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Estimating Driving Behavior by a Smartphone*

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Abstract—**In this paper, we propose an approach to understand the driver behavior using smartphone sensors. The aim for analyzing the sensory data acquired using a smartphone is to design a car-independent system which does not need vehicle mounted sensors measuring turn rates, gas consumption or tire pressure. The sensory data utilized in this paper includes the accelerometer, gyroscope and the magnetometer. Using these sensors we obtain position, speed, acceleration, deceleration and deflection angle sensory information and estimate commuting safety by statistically analyzing driver behavior. In contrast to state of the art, this work uses no external sensors, resulting in a cost efficient, simplistic and user-friendly system.**

Key words: Driver behavior, accelerometer, gyroscope, magnetometer, smart phone, unsafe driving, Bayesian classification.

I. INTRODUCTION

In this paper we introduce a system to estimate driving profile of drivers which is capable of detecting risky driving patterns likely to be generated by drowsiness, inattention or traffic violations. In return, the proposed system will increase safe driving habits, decrease accident rates and provide the passengers a safe travel. Our system can cope with variation in response time to unforeseen road conditions and affect of different emotional conditions to different traffic conditions. We conjecture that this study will lead to fuel efficient and better driving habits among its adopters.

There have been numerous studies for analysis of driving habits. Almost all these studies utilize multitudes of inputs including vehicles' own sensors and external sensors, such as video cameras, microphones, lidar and radar [1]. In [2], Oliver and Pentland mapped the temporal variation in car sensory data and the image stream by using hidden Markov models (HMM) to the driver behavior. In similar vein, Malik and Rakotonirainy introduced a driver training system to prevent road accidents due to unsafe driving [3].

In addition to using vehicle sensory data, Healey and Picard studied respiration, skin conductance and heart rate monitoring [6]. The additional data provided them with ambulatory monitoring to analyze the driver's stress levels. In [1], Johnson and Trivedi introduced the smart phone sensors to the pack of cameras and microphones. The increased robustness in their system came at the expense of cost and complexity.

Aforementioned and other similar studies set up complex and costly approaches to design a robust system. In order to offset the sensory data complexity, they used HMM models, warping methods and various windowing techniques [2, 4, 5]. In this study, we envision a simpler sensory setup with more intuitive algorithmic design and show that the same problem can be solved without the loss of robustness. In particular we only use sensory data acquired from accelerometer, gyroscope and magnetometer that are available in a typical smart phone, such as the iPhone. This choice provides us with a portable setup, such that changing vehicles will not affect the portability of the system. The sensory data provides the speed, position angle and deflection from regular trajectory of the vehicle. For algorithmic design, we use a set of well-studied tools. For instance, in order to identify risky driving from attitude information, we use the end-point detection algorithm. For estimating the optimal path between template event and the input driving data, we adopt the dynamic time warping (DTW). The final labeling of the driving behavior we use a Bayesian classification scheme, which provides us with how risky or safe the driving habits of the drivers. We should note that there are many effective methods in the literature [6-13]. Our choice is merely due to the practical adaptation of these techniques to our problem domain. In fact, these algorithms have been more frequently utilized in the field of voice recognition [6, 7].

The remainder of the paper is organized as follows; in the next section, we give theoretical background related to the end-point detection, warping algorithms, and Bayesian classification. We also discuss the sensory data acquired from the smart phone. In section 3, statistical

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classification, experimental results and their interpretations are detailed. The conclusions are drawn in Section 4.

II. Theory And Stages Of System Diagram

As sketched in Fig. 1, the first step in our design is the data acquisition and preprocessing of the data via smoothing filter. Next, we apply the endpoint detection algorithm to estimate the temporal range of the signal searching for important events. Once the events are detected we temporally scale the signal to identify the event within the selected portion of the signal using DTW. The main reason behind DTW is to overcome different temporal durations of the same event across different drivers. After this initial step, the Bayesian classifier is applied to identify risky of safe driving habit. Details of these steps are given in the following sections.

