Hidden Markov Model based Driving Event Detection and Driver Profiling from Mobile Inertial Sensor Data

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Abstract— **With the advent of smartphones and advancements in sensor capabilities, it is possible to actively monitor drivers and provide a viable solution necessary to reduce vehicle accidents. Driving maneuvers provide an insight to a driver's driving skills and behavior, which is an important aspect for applications such as driver profiling, driver safety, fuel consumption modeling, etc. Driver profiling requires detection of sharp and normal driving maneuvers having high and low Signal-to-Noise Ratio (SNR), respectively. Typical event detection techniques detect sharp driving maneuvers but fail to detect normal maneuvers. In this paper, we propose Hidden Markov Model (HMM) based technique to detect lateral maneuvers and Jerk Energy based technique to detect longitudinal maneuvers. Most driver profiling techniques consider only longitudinal events such as hard acceleration/braking, whereas the proposed approach profiles a driver by coupling lateral and longitudinal events. Based on collected datasets on diverse type of driving scenario, events are detected with 95% accuracy. For driver profiling, we achieve 90% accuracy in match between drivers subjective score and model-based estimated score.**

I. Introduction

For vehicle-passenger safety and providing recommendations for better driving, it is imperative to correctly profile a driver's driving style and behavior [1]. Many existing solutions for driver profiling available in the market require installation of expensive cameras and on-board sensors and some solutions make use of smartphone sensors, which is a viable, low-cost, effective and ergonomic alternative (see Section I-A). The scoring schemes used by many of these solutions are primitive and are restricted to longitudinal events only such as acceleration/braking and basic summaries such as average velocity, etc.

In this paper, we propose an analytics engine which includes method for detecting primitive events (lateral and longitudinal driving maneuvers) and for profiling the driver. For detecting lateral maneuvers, like lane changes (LC) and turns (T), we are using a novel approach based on Hidden Markov Model (HMM) (PS Application No. 1981/CHE/2015). HMMs are a ubiquitous tool for modeling time series data. We observed that the local temporal dependence could be modeled reasonably well by HMM fixing linearized signals as emission layer and occurrence of events as Markovian hidden layer and then probabilistically identify states at each time instant. For detecting longitudinal maneuvers, like hard acceleration (HA) and hard braking (HB), unlike some hard threshold based method, we consider the jerkiness of the maneuver by calculating a jerk index which is discussed in section III-B

For driver profiling, we propose a unique technique, which considers primitive events and all possible combination of them, like an accelerated lane change or a turn with hard braking etc., using a 4-state HMM. The states defined in the model give an insight into the consistency and skills of cruising and maneuvering. We then rate drivers with respect to a benchmark ideal driving sample, giving scores in 4 different fields namely consistent cruising, consistent maneuvering, cruising recoverability and maneuvering recoverability. Based on collected driving data from different drivers under diverse driving scenarios, we achieved 90% accuracy in match between driver's subjective score and model-based estimated score.

A. Related Work

Ubiquity of the smartphones coupled with different types of sensors embedded in it has made them a viable option for detecting driving maneuvers and thereby profile the drivers. The work presented in [2] uses accelerometer data to differentiate driving maneuvers and advise drivers of potential risks. MobiDriveScore [3] is a system that provides an analysis of driving patterns using accelerometer, GPS sensor and OBD-II data. It provides a risk index for the performed maneuvers to determine their severity. Technique for recognizing driving style using inertial sensor have been discussed in [4] and [5]. Sathyanarayana et al. [6] modeled the driver behavior by recognizing different maneuvers, that is subsequently used for route recognition, using HMM in two different techniques. SenseFleet [7] is a platform that profiles driver behavior using sensor fusion and a fuzzy inference system. In [8] and [9], technique for profiling driver behavior using accelerometer, gyroscope and magnetometer has been proposed. Other works presented in [10], [11] use multiple sensors and camera based techniques for analyzing driving behavior.

