Proceedings of the 2009 IEEE International Conference on Systems, Man, and Cybernetics
San Antonio, TX, USA - October 2009

Real-time Driving Behavior Identification Based on Driver-in-the-loop Vehicle Dynamics and Control

Dimitar Filev, Jianbo Lu, Kwaku Prakah-Asante and Fling Tseng
Research and Advanced Engineering
Ford Motor Company
Dearborn, MI 48150
{dfilev, jlu10, kprakaha, ftseng}@ford.com

***Abstract*—This paper studies to characterize driver driving behavior or driver control structure in real time. The three proposed methods use some of the signals such as the driver actuation measurements, the relative ranges between a leading and a following vehicle during a car-following maneuver, and the vehicle dynamic responses such as the vehicle's longitudinal acceleration and deceleration. All the used signals exist in various electronic control systems. Vehicle tests were conducted on a test vehicle to illustrate the effectiveness of the proposed methods in identifying aggressive and cautious driving behaviors.**

***Keywords*—driver behavior, driver model, identification**

I. Introduction

Driving vehicle involves non-monolithic systems such as the driver, the host vehicle, the surrounding vehicles, the environment, and the electronic control systems. Each of the systems has its own information flow and physical subsystems. The driving convenience, comfort, safety and fuel economy are compromised if the coordination or integration among those systems is poorly executed, whereas the integrated or well coordinated systems can provide even more functionality and performance than the simple sum of the constituent systems. This system approach is a critical enabler for the further advancement of automotive technology.

While the aforementioned needs require studying all the interactions, this paper focuses on the interaction between electronics and the driver. The electronic control systems equipped with traditional mass produced vehicles target a hypothetical nominal driver that represents a significant group of customers. They are generally designed to be robust with respect to any major driver deviations and are not considered to adapt to the driving behavior or style in real time. The driver is expected to accept and to adjust to the features, functions, attributes, and assumed performance that are offered by vehicle manufacturers.

Nowadays, the increased level of electronics, software, computational and communication power enables a different approach in which the electronic systems are transformed into intelligent and flexible ones that can better tune and adapt to the driver's wants. That is, we are observing an emerging trend in the opposite direction - towards creating vehicles with electronic control systems that are capable of sensing and estimating driver's behaviors, desires, and intents and choosing their own optimal control accordingly, i.e., there are opportunities to create "driver-aware" vehicles to maximize safety, performance, and comfort, while still leaving primary controls to the driver. The flexibility, adaptation, and intelligent features of the electronics presume a well defined mechanism for estimation, model learning, and optimization.

Therefore, for a vehicle to be flexible and adaptable, it is required the ability of its electronics to understand and characterize the driver. That is, the electronic control systems are able to develop realistic driver models in real time describing the intents, preferences and actions of the diver.

The existing attempts to model driver behavior are dominated by models that are inspired by control theory [1-5], fuzzy models [6, 7], stochastic approximators such as Ensemble Kalman Filters [8] and Hidden Markov Models [9, 10]. Although providing a high level of generalization of the driver characteristics, these models are typically not used for real time identification purpose but for the purposes of obtaining a better understanding of the interaction between the driver and the vehicle or for designing and testing purposes.

A real-time driver model can eventually enable electronic control systems as cooperative agents to work with the driver, at the same time, to adapt to the driver behavior for proper support. For instance, driving behavior might be used to prepare electronic control systems for earlier activation of safety functions to help novice or aged driver avoid accidents.

Driver control structure or behavior may be characterized as skill based, rule governed, and expressive activity based [11, 12]. A human driver can learn from his past experience, plan before entering a hazard situation, detect system malfunction based on the vehicle responses, conduct emergency maneuvers, and adjust his controls based on driving conditions. He can also make control decisions based on his physical and emotional state, experience level, cognitive load, and control capability. For instance, the driving behavior compromising safe driving results in a significant amount of U.S. accidents and traffic tickets. According to the National Highway Traffic Safety Administration (NHTSA), those behaviors might include following a car too closely, driving at speeds far in excess of the norm, and changing lanes very frequently and abruptly.

The current paper and its companion paper [13] suggest a unique approach in which the driving behavior is deduced in real-time through driver's throttling, braking, car-following, handling maneuvers, and the patterns of the driver actuation requests. Some other driver behavior characterizations might be found in [14-27].

