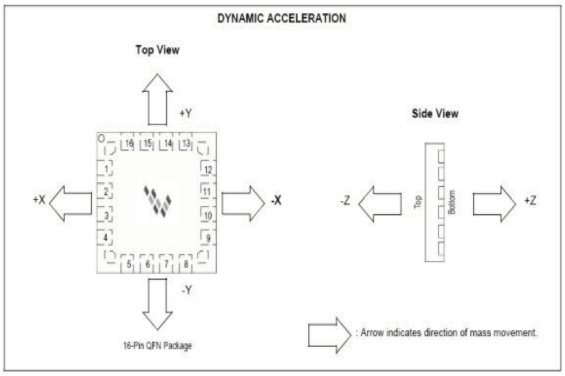

Figure 3. Smartphone axes when placed at CG of a car

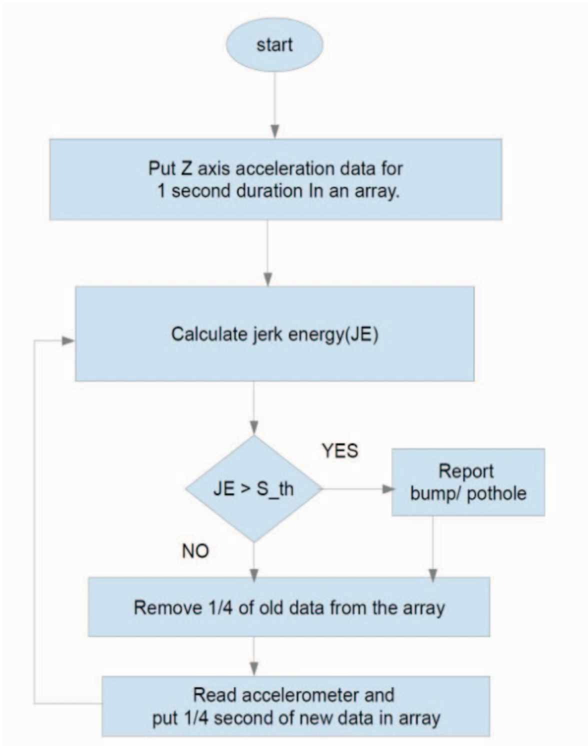

Figure 4. Detection of Hard Bump in MobiDriveScore

A. Risk Computation

In the earlier sections, we discussed the method of data collection (by individuals, using their own smartphones) and the signal processing techniques used to detect potential anomalies in driving behavior. Typically, in MobiDriveScore, we use jerk energy computation over 1 second sliding time windows [9] to detect such anomaly. Computation of jerk energy takes into account abrupt changes in acceleration in very short time duration. In this subsection, we detail the method for driving pattern assessment in MobiDriveScore. The proposed assessment calculates the risk involved in a particular driving pattern, where maximum risk is assigned to the event designated as "crash". Here, we consider that a crash occurs only due to the response of the moving vehicle on certain attempted maneuvers on rough road. We are not using a car-following model, thereby neglecting the possibility of the vehicle colliding with a leading (or trailing) vehicle.

A useful method of risk classification is outlined by Toledo et al [1], in which risk is computed using the formulation given equation:

$$R_{it} = \frac{\Sigma_j \Sigma_s \beta_{js} N_{ijst}}{DT_{it}} \quad - (3)$$

where,

R_{it} is the risk index of individual i at time t;
N_{ijst} represents number of maneuvers of type j & severity s, β_{js} are the weights for each maneuver and
DT_{it} is the driving time duration

This can also be used as trip-level risk index and classification. From equation (1), it is therefore paramount to identify the types of risk-prone maneuvers j, what constitutes the severity threshold for each maneuver s and how to calculate the weights of each such event. Four maneuver types are usually tracked for Auto-insurance purpose; these are (i) Hard Bump (ii) Hard Cornering (iii) Harsh Brake & (iv) Sharp Acceleration. For detection purposes, we have tried to offer quantitative figures to define 'hard' or 'sharp' etc. in MobiDriveScore.

