2008 IEEE International Conference on
Robotics and Automation
Pasadena, CA, USA, May 19-23, 2008

Driving Skill Characterization: A Feasibility Study

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Abstract— **Information about driver's driving skill can be used to adapt vehicle control parameters to facilitate the specific driver's needs in terms of vehicle-performance and driving-pleasure. This paper presents an approach to driving skill characterization from a pattern-recognition perspective. The basic idea is to extract patterns that reflect the driver's driving skill level from the measurements of the driver's behavior and the vehicle response. The preliminary experimental results demonstrate the feasibility of using pattern-recognition approach to characterize driver's handling skill. This paper concludes with the discussions of the challenges and future works to bring the proposed technique to practical use.**

I. INTRODUCTION

Vehicle driving is a process of driver-vehicle interactions. Satisfactory driving experience depends not only on the static design of good ride-and-handling systems of the vehicle, but also on the driver's dynamic interaction to operate and control the vehicle. During the vehicle operation, many tasks related to driver-vehicle interactions take place, from the most direct control of vehicle motion (the primary task) to the planning of vehicle guidance and navigation, as well as to all other auxiliary vehicle controls, such as the operation of the in-vehicle infotainment systems (the secondary tasks). Fig. 1 shows a high-level model of driver-vehicle interactions. Each task requires various degrees of driver's attention and mental capacity as well as physical responsiveness to execute. In general, they are all related to driver's capability to operate the vehicle.

Our research focuses on the innermost loop in Fig. 1. In the context of our research, the driving skill is defined as the capability of basic lane tracking and speed maintenance through various vehicle controls, including but not limited to speed control, lateral control, skid control, and disturbance control. While characterizing the driving skill is not a simple issue, the benefit of having such information for vehicle control is rather significant. Given the same vehicle and under the same situation, the vehicle maneuver and its performance can differ due to driver's capability of controlling the vehicle, including driver's intrinsic ability and the amount of workload imposed by the secondary tasks. If a driver's driving skill can adequately evaluated while the vehicle is being driven, vehicle control parameters can be adapted to facilitate the specific driver's needs in terms of vehicle-performance and driving-pleasure.

There have been significant activities in the field of driver response modeling in the past few decades, the primary goal of which was to generate vehicle control signals or commands so as to drive the vehicle automatically [1-4]. Very few research activities have been reported in explicitly evaluating a driver's driving skill. The objective of this research is to take the first step in the quantitative characterization of driver's driving skill.

This paper documents some preliminary results on driving skill characterization for lateral control, a small piece in the complicated picture of driver-vehicle interactions as illustrated in Fig. 1. To reduce the compound effects, in this research, we assume that the driver is fully concentrated on the primary task, and no other secondary vehicle control tasks are taking away his or her attention.

II. PROPOSED METHOD

We study the direct relationship between the driving skill level, and the measurements of driver's behavior and/or driving conditions, i.e., information of the vehicle and the driving environment. This relationship is modeled as a mapping, whose inputs are the measurements of the driver's behavior, such as steering control, and/or the driving condition, such as the lane position and the traffic level. The output of the mapping is the driving skill level, which can be either categorical (i.e. high, average, and low) or numerical (such as a rating from 1 to 10). This mapping is usually called a *recognizer* in the pattern-recognition domain. It can be established by a rich set of algorithms backed by the extensive pattern recognition research [5][6]. For the preliminary research reported here, we only consider driver's behavior as the input to the recognizer, as shown by the double arrow in Fig. 2.