The remainder of the paper is organized as follows. Section II presents a brief discussion on the drive-in-the-loop system.

978-1-4244-2794-9/09/$25.00 ©2009 IEEE

Section III discusses identifying the unstructured driving behavior during free form throttling. Section IV identifies a fuzzy structure of the driving behavior during a car-following maneuver. Section V studies identifying a PD feedback control structure of the driver. Section VI concludes the paper.

II. DRIVER BEHAVIOR FOR DRIVER-IN-THE-LOOP VEHICLE SYSTEM

The attempt to obtain a realistic but computationally feasible driving behavior model in real-time is a difficult if not unrealistic task. While expansive devices can be used to characterize a driver through direct measurements of a driver's facial expression, eye placement, heartbeat, blood pressure, etc., in this paper, we focus on indirect methods using vehicle dynamic responses measured through onboard sensors.

Namely, we are interested in the driver behavior relevant to the control of vehicle dynamics. Since a vehicle is under the influence of its driver and its electronic control systems, we are dealing with identifying driver control structure in a driver-in-the-loop system or identification using closed-loop system identification techniques. Such a driver-in-the-loop system can be illustrated in Fig. 1. The driver's control decisions are a result of a complex process driven by two main information flows - a cognitive flow including the quantitative information readily available to the driver through various sensors, control and advisory systems (solid lines) and a subjective flow including visual, perceptual, emotional, and experiential factors that are processed in the driver's mind (broken line). While the quantitative information flow is available to both the driver and the electronic systems, the subjective information flow is generally inaccessible to the electronic control systems - a fact that is a major reason for the difficulties in obtaining adequate driver behavior characterization. This fundamental uncertainty is the main reason for us to focus on the partial characterization of the driver's behaviors as they apply to specific control context and goals: straight line driving, handling, and car-following.

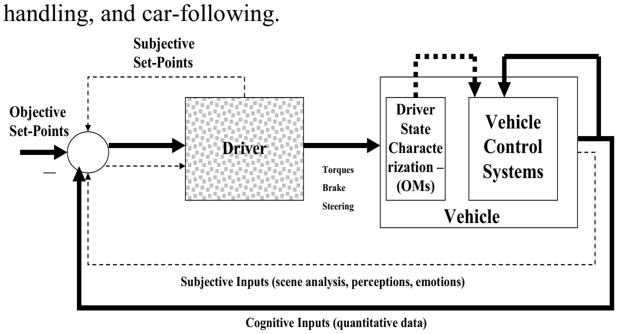

Fig. 1. Cognitive (solid line) and Subjective (broken line) flow of information in a driver – vehicle system.

Driver behavior can be thought as the control structure of a driver or a collection of all his control intents in response to all the driving conditions. Driver's instantaneous intent can be determined from a set of targets defining the speed and direction of travel, performance, fuel economy, and control actuations such as braking, throttling, and steering. Such a driver intent is already used by the electronic control systems. For instance, the driver actuation inputs are used in the electronic stability control (ESC) to derive driver support decision. When a vehicle does not follow the driver intent well (e.g., driving on an ice or snow road), the ESC system will be activated to enforce the vehicle to follow the driver intent. Not all drivers know that their specific intents might not be feasible for the driving conditions and might be problematic for the electronics to follow. If the problematic intent can be identified in advance, electronic control strategy might be designed differently. For example, roll stability control (RSC) [28] prevents a vehicle from following a very aggressive driver steering intent so as to prevent a rollover. However not all problematic intents can be identified by sensor measurements without knowing the driver control structure.

Notice that driver control structure or driving behavior can be characterized from many different angles, for instance, a road rage driver might show the behavior of: pursuing a vehicle, flashing head light, forcing a car off the road, forcing a car to pull over, verbal abuse, bumping into another car, tailgating, abrupt braking or slowing, deliberate obstruction, cutting off or swerving in front of another vehicle, etc. This paper and its companion [13] focus on some driver behaviors related to the normal driving conditions.