II. Analytics Engine

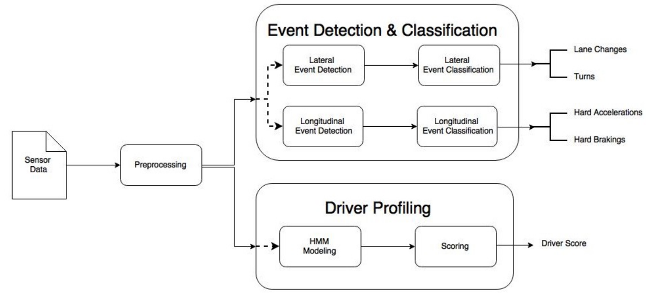

Fig. 1. System Design

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The system design of the analytics engine is shown in Fig. 1. The sensor data from the smartphone is preprocessed to filter out noise and then used for detecting driving maneuvers (described in Section III) and for profiling the driver (described in Section IV).

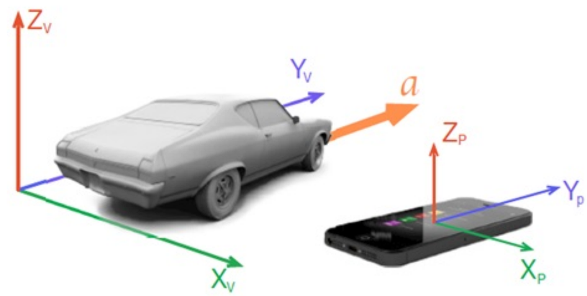

Fig. 2. Vehicles and smartphones coordinate system

The smartphone coordinate system $\{X_p,Y_p,Z_p\}$ is aligned with the vehicle coordinate system $\{X_v,Y_v,Z_v\}$, as shown in Figure 2, in order to track vehicles movement by smartphone sensors. The proposed technique would work accurately for other fixed orientations, provided calibration is done.

III. Driving Maneuver Detection

We have considered linear acceleration and gyroscope data from smartphone sensor for detecting driving maneuvers. The raw sensor data contains lots of noise, due to road conditions and micro corrections. This data is first filtered using a Low Pass Filter with smoothing factor ($\alpha = 0.1$). The velocity and lateral acceleration are corrected by 4-state Kalman Filter. The state transition in the Kalman filter is based on Kinematics.

$$V_t = V_{t-1} + (\Delta t * A_{y_{t-1}}) \tag{1}$$

$$A_{x_t} = G_{z_{t-1}} * V_{t-1} \tag{2}$$

Where V_t is the GPS Velocity at time t, Δt is the time difference between the samples (Sampling Rate=20Hz), $A_{y_t}$is the linear acceleration with respect to y-axis at time t, A_{x_t} is the linear acceleration with respect to x-axis at time t and G_{z_t} is the angular rotation about z-axis at time t.

A. HMM based Lateral Event Detection

The gyroscope data with respect to Z_p-axis provides the orientation of the vehicle, which can be leveraged to detect lateral driving maneuvers. This forms a high-dimensional observation vector. The sensor data segments are linear fitted by taking advantage of the local dependency, which reduces data dimension significantly. For each second, the slopes of linear fitted sensor data is calculated, then scaled and quantized. These slopes forms the input to the HMM model and forms the emission layer (as shown in Figure 3, for a portion of gyro-z signal). The possible values of the input variable slopes are $\{0, 1, 2, 3, 4\}$. The two hidden states of the HMM are:

1) Event - If the input slopes are high, representing high gyro-z values, followed and preceded by low slopes, it means a lateral driving maneuver has taken place
2) No Event - On the contrary, if the input slopes are low, it means that there was no lateral maneuver (straight driving)

The standard Hidden Markov Model and notations [12] are followed for calculations of forward (α_t) and backward (β_t) probabilities, and probability of a state i at a given time t ($\gamma_t(i)$)

$$\gamma_t(i) = \frac{\alpha_t(i)\beta_t(i)}{\sum_{i=1}^{2} \alpha_t(i)\beta_t(i)} \tag{3}$$

The time t at which γ_t of Event state crosses the predefined threshold ($T_{Event} = 0.9$) indicates the start of the event. Correspondingly, the time t at which γ_t of Event state falls below T_{Event} marks the end of event window.