B. *Hard Bump*

Hard bump is related to the vertical dynamics of the vehicle chassis. Hitting a road bumper even at moderate speed or traversing through a pit like pothole gives rise to sudden vertical vibration of high amplitude. When a vehicle undergoes repeated bumps, it leads to significant stress on the suspension and damper system of the vehicle. Hard bump is well measured by extracting the feature using computing jerk [9] on the Z-axis acceleration data. To classify a vertical vibration as 'hard', we use the given limits on the suspension travel. Typical allowable suspension travel for a passenger vehicle u_0 is 0.08m to 0.1m [8]. Therefore, in MobiDriveScore we have considered a safety limit on suspension travel as $\Delta u = u_0/2 = 0.05$m. To quantify the extent, we simulate the road vehicle interaction by inserting a pothole (rectangular shaped ditch like) of depth 5cm. The details of the method used are given in [9]. Here, it should be noted that the ISO [10] road classification is used; the different vehicle types are modeled using generic values of natural frequencies, their lengths and mass. Table I gives the results where the jerk energy values, namely Maximum Jerk Energy (MJE) and Normal Jerk Energy Range (NJER) are computed for travel over good road as well as when the vehicles hit the pothole at 20 Km/hr. It is seen that for small saloons (those used in our experiments), the jerk energy values are approximately 15000 m^2/sec^6 for pothole and 350 m/sec^3 for normal road travel.

TABLE I. SIMULATED JERK FOR VEHICLES TRAVELLING OVER 5CM POTHOLE AT 20 KMPH

Car Type	MJE	NJER
Small mass	12867	500
Small saloon	15392	350
Medium saloon	22947	250
Large saloon	33342	80

Such jerks are not memory-less, which means that each such phenomenon has a long-term degradation effect on the suspension and damper. For this reason, in MobiDriveScore we have arbitrarily chosen a threshold value of maximum jerk (as potential danger point) 1/10th of the peak jerk. For small saloons, the threshold value HBT (Hard Bump Threshold) is 1500 m/sec^3. All measured jerks are normalized with respect to HBT where,

Measured Bump Threshold (MBT) = 1 for MBT $\geqslant$ HBT.

We record all events where MBT > 0.5. The number of events and the relative weights are recorded as N_{ijst} and β_{js} respectively.

C. *Hard Cornering*

Hard cornering is related to lateral dynamics of the vehicle. We can define it in terms of overturning limit for a moving vehicle [8]. In this case, we assume that a vehicle with mass M is cornering with a lateral acceleration of a_x m/sec^2. The maximum permissible lateral acceleration is given by [8].

$$a_x^{max} = \mu . g \quad - (4)$$

where, μ is the coefficient of friction. Considering dry pavement, we may assume that $\mu = 1$. Therefore, the maximum lateral acceleration that can trigger an overturn is:

$$a_x^{max} = g \quad - (5)$$

Here, we have assumed also that the "static stability factor" for the vehicle (as given by the dimensions) is greater than 1.

We observe from the above equations that overturn is primarily determined by coefficient of friction between road and the tires of the vehicle. Thus, such effects (on key vehicle parts) are memory-less. We again normalize the measured lateral acceleration values, Measured Cornering (MC), with respect to g:

$$MC_T = \pm \frac{measuredlateralacceleration}{g} \leq \pm 1.0 \quad - (6)$$

Again, the $MC_T > 0.5 \in N_{ijst}$ with their relative weights β_{js}.

D. *Hard Stop or Acceleration*

This feature relates to longitudinal dynamics of vehicle. Rill [8] offers the limits of achieving longitudinal acceleration a_y. The limits are given by friction limits as well as the hazard of tilting.

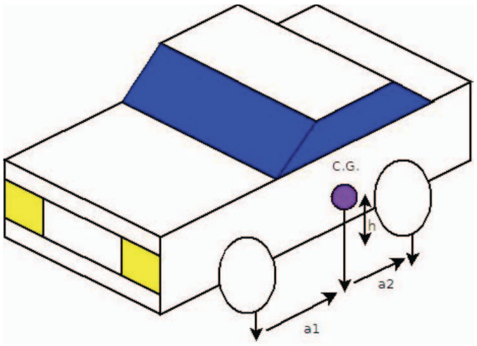

Figure 5. Car figure showing measures a1, a2 and h

$$a_y^{max} = \pm\mu.g \quad \text{- (7)}$$

Equation 7 gives the limits due to frictional force.

Consideration for tilting hazard is given by the relationship:

$$\frac{a2}{a1+a2} \geq \frac{h}{a1+a2} = \frac{a_y}{g} \quad \text{- (8)}$$

In equation 8, the definitions are as defined in the Fig. 5. For a small saloon, equation 8 gives $a_y/g <= 3.49$. Therefore, considering $\mu = 1$, the limit for longitudinal acceleration is given by equation 7 as Measured Acceleration (MA) = ± {(Measured longitudinal acceleration or retardation)/g} with maximum value as 1. Once all the necessary events are detected and the related severity computed in MobiDriveScore, we compute R_{it} per hour of drive time and normalize the computed value by dividing with 100. The association of such risk index value to the aggressive nature of driving in MobiDriveScore is done using controlled experiments.