III. UNSTRUCTURED DRIVER BEHAVIOR CHARACTERIZATION

During a normal driving maneuver, driver's long term longitudinal vehicle control behavior might be used to determine the driving behavior regardless the vehicle's dynamic response. For instance, a driver can exhibits a specific longitudinal control pattern during driving on a highway for a long period of time. His acceleration pedal activation pattern can be smooth or abrupt even he is away from any emergency condition. The variability of the pedal and its rate change can be used to differentiate the smooth application from abrupt application. Such a smooth or abrupt application shows strong correlation with fuel economy and acceleration performance when driving condition is unconstrained. Identifying such driving behaviors can be used, for instance, for fuel economy minder purpose. Anomaly (novelty) detection can be used to estimate major changes in the overall variability of the control actions indicating changes in corresponding behaviors.

Anomaly detection is a well established technique that puts a major emphasis on the continuous monitoring, machine learning, and unsupervised classification to identify a trend of departure from a normal behavior and predict a potential significant change. The determinant of the covariance matrix of the population of driver's actions is used as a measure of the generalized variance (spread) of the population, hence as an indicator for a change in the driver's behavior.

The feature space of driving torque request τ_d and its derivative is spanned by the vector $y = [\tau_d \; \dot{\tau}_d]$. The determinant D of the covariance matrix of the population can be recursively calculated as

$$D_{k+1} = (1-\alpha)^{k-1} D_k (1 - \alpha + (y_k - v_k) Q_k (y_k - v_k)^T) \quad (1)$$

with

$$
\begin{aligned}
&v_{k+1} = (1-\alpha)v_k + \alpha y_k \\
&Q_{k+1} = (I - G_k(y_k - v_k))Q_k(1-\alpha)^{-1} \qquad (2)\\
&G_{k+1} = Q_k(y_k - v_k)^T \alpha(1-\alpha+\alpha(y_k - v_k)Q_k(y_k - v_k)^T)^{-1}
\end{aligned}
$$

where v_k is a filtered version of y_k, Q_k is the estimated inverse covariance matrix, and α is a constant which reflects the forgetting factor related to the filter memory depth.

D_k thus computed in (1) has initial means and standard deviations for abrupt and smooth type of behaviors. The instantaneous behavior is classified as abrupt if its value is higher than a control limit l_{abrupt} it is classified as smooth if its value is lower than a control limit u_{smooth}. l_{abrupt} and u_{smooth} are defined as $l_{abrupt} = \mu_{abrupt} - 3\sigma_{abrupt}$, $u_{smooth} = \mu_{smooth} + 3\sigma_{smooth}$ where μ_{abrupt} and σ_{abrupt} are the mean and the standard deviation of the abrupt behavior class; μ_{smooth} and σ_{smooth} are similarly defined as parameters for the smooth behavior class. If the current behavior is classified as either "abrupt" or "smooth", the corresponding mean and standard deviation of the matching behavior are recursively updated:

$$
\begin{aligned}
&w_{k+1} = (1-\beta)w_k + \beta D_{k+1} \\
&H_{k+1} = (1-\beta)H_k + (\beta-\beta^2)(D_{k+1} - w_k)^T(D_{k+1} - w_k) \qquad (3)\\
&\sigma_{k+1} = \left(H_{k+1}\right)^{1/2}
\end{aligned}
$$

where w and H are the estimated mean and variance and β is another forgetting factor.

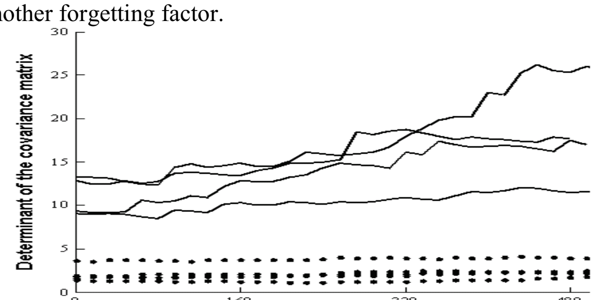

Fig. 2. Determinant of smooth (dotted lines) and abrupt (solid lines) driving behaviors

The scatter in Fig. 2 shows the determinant of the covariance matrix from the vector of the acceleration pedal position and its rate change for 8 runs of vehicle tests. The 4 runs with solid lines of determinant in Fig. 2 were for abrupt acceleration pedal applications where the determinant of the covariance shows large value, for instance, greater than 7. The 4 runs with dotted lines of determinant in Fig. 2 were for smooth acceleration pedal applications where the determinant of the covariance shows very small value, for instance less than 4. Hence the size of the determinant shows the unique informative patterns which can be used to identify the smooth driving behavior from the abrupt driving behavior. Since interactions between the driver and the driving environment consists of frequent vehicle stops with varied durations, suspense of the continual updating is required to prevent numerical problems during recursive computation. The following suspension conditions are used:

- If the vehicle speed is lower than 1 mph, vehicle speed and acceleration related recursive calculations are suspended.
- If the accelerator pedal position is lower than 1%, pedal related recursive calculations are suspended.