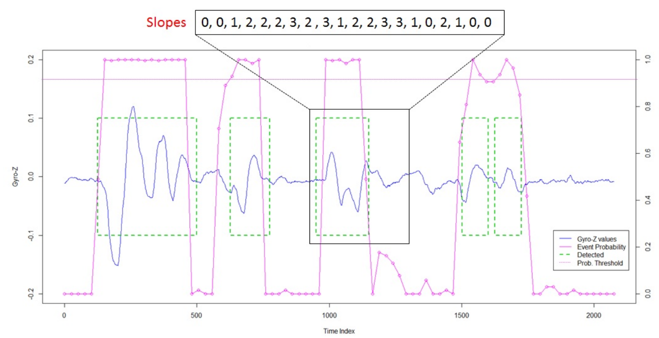

Fig. 3. Lateral Maneuvers detected by proposed HMM based technique indicating slopes for a portion of signal

As shown in Figure 3, even the lateral maneuvers with very low SNR, which are difficult to detect with other event detection techniques, are detected as highlighted in dotted rectangles. It clearly shows that the event window boundaries are determined accurately. The gyro-z data in the detected event window is passed on to the Random Forest classifier to classify it as lane change or turn.

B. Jerk Energy based Longitudinal Event Detection

The linear accelerometer data with respect to Y_p-axis can be leveraged to identify longitudinal maneuvers. Jerk is defined as the rate of change of acceleration and it captures the fluctuations in the acceleration data. Jerk Energy value calculated based on [3] is compared with prefixed thresholds (T_{Max} and T_{Min}) to determine the event window. Severity of longitudinal maneuvers depends on jerkiness, which relates to the abrupt change in jerk energy as well as the rate of change of velocity. For the detected event window, the risk index is calculated, which provides the severity measure of the event.

$$Index = (RoV * (JE_{max} - JE_{min}))/100 \tag{4}$$

Where RoV is the Rate of change of Velocity and JE_{max} and JE_{min} are the maximum and minimum jerk energy in the event window.

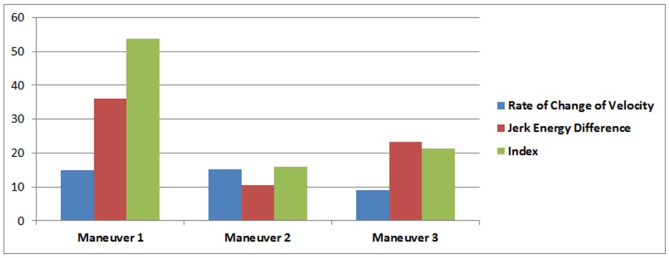

Fig. 4. Comparison of Longitudinal Maneuvers based on Jerk Index

From empirical study, the hard threshold for $Index$ is fixed as 50. Events with $Index$ above the hard threshold are classified as aggressive events. In Figure 4, maneuvers 1 and 2 have same RoV, but maneuver 1 was performed jerkier than maneuver 2, so the $Index$ of maneuver 1 is higher than maneuver 2. Also, from maneuvers 2 and 3, maneuver 3 has lesser RoV but higher jerk energy compared to maneuver 2, so maneuver 3 has higher $Index$ than maneuver 2. The $Index$ of maneuver 1 is above the hard threshold, hence it is an aggressive event.