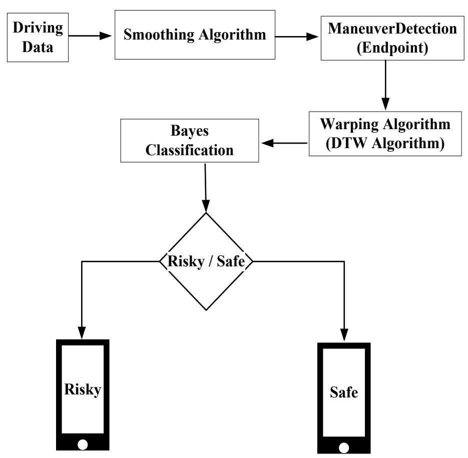


Fig. 1. System block diagram

A. Endpoint Detection

In order to detect the current event, our algorithm continuously acquires data from the accelerometer, gyroscope, and magnetometer. We conjecture risky events occur when there are sharp or sudden maneuvers, unsafe left or right turns, lane departures, and sudden braking or speed-up. These events may result in potential risks for driver, passengers and pedestrians. The reason for these maneuvers may be related to drivers' present mood/behavior such as aggressive driving, drowsiness, inattention and driving while intoxicated.

The signal that relates to such events is estimated by end-point detection algorithm. As an example we show the start and end points of left and right turns in Figure 2. The detection of left turn, right turn, lane departure, acceleration with throttle and deceleration by braking is performed by matching training templates for these events with the test data. The templates for these events are manually selected and labeled as safe driving habits. Given the event templates, the analysis is continuously performed while acquiring the input data during driving sessions.

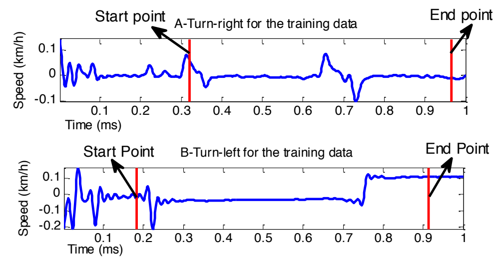


Fig. 2. Turn left/right driving templates

In the end point detection, the algorithm works by organizing the samples using windowing method. For each window, the energy of samples lying within is estimated by;

$$E=(s[k]-\mu)/\sigma \qquad k=1,2,\ldots,m \tag{1}$$

where E is the energy for one window, s[k] is the data residing in each window, μ is the mean value of the data for the window, σ is the standard deviation of these data and m is the window size. The threshold for the estimation problem is determined empirically from the observed energy patterns in the training data. The energy scores beyond the threshold range are eliminated. This process provides us with the signal portion that will be processed for a potential event.

B. DTW Algorithm

Once the start and end points of a potential event is detected, our system accommodates differences between the training and test event durations using the DTW algorithm. In order to estimate the optimal path, DTW proceeds as sketched in Table 1.

TABLE I.
SAMPLE DATA TO FIND OPTIMAL PATH USING DTW

Template										
3	3	3	-3	1	-3	3	3	0	1	2
3	3	3	-3	1	-3	0	0	0	1	2
0	0	0	-6	-2	-6	0	0	-3	-2	-1
0	0	0	-6	-2	-6	6	6	-3	-2	-1
6	6	6	0	4	0	2	2	3	4	5
2	2	2	-4	0	-4	6	6	-1	0	1
6	6	6	0	4	0	0	0	3	4	5
0	0	0	-6	-2	-6	3	3	-3	-2	-1
Test data	**0**	**0**	**6**	**2**	**6**	**0**	**0**	**3**	**2**	**1**

To simplify the pictorial representation we divide the speed by 10. Therefore 6 refers to 60 km in the Table 1. Here the left column represents the data from the template event ordered in top-down direction; while bottom line indicates the test-driving data from left to right;

Template event data (x)............ →06260033
Test data (y) .... →062600321
Difference for x-y .... →06-44-6030

As shown in Table 1, computing distances for neighboring elements within the matrix created estimate the minimum path. Optimal threshold for the distance between the present and candidate neighbors are empirically determined and is set at 0.05. In DTW algorithm, two input vectors X={x_1, x_2,…,x_i,…,x_m} and Y={y_1, y_2,…,y_i,…,y_m} respectively represent the training and test data. The DTW algorithm starts with computing the Euclidean distance between X and Y vectors in order to compute the optimal similarity between them;

$$D(i,j)= |x_i - y_j| \quad (2)$$

The optimal graph path between these temporally ordered templates, hence, the distances for every element in D matrix of mxn size are calculated. Minimum path to neighbor element is saved in matrix M_p given by;

$$M_p = \sum_{i=1}^{n} \sum_{j=1}^{m} \min([D(i-1,j), D(i,j-1), D(i-1,j-1)]) \quad (3)$$