Although the above deviation focuses on the acceleration pedal, it can be easily applied to braking case. Since sudden aggressive braking can happen during emergency situations, which are not necessary the indication of the driver's typical driving behavior, therefore, the conditions used for computation screening during driver braking is the quasi-steady state driving where both braking is not at its extreme value.

During transient acceleration and deceleration, certain wheels of the vehicle might experience large longitudinal slip and the tire longitudinal forces of those wheels reach their peak values. Such conditions can be identified through monitoring the rotational motion of the individual wheels in relation to the vehicle's travel velocity, and consequently the driver behavior during transient maneuvers can be determined as in [13].

IV. SEMI-STRUCTURED DRIVING BEHAVIOR CHARACTERIZATION

While the last section considers the unconstrained driving condition where only the driver's control application is used to learn the driver behavior, in this section, we will study the fuzzy structure of the driver behavior during a constrained driving condition such as a car-following maneuver.

Although not all the inputs to the driver are accessible by electronic control systems, certain variables construct an input-output pair that might be used to deduce control structure of the driver. For example, during a car-following maneuver, the relative distance between the leading and following car and the driver's braking and throttle requests are usually well coordinated. Here we consider using a Tagaki-Sugeno (TS) model to relate the variance of the driver's braking and throttling commands to the relative range and velocity between the leading and the following car.

For determining the driver aggressiveness or cautious style, the fuzzy system utilizes the signal conditioned mean driving headway (gap-time) relative to other vehicle, as well as the standard deviation of the rate changes of the accelerator pedal and brake pedal. The Driver Index value from fuzzy computation and rule evaluation determined the aggressiveness of the driver based on car following, vehicle speed and the driver's control actions on acceleration and deceleration.

For real-time vehicle implementation, the recursive estimation of the mean and variance of a variable of interest is applied. The signal conditioned average mean gap-time at sample time k can be computed as

$$g_k = g_{k-1} + \alpha\left(\Delta s_k / v_{f_k} - g_{k-1}\right) \qquad (4)$$

where Δs_k is the relative distance between the leading and the following vehicle and v_f is the velocity of the following vehicle. α is a filter coefficient similar to the one used in (2). Fig.3 shows the mean gap-times computed from two runs of vehicle testing: one for aggressive driving and the other for cautious driving.

The acceleration pedal rate mean can be computed as

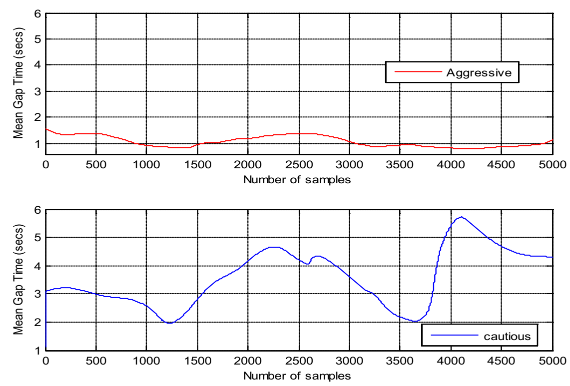

Fig. 3. Mean gap time for aggressive/cautious driving

$$\bar{\rho}_k = \bar{\rho}_{k-1} + \alpha\left(\left(\rho_k - \rho_{k-1}\right)/\Delta T - \bar{\rho}_{k-1}\right) \qquad (5)$$

where $\bar{\rho}$ is the acceleration pedal mean and ΔT is the sample time. The corresponding variance can be computed as

$$\upsilon_k = \alpha \upsilon_{k-1} + (1-\alpha)\left(\rho_k - \bar{\rho}_k\right)^2 \qquad (6)$$

and the standard deviation is obtained from the square-root of the variance. Fig. 4 shows the standard deviations of two runs of test data for aggressive and cautious driving.