There are two major engineering steps associated with the pattern-recognition approach of driving skill characterization. The first one is to identify the attributes that have the power to discriminate the driver's driving skill. We call these attributes, *discriminant features*. Previous research shows that drivers with different skill levels vary in preview time, physiological limitations, such as transport delay, path planning ability, and etc. However, these parameters are not easily assessable and, therefore, are not suitable to be discriminant features directly. In general, there are two basic driving controls, i.e., directional (e.g. steering) and longitudinal (e.g. speed) control. Difference in driver's handling skills is eventually reflected in the difference of these two basic driving behaviors. In this research, we use driver's steering behavior, in particular, the coefficients of the discrete Fourier transform (DFT) of the steering wheel

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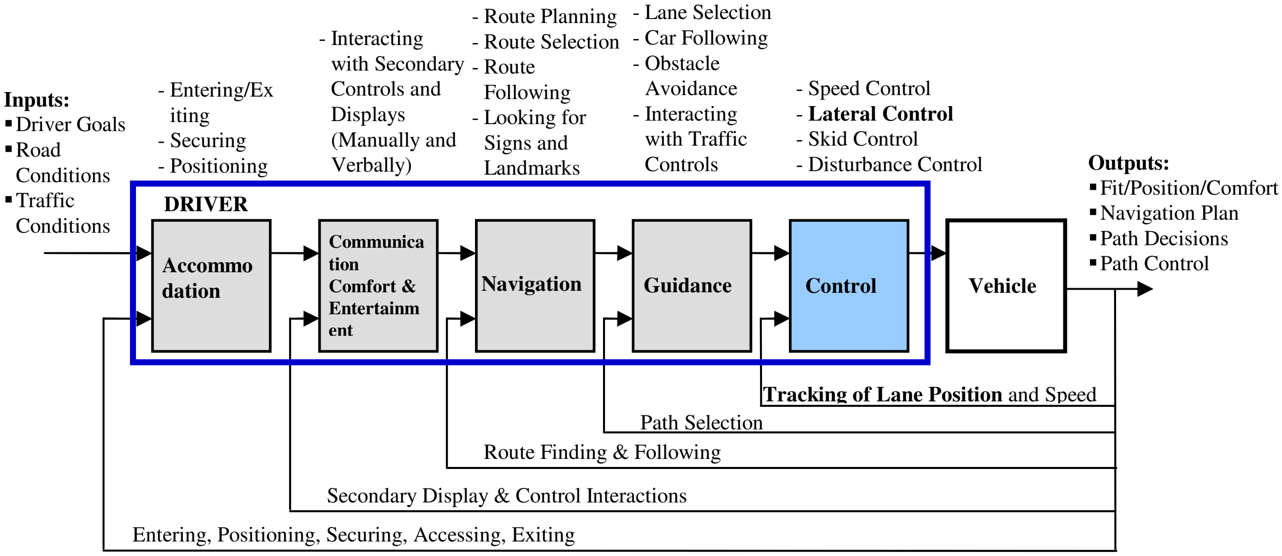


Fig. 1. Multi-level structure of driver-vehicle Interactions

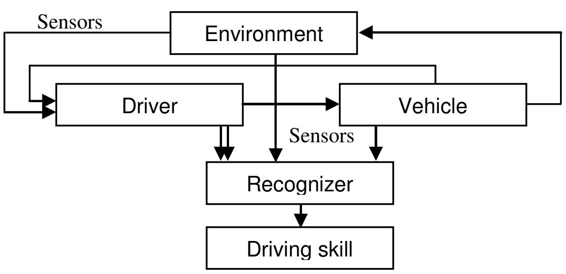
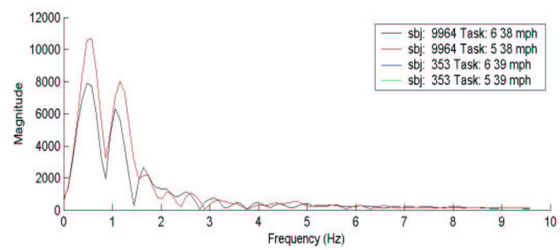
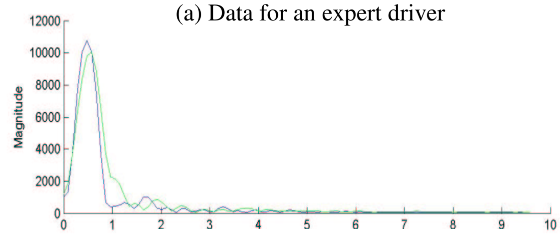


Fig. 2. The proposed approach for driving skill recognition.