V. THE HAZARD FUNCTION

In addition to computing risk index as given in previous section, it is also possible to predict potential degradation of suspension-damper system of the vehicle due to unevenness of road surface. This is done in MobiDriveScore by observing the jerk energy values as computed from Z-axis raw acceleration data. It is seen that for a typical drive, the x = 1/*jerk energy* follows the Weibull distribution as given by:

$$p(x) = \frac{k}{\lambda}\left(\frac{x}{\lambda}\right)^{(k-1)} e^{-\left(\frac{x}{\lambda}\right)^k} \forall x \geq 0 \quad \text{- (9)}$$

From the observed data, we need to derive the scale parameter λ and shape parameter k of equation 9. In Fig. 6, we present a comparison of the histogram plot of observed "x" values in one trip and the corresponding Weibull distribution.

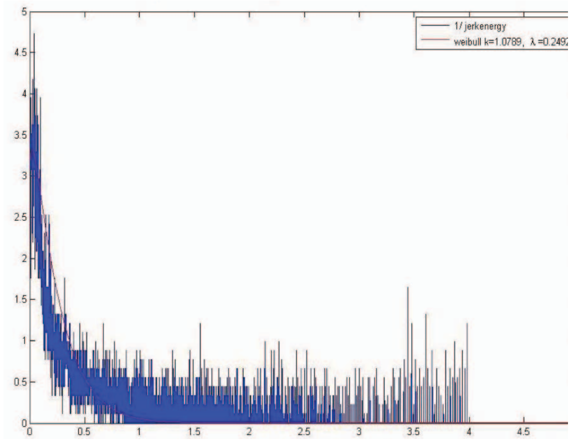

Figure 6. Comparison of Observed Jerk Values with Standard Weibull

Empirically, for the observed distribution of 1/ jerk values, $\lambda = 0.2492$, k = 1.0789. Validity of this parametric numbers are obtained by using *fitdistr()* method available in MASS library of the "R" statistical tool.

Since "x" relates to the signature of jerk as inverse of jerk (1/jerk energy) felt by the moving vehicle and each such abrupt change in acceleration leads to progressive degradation of the system, we may treat the observed density distribution p(x) as Weibull Hazard Function given as:

$$h(x) = \frac{k}{\lambda}\left(\frac{x}{\lambda}\right)^{k-1} \quad \text{- (10)}$$

When the accelerometer records related to the driver I for multiple trips on regular routes (like home to office) are computed, and the risk index (or failure rate as per conventional notations) is computed using the Hazard Function. It is to be noted that we have used Weibull distribution in a manner where time axis is replaced by 'x', which is the inverse of jerk energy. In the above case, therefore, the function h(x) does not define 'mean-time-to-failure'. Here, the understanding is as follows: when a moving vehicle experiences severe form of jerk (dependent on the driving style), it results in degradation of the vehicle system. Thus, h(x) defines a measure of defining the degradation where it is assumed that it has survived the jerks till 'x'. The hazard rate, when measured on a regular basis shows a definite increasing trend thereby indicating that the probability of failure is increasing as the vehicle continues to traverse over rough road.

VI. EXPERIMENTAL SETUP AND RESULTS

For MobiDriveScore, a number of experiments are being carried out for both validation of the proposed method as well as its utilization in obtaining typical driving patterns. Initially, we selected a few volunteers from our peer-group within an age group of 30~35 years. Each participating member of this trial, drive their own car. For preliminary analysis in

MobiDriveScore, we limited the dataset only to that acquired during travel from home to workspace and back, at specific timezones. We present the results of MobiDriveScore for the preliminary experimentation.

Table II presents the statistical features of the dataset acquired by driver "I" for Home to Office trips on consecutive days. In this case, the Z-axis acceleration data is used to compute jerk energy as per equation 2 and histogram plot of (1/jerk energy) is done (like the one shown in Fig. 6).

Treating the distribution as Weibull, we calculate the two-parameter k and λ in MobiDriveScore, thereby permitting us to quantify the driving signatures in terms of Hazard h(x) using equation (10). It is seen that typical hazard value for driver "I" is above 1.