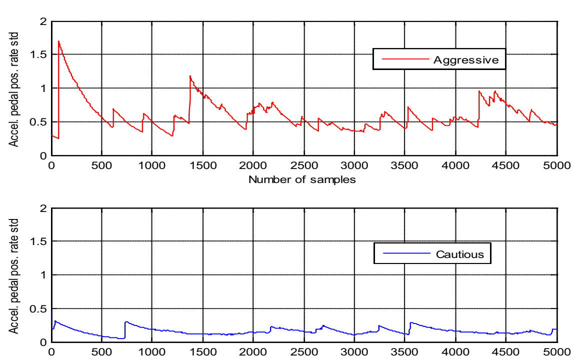

Fig. 4. STD of acceleration pedal rate for aggressive/cautious driving

Similar to (5) and (6), the mean and the variance of the brake pedal rate change can be computed. Fig. 5 shows the standard deviations of two runs of test data for aggressive and cautious driving.

The variables are first normalized before presenting to the fuzzy inference system. The fuzzy sets and membership functions were determined for the features to transform the crisp inputs into fuzzy terms. The mean gap-time fuzzy set G_s is defined by

$$G_S = \{(g, \mu(g)) \mid g \in G\} \qquad (7)$$

where G is given by the bounded collection of gap-times g in the vehicle path. The gap-time membership function μ is chosen to be a Gaussian function.

A zero-order TS model was used to compute the driver index level. A normalized output scale from 0-1.0 represented the levels from cautious to less aggressive to aggressive driving behavior. The driver index is obtained from fuzzy computation and rule evaluation. Table 1 shows the used rules. Notice that a higher gap-time is relatively more safety conscious compared to a lower gap-time. Fig. 6 shows the driver index computed from two runs of vehicle testing data: one for aggressive driving with driver index above 0.8 and the other for cautious driving with driver index less than 0.2.

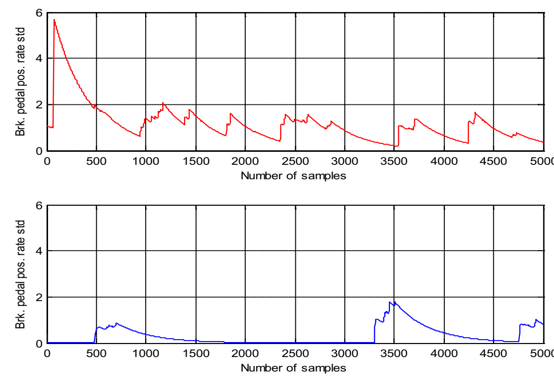

Fig. 5. STD of brake pedal rate for aggressive/cautious driving

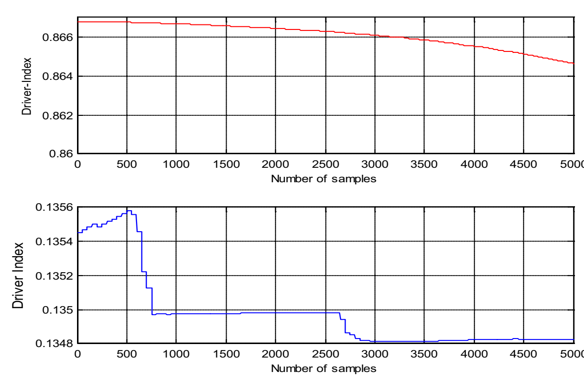

Fig. 6. Driver index for aggressive (top) and cautious (bottom) driving

Table 1. Rules for driving behavior characterization

If gap-time is	If accel pedal rate STD is	If brake pedal rate STD is	Then driver index is
Low	Low	Low	Less Aggressive
High	Low	Low	Cautious
Low	High	Low	Aggressive
Low	Low	High	Aggressive
Low	High	High	Aggressive
High	High	High	Less Aggressive
High	Low	High	Cautious
High	High	Low	Less Aggressive

V. STRUCTURED DRIVER BEHAVIOR CHARACTERIZATION

While the fuzzy structure of driver behavior provides certain control structure of a driver during car following maneuvers, it does not fully utilize the vehicle dynamic response information. The car-following task requires the driver to maintain with the leading vehicle one of the followings (i) zero speed difference; (ii) a constant relative distance between the leading and the following; (iii) a constant relative gap-time defined by the division of the relative distance by the relative velocity.