(a) Data for an expert driver



(b) Data for a low-skill driver

Fig. 3. The magnitude of DFT coefficients of the steering wheel angle readings of drivers with different skill levels. Subject 9964 is an expert driver while subject 353 is a low-skill driver. Task 5 and 6 are double lane change on a wet and dry road, respectively.

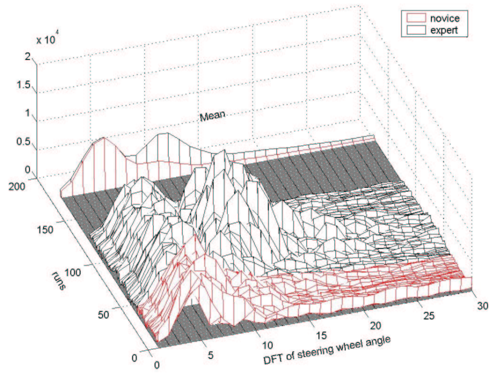
angle, to identify driving skill level.

The second major engineering step in the pattern-recognition approach is to design the recognizer that infers driving skill level. One way to design the recognizer is to use heuristics and manually generate rules for recognition or inference. The other strategy is to use machine-learning techniques to derive the recognizer. In the latter case, depending on the particular technique used, the recognizer can be rules, regression functions, decision trees, neural networks, and etc. We focus on the second strategy in this research.

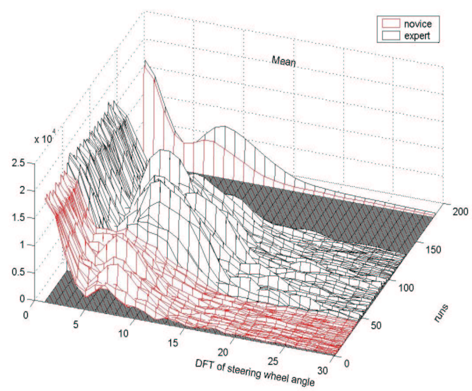
A. *DFT COEFFICIENTS AS DISCRIMINANT FEATURES*

To capture the temporal characteristics of driver's limit-maneuver handling, we conducted DFT on the steering wheel angle readings during test maneuvers.

Fourier analysis decomposes a waveform signal into sinusoidal components and results in a representation of the signal in the frequency domain. The upper panel of Fig. 3 shows the magnitude of DFT coefficients of an expert driver's steering wheel angle readings during two double-lane change (DLC) maneuvers. The magnitude of the DFT coefficients can be interpreted as the power (or the energy) of the components with different frequencies in the waveform signal. The two regions of emphasis (foments in a short phrase) around 0.5 Hz and 1.1 Hz imply that this driver's steering behavior have two major components, a slow one at about 0.5 Hz and a faster one at about 1.1 Hz. In contrast to the upper panel of Fig. 3, the bottom panel shows the data of a low-skill driver. Compared to the expert driver, the low-skill driver does not produce the high-frequency foment, which makes sense because low-skill drivers are not prompt in steering the vehicle. This difference between expert and low-skill drivers gives us the chance to differentiate drivers with different skill levels.



(a) Data for Double Lane Change



(b) Data for Lane Change in Curve

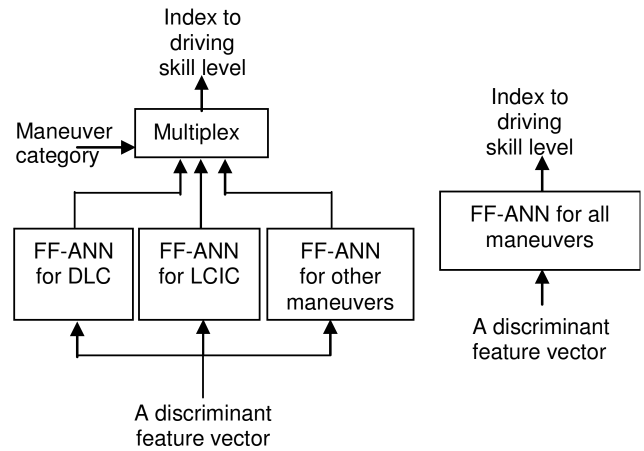
Fig. 4. The magnitude of DFT coefficients of the steering wheel angle readings of different drivers in different driving scenarios. The averages of the data from different runs are given in the far end of the figures.