In Table III, we compare the driving pattern of driver "I" with other two drivers using MobiDriveScore. Driver “J” is known to be a new driver whereas driver “K” is known to be an experienced driver. From Table IV, we obtain a reasonable validation of the intuitive assumption (of receptive driving pattern). J displays higher value of HPH when such value for k is moderate. Even though, we are normalizing the Hazard value in MobiDriveScore in terms of total driving time (hours), the results are likely to alter significantly under dynamic traffic condition and non-uniform road condition.

In Risk Computation section in MobiDriveScore, we proposed methods for determining the events like hard bump etc. These are used to compute risk index in MobiDriveScore. In Table IV, we display the records detected from the 3-axis acceleration data acquired by driver I where the following notation is used:

TABLE II. FEATURES OF JERK ENERGY AS BBSERVED FOR DRIVER I IN CONSEQUENT TRIALS

Mode	Median	MJE	λ	K	h(x)
0.05	1.69	237.8	0.25	1.08	4.92
0.03	3.79	122	0.26	1.31	7.64
0.05	1.14	37.7	1.16	1.02	1.45
0.05	1.09	55.3	0.89	1.15	1.63

TABLE III. EVALUATION OF HAZARD FUNCTIONS FOR MULTIPLE DRIVERS (TDU = TRIP DURATION IN HOURS, HPH = HAZARD PER HOUR)

Driver	TDu	λ	k	x	h(x)	HPH
I	0.87	0.25	1.08	1.27	4.92	5.66
J	0.52	0.06	1.08	0.28	22.2	42.83
K	0.53	0.2	1.14	0.92	7.18	13.55

TABLE IV. RISK INDICES FOR DRIVER I FOR MULTIPLE TRIPS (TDI = TRIP DIRECTION, TDU = TRIP DURATION IN HOURS, AS = AVERAGE SPEED IN KMPH, NHB = NUMBER OF HARD BUMPS, NHC. = NUMBER OF HARD CORNERING, NSA = NUMBER OF SHARP ACCELERATIONS, NRR = NORMALIZED RISK RATE)

TDi	TDu	AS	NHB	NHC	NSA	NRR
HO	0.87	15.06	4	9	15	0.18
HO	0.37	34.7	2	0	0	0.03
HO	0.63	20.5	3	0	0	0.02
HO	0.86	15.1	5	1	1	0.04

NHB = Number of Hard Bumps; NHC = Number of Hard Cornering; NSA = Number of Sharp Acceleration & NRIPH = Net Risk Index per Hour of driving time.

From the records, it is seen that such risk index is primarily driven by NHC & NSA. A rational driver is expected to course correct his/ her path on a continuous basis. This is based on the driver's perception about the optimum path to reach destination. Thus, sharp turns, brakes and accelerations are unusual behavior and are needed to be minimized if one wishes to keep risk score minimum.

While calculating driving score in MobiDriveScore, we assume 9 NHB or NSA or NHC makes one crash in 15 seconds duration. In MobiDriveScore, we have sampling rate = 20 Hz. Hence in 15 seconds maximum NRR (Normalized Risk Rate) can be $NRR_{max} = 15*20*9*4 = 10800$; hence the obtained score is normalized by this NRR_{max}.

In MobiDriveScore, we did not make an attempt to classify the evaluated driving patterns as aggressive or passive etc. It needs more experimentation to reach a firm conclusion.

VII. CONCLUSION

Based on the inferences drawn from results of MobiDriveScore trials as illustrated in “Experimental Setup and Results” section, we conclude that smartphone based 3-axes accelerometer can be effectively used for analysis of road vehicle driving patterns. We have demonstrated that the risk index calculation, based on identification of high-risk maneuvers, can be a good measure of how safe a particular trip was. We have shown in MobiDriveScore that jerk energy also is a good indication of vehicle damage. Since inverse of jerk energy (1/jerk energy) roughly follows a Weibull distribution, the corresponding hazard function can be used to predict the further damage of vehicle en-route. Although, at this point, we have not specifically categorized drivers in MobiDriveScore, the parameters we have extracted can be used to classify trips with respect to the risk therein. We believe that this measure will be useful for both insurance firms as well as end-consumers like drivers and car/fleet owners.

We are currently encouraging large number of our friends and peer-group members to use MobiDriveScore so as to give us more data, using which we can further prove our theory and also make MobiDriveScore more robust.

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