Based on [15], a human driver can be modeled as mimicking a PD feedback controller. The closed loop system during a car following maneuver might be expressed as

$$(\ddot{x}_l - \ddot{x}_f - \ddot{\bar{x}}_g) = -c_v(\dot{x}_l - \dot{x}_f - \dot{\bar{x}}_g) - c_s(x_l - x_f - \bar{x}_g) \quad (8)$$

where x_l and x_f are the leading and the following vehicle travel distance and $\bar{x}_g$ is the gap offset reference.

Due to the implementation of radar used in vehicles equipped with adaptive cruise control function, the relative distance and velocity are measured and defined as

$$\Delta s = x_l - x_f, \quad \Delta v = \dot{x}_l - \dot{x}_f \quad (9)$$

The vehicle equipped with stability controls has a longitudinal accelerometer with output a_x which measures $\ddot{x}_f$. (8) can be further expressed as

$$a_x = c_v(\Delta v - \dot{\bar{x}}_g) + c_s(\Delta s - \bar{x}_g) + (\ddot{x}_l - \ddot{\bar{x}}_g) \quad (10)$$

The unknown parameters c_v and c_s in (13) can be used to characterize a driver's control structure during a car following. Using the low-pass filtered Δs and Δv to replace the gap offset reference $\bar{x}_g$ and its derivative $\dot{\bar{x}}_g$ and considering the time delays, we have the following equations

$$a_{x_{k+i}} = c_v[\Delta s_k - \mu_k(\Delta s)] + c_s[\Delta v_k - \mu_k(\Delta v)] + w$$
$$\begin{bmatrix} \mu_k(\Delta s) \\ \mu_k(\Delta v) \end{bmatrix} = (1-\alpha)\begin{bmatrix} \mu_{k-1}(\Delta s) \\ \mu_{k-1}(\Delta v) \end{bmatrix} + \alpha \begin{bmatrix} \Delta s_k \\ \Delta v_k \end{bmatrix} \quad (11)$$

where subscript i in $a_{x_{k+i}}$ reflects the time delay between the driver's braking/throttling actuation and the measured relative distance and velocity and the acceleration, α is a low-pass filter coefficient similar to the one used in (2), and w is a high frequency uncertain signal that might be treated as a white noise. Using a conditional least square identification algorithm, c_v and c_s can be identified in real-time from (11). The response time t_p and the damping ratio ζ of the driver-in-the-loop system can be related to c_v and c_s as

$$t_p = 2\pi c_s / \sqrt{4c_s - c_c^2}, \quad \zeta = c_v / 2\sqrt{c_s} \quad (12)$$

which can deduce the driver's driving behavior: (i) for a normal driver, it is desired that the transient response of the driver-in-the-loop system be sufficiently fast (sufficiently small t_p) and damped (sufficiently large ζ); (ii) for an aged or a driver with physical limitation, t_p might be very large; (iii) for an aggressive driver, ζ is likely to show a small value, such as one less than 0.5, and the system response yields excessive overshoot; (iv) for cautious driver, ζ is likely to show a reasonably large value, such as one greater than 0.7.

A least-square parameter identification was implemented for calculating c_v and c_s. Two runs of vehicle testing were conducted. In the 1st testing the driver in the following car tried to use aggressive throttle and braking to achieve constant relative gap-time between his vehicle and a leading vehicle, which led to larger range error $\Delta s_k - \mu_k(\Delta s)$, see Fig. 7. The identified c_v is around 0.2 and c_s around 0.05, see Fig. 8. The damping ratio thus computed from (12) showed a value less than 0.5, which is an indication of a light damping driver-in-the-loop system, hence corresponding to aggressive driving behavior.