The analysis of the data from more subjects and more maneuvers confirms our findings. Also observed is that the first 30 DFT coefficients are good enough to characterize the difference of the driving skill. Therefore, these first 30 coefficients are used as the discriminant features for the driving skill recognizer. Fig. 4 shows the data of different drivers in different driving scenarios.

B. RECOGNIZER DESIGN

The function of the recognizer is to discriminate drivers with different skill levels according to the discriminant features. We choose to use the feed-forward artificial neural-network (FF-ANN) to be the recognizer. FF-ANN is one of the mostly well-studied neural-network architectures. It has been widely used in classification and control areas [5][6][7].

Our goal is to find out a set of weights and biases, with which the FF-ANN can produce the desired output, i.e. the index of driving skill level, given a discriminant feature vector of a particular maneuver. The process of finding the weights and biases is called training. The training data is a set of discriminant features, e.g. the DFT coefficients of steering wheel angle, together with their labels, e.g. the



(a) (b)

Fig. 5. Two recognizer configurations. (a) Two-step recognizer; (b) All-in-one recognizer.

actual driving skill level.

In practice, we evaluate two recognizer configurations. The one shown in Fig. 5 (a) is referred to as a two-step recognizer. With this configuration, the driving maneuver, such as double lane change, lane change in curve, left turn, and etc., is first identified based upon sensor information such as yaw, and lateral acceleration. Then the output from the FF-ANN corresponding to the particular maneuver is chosen as the system output. The other configuration, called an all-in-one recognizer, is shown in Fig. 5 (b), in which a single FF-ANN is used to handle various maneuvers. Since each FF-ANN of the two-step recognizer deals with the data specific to a particular maneuver, we expect the recognition performance to be better than that of the all-in-one recognizer. However, the latter one has a simpler system architecture than the former one, and does not rely on the performance of maneuver identification.

III. SIMULATOR DATA

We conduct the analysis on the data collected on a driving simulator test vehicle, a 2000 GM Silverado 2500/HD (3/4 ton) 2WD pickup (Fig. 6). The simulator recorded a list of parameters such as vehicle position, steering wheel angle, forward speed, yaw rate, roll angle, lateral acceleration, longitudinal acceleration, at a rate of 50 Hz.

The testing variables include two loading configurations (full load and no load), two tire/road surface conditions (web and dry), and two primary maneuvers (double lane change and lane-change in a curve) whose driving courses are constrained by cones as shown by the blue dots in Fig. 7. In summary, there are totally eight testing configurations of interest after combining the testing variables.

Each test run was executed under one testing configuration, starting from about 50 meters before the first pair of the cones and ended at the last pair of the cones. The driving speed was fixed in each of the test runs. The driving subjects were asked to perform the maneuvers with steering

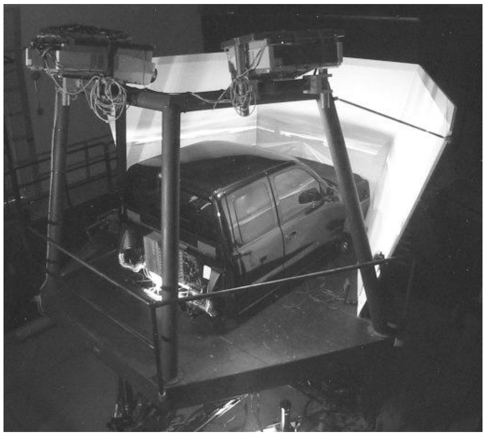
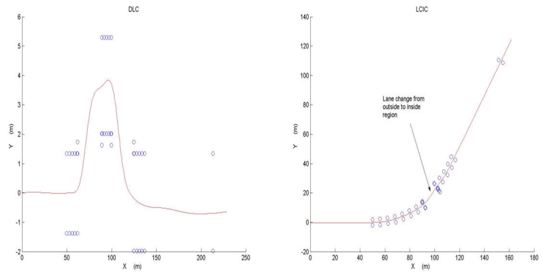


Fig. 6. Silverado pickup cab on driving simulator.