IV. Driver Profiling

We have considered linear acceleration and gyroscope data to model the driver's behavior. The gyroscope data (G_{z_t}) provides orientation information whereas the linear acceleration (A_{y_t}) provides a measure of driver's aggressiveness. The slopes of gyro-z signal as calculated in section III-A are considered as the observations (O_1). As for the aggressiveness factor observations, to maintain consistency of number of observations with O_1, we take mean of the (A_{y_t}) signal over blocks of duration $1s$ to generate observation O_2. Like O_1, O_2 is also mapped on a scale of 4 (with 0 being low and 4 being high values) and an observation vector $(\overrightarrow{O})$ is formed of the form (O_1, O_2). In addition to A_{y_t} signal, we can add more factors of aggressiveness to the observation vector in the future.

A. Driving Style Modeling using HMM

We define a 4-state HMM, $\lambda = (A, B, \pi)$, where states are defined in the Table I. The observation vector $(\overrightarrow{O})$ forms the input to the HMM and the model is initialized in such a way that it clearly reflects the definition of states.

TABLE I : Definition of States

State	Vector with High Probability of Occurrence
Straight Normal	Low slopes(Straight) and Low accelerations(Normal)
Straight Hard	Low slopes(Straight) and High accelerations(Hard)
Event Normal	High slopes(Event) and Low accelerations(Normal)
Event Hard	High slopes(Event) and High accelerations(Hard)

The model is optimized such that the probability of observation sequence given the model $P(O|\lambda)$ is maximized. The maximization is done iteratively by an EM- algorithm (Baum-Welch Algorithm)[12] until the difference in the log probabilities is sufficiently low (10^{-6}). The model parameters thus optimized, $\lambda^{'} = (A, B)$ are then used for scoring the test driver.

B. Scoring Method

TABLE II : Definition of Fields

Fields	Description
Consistent Cruising	Maintaining 'Straight Normal' state for consecutive time intervals
Consistent Maneuvering	Maintaining 'Event Normal' state for consecutive time intervals
Cruising Recoverability	Alternating between 'Straight Normal' and 'Straight Hard' states for a time period
Maneuvering Recoverability	Alternating between 'Event Normal' and 'Event Hard' states for a time period

For test driver and a benchmark driver, based on respective model parameters, probabilities of different fields as defined in Table II are calculated as p'_T and p_T respectively, where T is the time interval and $T \in N = \{1, 2, 3...\}$. These probabilities essentially profile a driver with respect to his/her likelihood of maintaining consistency in comparison to a benchmark driver. The drivers are scored based on a monotonic score function denoted by $\phi(.) : N \to (0, \infty)$.

The final score S, is obtained by taking a weighted sum of the score function evaluated over increasing duration and then taking a ratio with that of the benchmark driver. The scoring function uses equation (5) for Consistency Score and equation (6) for Recoverability Score.

$$S = \frac{\sum_{T \in N} p'_T \phi(T)}{\sum_{T \in N} p_T \phi(T)} \tag{5}$$

$$S = \frac{\sum_{T \in N} log(p'_T) \phi(T)}{\sum_{T \in N} log(p_T) \phi(T)} \tag{6}$$