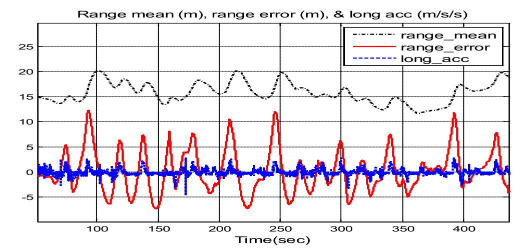

Fig. 7. Relative range between the leading and following car for an aggressive driving

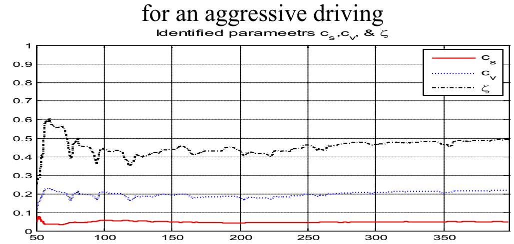

Fig. 8. The identified parameters c_s and c_v with damping ζ for an aggressive driving of relative range in Fig. 7

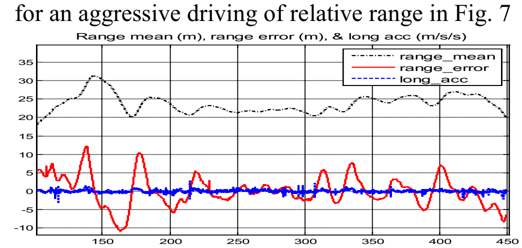

Fig. 9. Relative range between the leading and following car for a cautious driving

In the 2nd run of the vehicle testing, the driver was using cautious throttle and brake application to achieve car following, the relative range error $\Delta s_k - \mu_k(\Delta s)$ in Fig. 9 had less magnitude in comparison with the one shown in Fig. 7. The identified c_v and c_s are depicted in Fig. 10. The damping ratio showed a value above 0.8 except during the first 150 seconds, see Fig. 10. This is an indication of a heavy damping driver-in-the-loop system, hence corresponding to a cautious driving behavior.

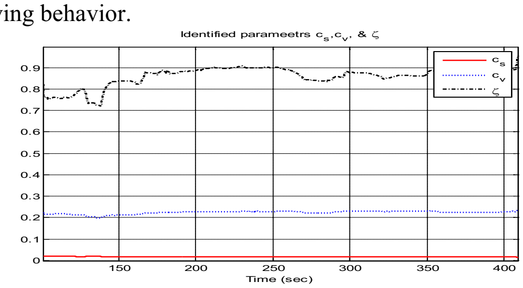

Fig. 10. The identified c_s and c_v with damping ζ for a cautious driving of relative range in Fig. 9

VI. CONCLUSION

This paper discusses three methods to characterize driving behavior. The 1st method uses only the driver's actuation requests to capture the long term driving pattern, which is an unstructured approach to capture the driver's average control structure. The 2nd method uses the input-output relationship between the driver's actuation requests and the relative rage between the leading and the following car during a car-following maneuver to construct a fuzzy structure of the driver control. The 3rd method identifies the PD control structure of a driver during a car-following maneuvering by using the input-output relationship between the vehicle's dynamics response (vehicle's longitudinal acceleration and decelerations) and the relative range between the leading and the following car. Each of the methods has its own merit for real-time implementation and has its own operation range. While the paper provides practical treatment that can be used to typify specific driver characteristics with respect to certain set of objectives, e.g. fuel economy, performance, traffic, vehicle handling, etc., a more detailed study of the structure and parameters of a generic model for driver characterization will be the subject of future work.

ACKNOWLEDGMENT

This work has been partially sponsored through NSF grant no. CMMI-0727768.

REFERENCES

[1] E. Boer, N. Ward, M. Manser, and N. Kuge, "Driver-model-based assessment of behavioral adaptation," Proc. of JSAE, May 16-20, Yokohama, Japan, 2005

[2] E. Boer and M. Hoedemaeker, "Modeling driver behavior with different degrees of automation: Ahierarchical framework of interacting mental models," Proc. of the 17th European Annual Conference on Human Decision Making and Manual Control, Valenciennes, France, 1998

[3] G. Prokop, "Modelling human vehicle driving by model predictive online optimization," Vehicle System Dynamics, Vol. 35, No. 1, pp. 19-53, 2001

[4] C. MacAdam, "Understanding and modeling the human driver," Vehicle System Dynamics, Vol. 40, No. 1-3, pp. 101-134, 2003

[5] I. Delice and S. Ertugrul, "Intelligent modeling of human driver: a survey," Intelligent Vehicles Symposium, Vol. 13-15, pp. 648 – 651, 2007