(a) (b)

Fig. 7. The driving paths for (a) double-lane change (b) lane-change in curve. The red lines are samples of vehicle trajectories from the simulator dataset.

control only. Twelve drivers participated in the simulator study. They ranged in age from 15 to 67 and included three basic skill designations (2 low-skill, 6 typical, and 4 expert). Each driver started with a low speed at about 8 m/sec in each testing configuration. The test speed was incremented by about 1 m/sec for each subsequent run. The increment stopped when the subject failed a run, which was defined as striking more than four cones, spinning out, or driving off the course. The expert drivers tended to fail at higher speeds than the typical and low-skill drivers did.

There were cases when expert drivers did not maintain their skill level and failed in some runs. To accommodate the skill fluctuation factor, we do not use those expert drivers' runs that involve one or more cone strikes. For typical and low-skill drivers, we use all the runs except for those involving vehicle spinning. We call the selected runs eligible runs. Table I shows the breakdown of the runs with respect to driver groups and maneuvers.

TABLE I
BREAKDOWN OF ELIGIBLE RUNS

	Expert	Typical	Low-skill	Total
DLC	178	303	70	551
LCIC	156	283	75	514
Total	334	586	145	1065

IV. PRELIMINARY RECOGNITION RESULTS

Various analysis has been conducted on the simulator data presented above. Reported here is an experiment in which we grouped typical and low-skill drivers together to test how well the recognizers may differentiate them from the expert drivers.

We conducted a 1024-point DFT over the steering wheel angle readings starting from the first pair of cones in each run. The first 30 DFT coefficients formed the feature vector for each run.

A 3-layer topology was chosen for the FF-ANN recognizer. The input layer had 30 neurons holding the 30 DFT coefficients for each maneuver. The hidden layer had 40 neurons with the *logsig* transfer function. The output layer had one neuron with the *linear* transfer function, whose output was rounded to 1 and 2 to indicate expert driver and typical/low-skill driver, respectively. The Levenberg-Marquardt algorithm was used for training. The whole training and testing was done using MATLAB neural network toolbox.

A widely-used evaluation scheme, called cross validation, was adopted to evaluate the recognition performance of both the two-step recognizer and the all-in-on recognizer. To do cross validation, the training dataset is divided into subsets called folds. All the folds except one is used for training and the left-out fold is used for assessing the performance of the learned model. This process rotates through each fold and the average performance on the left-out folds is used as the performance measure of the algorithm. A cross validation process involves ten folds (ten subsets) is called a ten-fold cross validation. Cross validation makes sure that the data used for training the recognizer be disjoint from the data used for testing.

The correct recognition rate (CRR) of a driver skill recognizer is defined as,

$$CRR_e = \frac{n_{ee}}{\sum_{h \in \{e,t\}} n_{eh}}$$

and,

$$CRR_t = \frac{n_{tt}}{\sum_{h \in \{e,t\}} n_{th}}$$

for the expert driver group, and typical/ low-skill driver group, respectively. The first and second subscriptions of $n_{\bullet\bullet}$ are the actual driver group and the driver group labeled by the recognizer, respectively. For example, n_{et} represents the number of runs that are contributed by expert drivers and labeled by the recognizer as being contributed by typical/low-skill drivers. The overall correct recognition rate of the recognizer is defined as,

TABLE II
CONFUSION TABLE FOR THE TWO-STEP RECOGNIZER

Actual \ Recognized	Expert	Typical/Low-skill	CRR(%)
Expert	210	123	63.3
Typical/Low-skill	73	654	90.0
Overall			81.5