B. Behavior Classification Algorithm

The statistical classification algorithm used in this study adopts Bayesian inference. We assume the existence of two classes related to safe and unsafe driving habits. Mathematical expression for proposed classification is given by;

$$P(r_1|s) = \frac{P(r_1)P(s|r_1)}{P(s)} = \frac{P(r_1)P(s|r_1)}{P(r_1)P(s|r_1)+\cdots+P(r_n)P(s|r_n)} \quad (4)$$

where r_1 is the class, s is observations for driving events. Given the priori probabilities of these two classes for driving events, the system output can be obtained by comparing the posteriori probabilities;

$$P(r_1|s) > P(r_2|s) \rightarrow \text{Driving at risk} \quad (5.a)$$
$$P(r_1|s) <= P(r_2|s) \rightarrow \text{Driving safe} \quad (5.b)$$

D. iPhone Accelerometer and Gyroscope Sensor

In our design, we used the sensors available in iPhone. We should note that current smart phones generally provide these sensory data and our implementation is not iPhone specific. There are several sensors located in iPhone. Among others, we use the gyroscope and accelerometer data in this study.

In our context, accelerometer sensor data gives the amount of acceleration applied to the vehicle in the (*x*, *y*, *z*) planes. The accelerometer data also provides the position and speed information of the vehicle. On the other hand, the gyroscope measurements provide reliable information regarding the lane departure and turning events.

The accelerometer provides data in the range of [−1,1] and the data from gyroscope range between [−180° 180°]. In order to emphasize sudden variations in the raw data, we first apply a high pass filter to it by;

$$R_{x,y,z}=\text{accel.}(x,y,z)*\text{filtsbt}+R_{x,y,z}*(g-\text{filtsbt})*(\text{accel.}(x,y,z)) \quad (6)$$

where "accel.(x,y,z)" represents the data obtained by accelerometer; *g* is the gravitational acceleration which is constant rate, *g*=1.0, and filtsbt is the frequency rate for the gravity.

III. Experimental Results

In our experiment design, we have chosen to analyze driving patterns of a group of 15; five of them have been selected from experienced drivers, the other five have been from novice ones, and the rest has been selected randomly. For each driver, we conducted two experiments to account for different weather (rainy, snowy, sunny) and road conditions. This diversity let us analyze the system's reliability in different environmental conditions [14]. The route map for the experiments is shown in Figure 3. We have selected two experienced drivers for observation and evaluation of test drivers, while 15 drivers have been asked for test-driving. We have prepared a short survey for 2 evaluators who are experienced drivers. They have been asked for sitting on the passenger side of the vehicle to observe the driving safety. Then, they have filled out the survey. As to their observation, we have determined most safe 5 drivers to obtain the template and ground truth data for each event. Afterwards we have checked the surveys for initial 5 minutes by grading overall scores of drivers out of 15 (except most safe 5 selected as template) to estimate prior risky driving probability. As to the survey result 2 drivers have been estimated as unsafe and 8 drivers as safe. Consequently, we have assigned 0.2 to $P(r_1)$ for prior unsafe probability and 0.8 to $P(r_2)$ for prior safe driving probability rate at first. In the experiments, departure point is chosen as the Firat (Euphrates) Technology Development Center and the arrival point is chosen as the Organized-Industrial-Zone. In all the experiments, we have observed lane change, instant acceleration and deceleration, left and right turns, as well as abnormal driving habits.

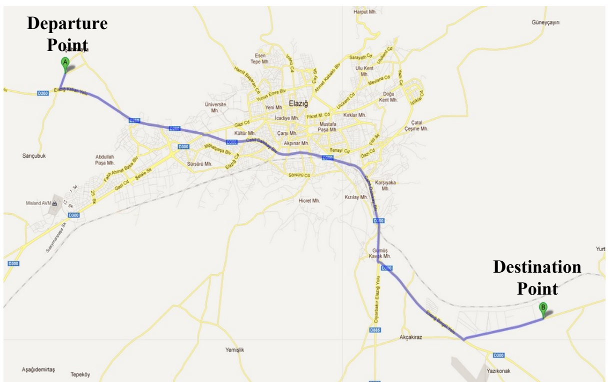


Fig. 3. Experimental route

The vehicle reference frame for the car is defined as follows; the +y axis points in the hood direction, the +x axis points in the driver side direction and the +z axis points in the roof direction of the vehicle as shown in Figure 4.

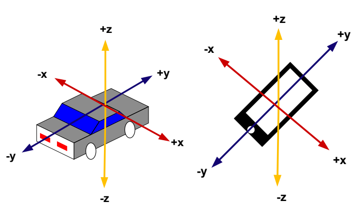


Fig. 4.Vehicle and iPhone coordinate system.

The processing of sensory data in the proposed system has been done considering described reference frames. Below, we detail our results in the order of the processing steps applied to the acquired sensory data.