[6] H. Takahashi, "Human sensor system that predicts driving environment using driver's fuzzy operational data," Japanese J. of. Fuzzy Theory and Systems, Vol. 4, pp. 709-734, 1992

[7] L. Qiao, M. Sato, and H. Takeda, "Learning algorithm of environmental recognition in driving vehicle," IEEE Trans. on Systems, Man and Cybernetics, Vol. 25, pp. 917-925

[8] N. Kuge, T. Yamamura, O. Shimoyama, and A. Liu, A. "A driver behavior recognition method based on a driver model framework," SAE 2000-01-0349

[9] A. Liu and A. Pentland, "Towards real-time recognition of driver intentions," Proc. of the IEEE Intelligent Transportation Systems Conference, pp. 236-241, 1997

[10] A. Liu, L. Veltri, and A. Pentland, "Modeling changes in eye fixation patterns while driving." A.G. Gale et al., (Eds.), Vision in Vehicles VI, pp. 13-20, Amsterdam

[11] S. Stradling and M. Meadows, "Highway code and aggressive violations in uk drivers" , www.aggressive.drivers.com

[12] T. Lajunen and H. Summala, "Driving experience, personality, and skill and safety-motive dimensions in drivers self-assessments," Person. Individ. Diff. Vol 19, No. 3. pp. 307-318, 1995.

[13] J. Lu, D. Filev, K. Prakah-Asante, and F. Tseng, "From vehicle stability control to intelligent personal minder: real-time vehicle handling limit warning and driver style characterization," Proc. of IEEE Symposium Series on Computer Intelligence, 2009.

[14] U. Kiencke et al, "Modeling and performance analysis of a hybrid driver model," Control Engineering Practice, Vol. 7, pp.985-991, 1999

[15] G. Burnham, J. Seo and G. Bekery, "Identification of human driver models in car following," IEEE Trans. on Automatic Control, Vol. 19, pp. 911-915, 1974

[16] B. Wanga, M. Abeb, Y. Kanob, "Influence of driver's reaction time and gain on driver–vehicle system performance with rear wheel steering control systems: part of a study on vehicle control suitable for the aged driver," JSAE Review, pp. 75–82, 2002

[17] M. Hashimoto, T. Suetomi, A. Okuno and H. Uemura, "A study on driver model for lane change judgment," JSAE Review, pp. 183-188, 2001

[18] T. Pilutti and A. Ulsoy, "Identification of driver state for lane-keeping tasks," IEEE Trans. on Systems, Man, and Cybernetics - Part A: Systems & Humans, Vol. 29, pp. 486-502, 2001

[19] A. Pick and D. Cole, "A mathematical model of driver steering control including neuromuscular dynamics," ASME J. of Dynamic Systems, Measurement, and Control, Vol. 130, 2008

[20] R. Onken and J. Feraric, "Adaptation to the driver as part of a driver monitoring and warning system," Accident Analysis and Prevention, Vol. 29, pp. 507-513, 1997

[21] W. Wierwille, et. al, "Identification of driver errors: overview and recommendations," FHWA-RD-02-003, USDOT, 2002.

[22] P. Cacciabue, Modeling driver behavior in autonomous environments, Springer-Verlag, London, 2007

[23] P. Zheng and M. McDonald, "Manual vs. adaptive cruise control-can driver's expectation be matched?" Transportation Research Part C, 13 pp. 421-431, 2005

[24] T. Wenzel and M. Ross, "The effects of vehicle model and driver behavior on risk," Accident Analysis and Prevention, 37, pp. 479-494, 2005

[25] N. Dapzol, "Weight semi-hidden markov model and driving situation classification for driver behavior diagnostic," Transportation Research Part F 2, 181~196, 1999

[26] R. Fuller, "Accident analysis and prevention towards a general theory of driver behaviour,"Accident Analysis and Prevention 37,pp.461–47, 2005

[27] Y. Yin and H. William, "Influence of driver's reaction time and gain on driver–vehicle system performance with rear wheel steering control systems: part of a study on vehicle control suitable for the aged driver," JSAE Review 23, pp.75–82, 2005

[28] J. Lu, D. Messih and A. Salib, "Roll rate based stability control - the Roll Stability Control system," ESV-07-0136, Proc. of the 20th Enhanced Safety of Vehicles Conference, 2007