TABLE III
CONFUSION TABLE FOR THE ALL-IN-ONE RECOGNIZER

Actual \ Recognized	Expert	Typical/Low-skill	CRR(%)
Expert	196	136	59.0
Typical/Low-skill	57	671	92.2
Overall			81.8

TABLE IV
RECOGNITION PERFORMANCE FOR BALANCED TRAINING DATASET

CRR (%)	Balanced training	
	Two-step recognizer	All-in-one recognizer
Expert	76.4	74.0
Typical/Low-skill	81.8	83.5
Overall	79.2	79.1

$$CRR_o = \frac{n_{ee} + n_{tt}}{\sum_{g \in \{e,t\}} \sum_{h \in \{e,t\}} n_{gh}}$$

Note that, mathematically, the overall CRR is not necessarily equal to the average of the CRRs of expert, typical/low-skill driver groups.

Table II presents the recognition performance for the two-step recognizer, which is not significantly different from the performance of the all-in-one recognizer as shown in Table III. Since we have four expert drivers and eight typical or low-skill drivers, the number of runs is not balanced between different driver groups. As we can observe from Table II and Table III, the group with more training data biases the overall performance of the recognizers.

To alienate the effect of the unbalanced data, we randomly picked up four drivers from the typical and low-skill driver group, whose runs were joint with the runs by all four expert drivers to train and test the recognizers. This random selection was done ten times in order to reduce the sampling error. As shown in Table IV, the average CRR for expert drivers and typical/low-skill drivers are 76.4% and 81.8%, respectively for the two-step recognizer. Those for the all-in-one recognizer are 74.0% and 83.5%, respectively. In both cases, the recognizer performance is more balanced, compared with the results based on the unbalanced data. While the overall CRR degrades a few percentage points to 79.2% and 79.1% compared to the results in Table II and Table III, the performance based on balanced training data is probably more reliable.

A deeper investigation to the errors made by the recognizer showed that driver 357 (an expert driver) tended to be mis-classified as a typical/low-skill driver. We plot the mean of the DFT coefficients of driver 357 against that of expert, typical, and low-skill drivers in Fig. 8. It can be seen from Fig. 8 that the steering wheel angle profile of driver 357 is very close to that of the typical and low-skill drivers. After excluding driver 357 from the expert driver group and running the balanced training and testing again, we achieved average CRRs in the range of 85% to 90%, as summarized in Table V.

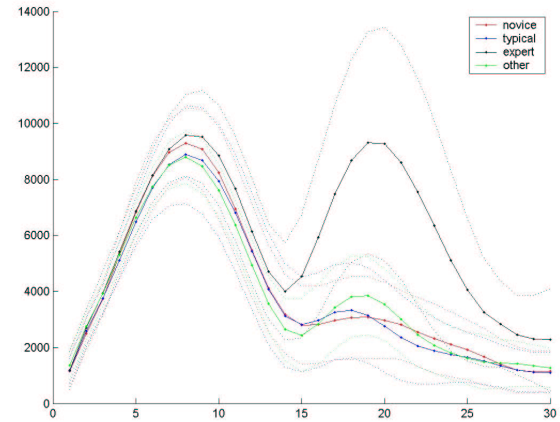


Fig. 8. Mean of driver 357's data (green) vs. that of expert (black), typical (blue), and low-skill (red) driver groups in DLC maneuvers. The dash lines with different colors mark mean +/- standard error of the data from different groups, accordingly.

TABLE V
RECOGNITION PERFORMANCE FOR BALANCED DATASET WITHOUT DRIVER 357

CRR (%)	Balanced training	
	Two-step recognizer	All-in-one recognizer
Expert	85.7	84.8
Typical/Low-skill	89.7	89.1
Overall	88.2	87.5

V. CONCLUSION AND FUTURE WORKS

In this paper, we present a pattern-recognition approach to characterize driver's driving skill. The preliminary results show that, using the DFT coefficients of the steering wheel angle as the discriminant features, the driving skill recognizers are reasonably effective in differentiating expert drivers from typical or low-skill drivers in general. However, an array of research issues are yet to be addressed in order to bring this technique into practical use.