Once the template and input data warping is performed, the Bayesian classifier is used to make the event type decision based on the maximum a posteriori estimate across different events, and also we can estimate the system output as;

System Output= P(r | Steering Angle Bayes Classification, Acceleration Bayes Classification, Slowdowns Bayes Classification, Lane Change Bayes Classification)

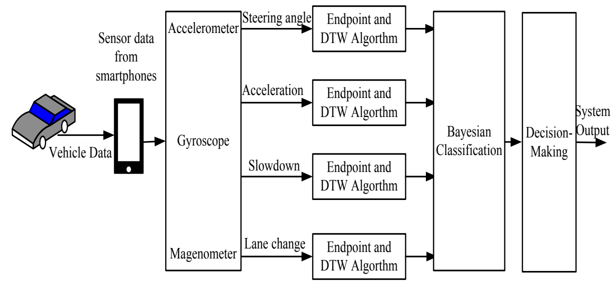


Fig. 5. Utilizing iPhone sensors in the proposed system

Experimental setup is given in Figure 5. The accelerometer data from the iPhone sensors is first smoothed prior to analyzing the speed of the vehicle. As shown in Figure 6, we applied various smoothing filters to the raw sensor data for eliminating the effect of noise. As seen in the figure we observe that the effect of noise is minimum for the moving average filter. After this step, the endpoints of the events of interest are detected on the smoothed signal to find the range of action.

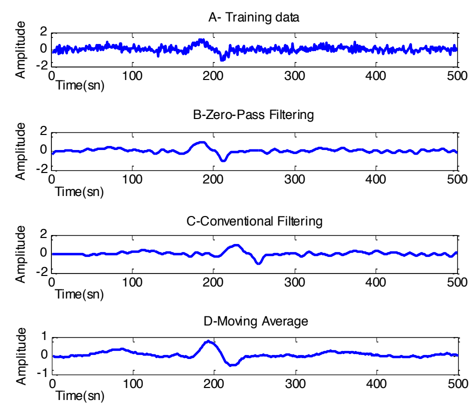


Fig. 6. Smoothing of the raw data using different smoothing techniques

We present detected end-points for an exemplar turn left event in Figure 7. The training and test data in the proposed system is prepared as follows;

Step 1. An experienced driver is asked to prepare training templates of various events, such as the safe turning-left action.

Step 2. A volunteer driver is asked to drive the car without describing the system to reduce the effect of bias. The data is analyzed to detect events. The events are classified using the trained Bayesian classifier.

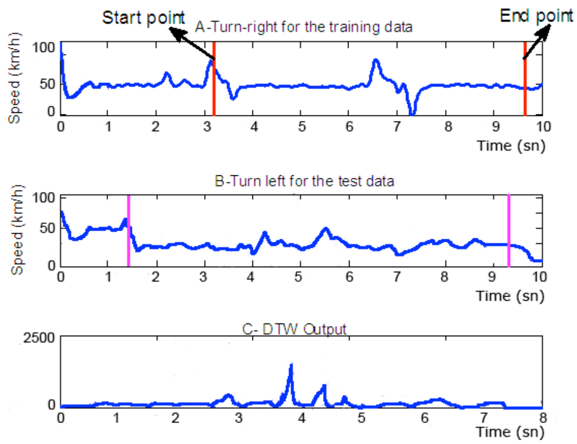


Fig. 7. Turn-Right data

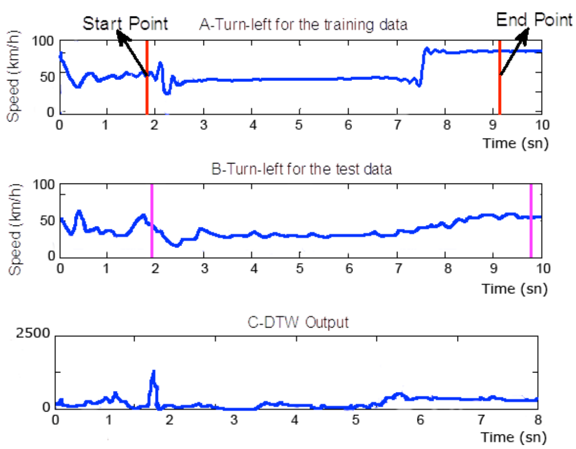
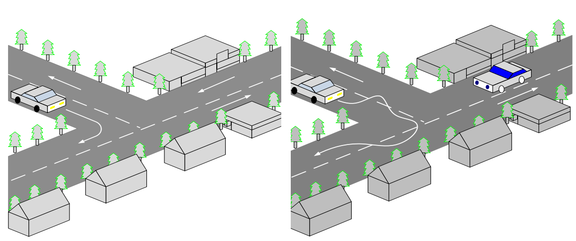


Fig. 8. Turn-Left event data

Opposite to the signals in Figure 7, which exemplify turn-right driving pattern and are taken by iPhone sensor, turn-left signals are shown in Figure 8. The visualization of the safe and unsafe driving pattern of Figures 7 and 8 is given in Figure 9.