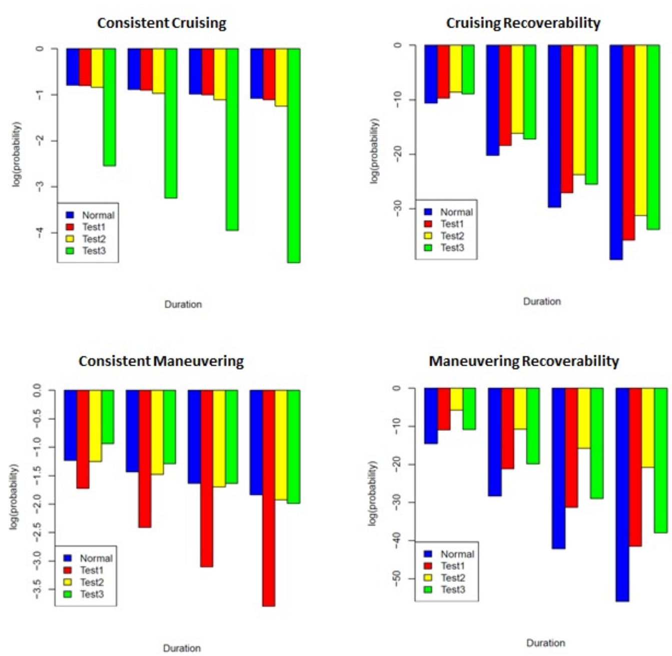

Fig. 5. Plot of Log Probabilities based on which a driver is rated or scored

The calculated values of log probabilities, used in the scoring function, for three drivers are plotted against the bench mark values (indicated in blue) as shown in Figure 5. Greater value of log probabilities in 'Consistent Cruising/Maneuvering' imply better driving whereas lower values of log probabilities in 'Cruising/Maneuvering Recoverability' imply better recoverability from inconsistency, thus a better driver. The monotonic score function $\phi(.)$ is defined to take care of this incongruity. The computed scores are then normalized to a $0-100$ scale to get the final score, where higher score represents better driving.

V. Experimental Setup and Results

The setup comprises of a Samsung Galaxy S5 smartphone that includes the Invensense MPU-6500 6-Axis MEMS Gyroscope and Accelerometer. The analytics engine that detects the maneuvers and profiles the driver can run on any mobile device with gyroscope, accelerometer and GPS sensor. Our Android application, encompassing the analytics engine, with three distinct drivers, in three distinct vehicles, was used to collect data in urban and highway conditions. Filtered accelerometer and gyroscope signals were recorded for each trip.

TABLE III : Driving Maneuvers Detection Results

Driver	Maneuvers Performed				Maneuvers Detected				Accuracy (%)
	LC	T	HA	HB	LC	T	HA	HB	
1	68	33	5	1	65	33	4	1	96.2
2	64	36	0	5	59	36	0	5	95.2
3	100	6	2	4	95	6	2	4	95.5
Total	232	75	7	10	219	75	6	10	95.67

The driving maneuvers detection is tested on 3 test drivers and the cumulative results for each driver for detection of various maneuvers like turns (T), lane changes (LC), hard accelerations (HA), and hard braking (HB) are tabulated in Table III. The overall accuracy of event detection is 95%, which is the ratio of maneuvers detected to the ones performed.

TABLE IV : Driver Profiling scores evaluated for multiple test drivers

Test #	Consistent Cruising	Consistent Maneuvering	Cruising Recoverability	Maneuvering Recoverability
1	83.78	36.80	79.46	68.75
2	78.75	81.34	72.52	40.34
3	19.95	87.70	76.02	65.33
4	16.18	17.35	39.73	52.23
5	35.34	17.34	46.34	66.76
6	79.90	18.67	49.54	47.32
7	99.78	15.90	68.76	81.65

The driver profiling module is tested on 3 test drivers in different traffic scenarios and their scores, as evaluated by our approach, are tabulated in Table IV. The scores are validated by taking subjective feedback from the drivers and co-passengers. The results of the feedback survey correlate with the scores generated and we found 90% accuracy in match between drivers subjective score and model-based estimated score.

VI. Conclusion

We have demonstrated the efficiency of our proposed approach considering different datasets based on diverse driving scenarios. Both the techniques (HMM and Jerk Energy) are able to detect driving maneuvers with an accuracy of 95%. These form the building blocks for further complex applications such as driver profiling, fuel economy, driver alert system etc. While most of the existing applications make use of in-vehicular sensors, OBD, stand-alone devices etc., our proposed technique can be used with any smartphone which comprises of accelerometer and gyroscope sensor.
Along the same line as described above, properly defining the states of the HMM and combining the states suitably, different relevant complex driving events can be constructed. Here the states are so defined that the interaction of lateral and longitudinal events can be suitably incorporated in the scoring scheme. For future work, we are developing a comprehensive method for profiling of a given test driver in different context especially, when vehicle dynamics are interacting with each other in a complex dependence structure.

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