A. Additional Discriminant Features for pattern recognition

The first issue is whether the DFT coefficients of steering wheel angle alone have sufficient discriminative power. The preliminary experiments show that one particular expert driver, driver 357, although possessing excellent driving

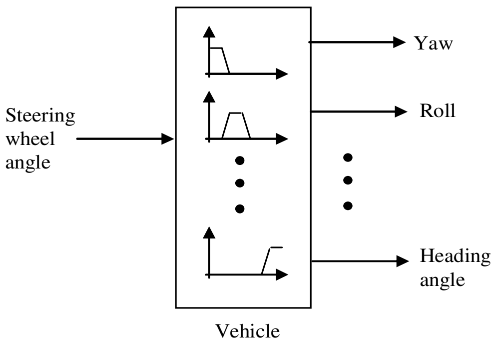


Fig. 9. A vehicle can be viewed as a filter bank.

skill, is recognized as a typical/low-skill driver. In addition, as shown in Fig. 8, the selected discriminant feature has difficulty differentiating typical drivers from low-skill drivers.

In the simulator dataset, there are data from other channels, such as yaw and roll. We choose to focus on the steering wheel angle in this study because of the following considerations. If we view the vehicle as a filter bank, the data from other channels, such as yaw, roll and etc., can be viewed as the convolution of the steering wheel angle and the mathematical model of the vehicle (Fig. 9). The steering wheel angle is the direct output of the driver's response to the attending circumstance of the driving conditions and contains the primary information reflecting driver's handling skill.

Apparently, other data channels, such as yaw and roll, need to be studied in its totality for a good result of driving skill characterization using pattern recognition because the filter bank may amplify the difference that is subtly reflected in the steering wheel angle. Along this line of thinking, we plan to extend the set of candidate parameters for discriminant features and extend the frequency domain analysis to the time domain analysis. The candidate parameters we are going to investigate include the steering onset, and its correlation with the yaw acceleration and the lateral acceleration, just to name a few. Beyond vehicle dynamics sensors, another potential extension is to include sensory information that directly reflects driver's behavior, such as eye movements, which have been proved to be different between experienced and low-skill drivers [8][9].

B. Identification of vehicle operating conditions for algorithm validity

Although the pattern recognition approach in this preliminary study shows promising results, many questions still remain open as to its validity of general applicability. For example, how should the driving skill be evaluated so that the recognizer can be trained? Other related questions are: Does a driving skill level fluctuate across different test runs? Do typical drivers really have better skills on maneuvers such as DLC and LCIC than low-skill drivers? Is a driver more skillful in one type of maneuvers necessarily skillful in all other maneuvers? Apparently without addressing some of the key questions satisfactorily, the algorithm can hardly be useful.

C. Effect of vehicle longitudinal dynamic control

In this preliminary study of driving skill characterization, the information of vehicle direction control is the only data utilized for analysis and design. A natural question can be raised whether the drivers' behavior would change when they have the chance to control both the steering wheel and the vehicle speed so that the inclusion of such information is beneficial to the skill characterization. However, there is an inherent complication of using the longitudinal dynamic information for driving skill characterization in the real-time implementation in real-world driving. The apparent difficulty of differentiating the application of brake with and without object in front of the vehicle cannot easily be resolved. Again, depending on the availability of on-board vehicle sensors such as radar or camera, the validity of the condition could further be refined for such future work.

D. Naturalistic driving condition

Finally, the maneuvers included in the simulator dataset were originally designed to test near/at-limit vehicle handling performance. These maneuvers do not occur frequently in day-to-day driving conditions. Ideally, the driving skill recognition system should be able to function during naturalistic driving conditions for the algorithm to be useful. Additional study of driver behavior in these driving conditions is apparently necessary.

ACKNOWLEDGMENTS

Special thanks to Brian Repa for his insightful contribution on the driver-vehicle interaction model, and to Weiwen Deng for the valuable discussions about driver modeling.

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