(a) Safe driving (b) Unsafe driving

Fig. 9. A sample safe/unsafe driving event scenes for right turn

TABLE II.
BAYES' VARIABLES FOR PROPOSED SYSTEM

Events (s)	Represented Variable	Correspondent Situation
1. Steering Wheel Angle	r_{1_swa}	Unsafe
	r_{2_swa}	Safe
2. Acceleration	r_{1_alt}	Unsafe
	r_{2_alt}	Safe
3. Slowdown	r_{1_sd}	Unsafe
	r_{2_sd}	Safe
4. Lane Change	r_{1_lc}	Unsafe
	r_{2_lc}	Safe

We show the results of the Bayes classification in Figure 10. The final output of the classification is recorded as safe or unsafe driving. Variables used in the Bayesian classification step for the proposed system and their definitions are given in Table II.

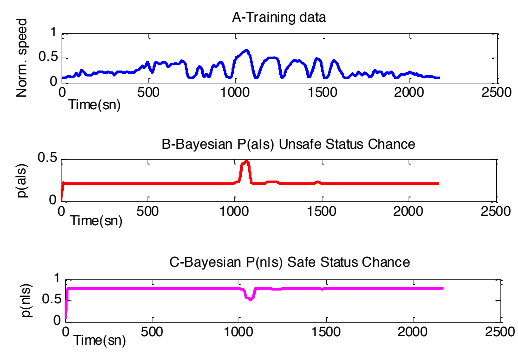


Fig. 10. Bayesian classification using steering wheel,
(a) Template data for the system
(b) P(a|s) unsafe probability obtained by the result of Bayesian classification process.
(c) P(n|s) safe driving probability obtained by the result of Bayesian classification.

Table III has been designated by considering some of related works. Therefore, we can conclude that process duration of Bayesian classification is less than the others, and it has greater success rate. In the experiments, 14 out of 15 drivers involved in the test-driving have been classified as correct.

TABLE III.
PERFORMANCE COMPARISON FOR DIFFERENT METHODS

Method	Time (second)	Correctly Classified Instances (%)
Random Forest [10]	24.4	93.0
J48 [10]	78.8	90.6
HMM [2]	N/A	85.7
Bayes Classification (Proposed)	3.6	93.3

The instant error estimation is obtained by;

$$\Delta X_{error} = \left| X_{\mathrm{groundtruth}} - X_{\mathrm{estimated}} \right| \quad (8)$$

Ground truth, observation signal and the error signal, respectively, are shown in Fig. 11.

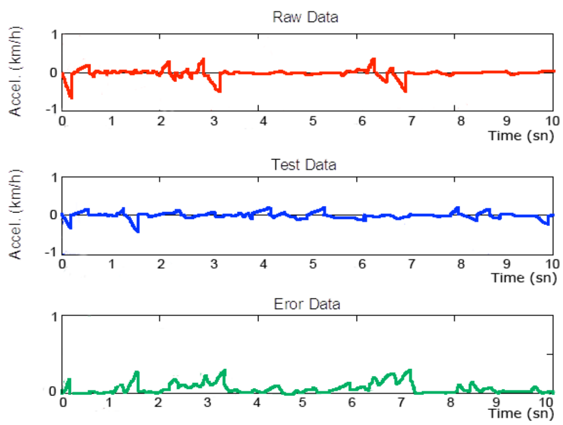


Fig. 11. Error for left-turn driving event (ground-truth data, estimated signal and error, respectively)

IV. CONCLUSION

In this paper we have investigated driver behavior as safe or unsafe using optimal path detection algorithm and Bayesian classification. Event data are acquired by smart phone sensors, which are accelerometer, gyroscope and magnetometer. And also, we have compared the proposed algorithm to the other methods used. Consequently, Bayesian classification output for experiments have showed that the event type and its safe/unsafe driving style have been found as correct for 14 drivers out of 15.

On the other hand, both computational and implementation cost of the proposed method are promising in compared to the other methods.

In the future work, we are planning to combine driver ambulatory data, CAN bus data from the car and environmental data. Therefore, we will investigate the impact of different driving parameters on driver mood.

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