

Real-time Determination of Driver's Driving Behavior during Car Following

Jianbo Lu, Dimitar Filev, and Finn Tseng
Ford Motor Co.

ABSTRACT

This paper proposes an approach that characterizes a driver's driving behavior and style in real-time during car-following drives. It uses an online learning of the evolving Takagi-Sugeno fuzzy model combined with the Markov model. The inputs fed into the proposed algorithm are from the measured signals of on-board sensors equipped with current vehicles, including the relative distance sensors for Adaptive Cruise Control feature and the accelerometer for Electronic Stability Control feature. The approach is verified using data collected using a test vehicle from several car-following test trips. The effectiveness of the proposed approach has been shown in the paper.

CITATION: Lu, J., Filev, D., and Tseng, F., "Real-time Determination of Driver's Driving Behavior during Car Following," *SAE Int. J. Passeng. Cars – Electron. Electr. Syst.* 8(2):2015, doi:10.4271/2015-01-0297.

1. INTRODUCTION

In the foreseeable future, vehicles will need to have enhanced level of intelligence and awareness relevant context (including driver, vehicle, environment and their interactions). This is due to rapid increase in the amount of software, hardware, improvements on in-vehicle computation and connectivity. This together with the increased demand for higher level of driving automation and the ability to manage and make use of the rich information for both the driver and the vehicle itself is driving many no-traditional development.

If we think of the current level of vehicle intelligence for onboard control and information systems as the 1st order intelligence, we can foresee that the next (called the 2nd order intelligence) would most likely include:

- proactive instead of reactive,
- multi-agents instead of single agent,
- adaptive instead of fixed,
- personalized instead of generalized.

One of distinctive requirements in the envisioned 2nd order intelligence is the so-called "personalization", where the onboard electronic controls adapt to the driver's preference, capability of handling driving scenarios, driving behavior, etc. This requirement is demanding "driver-aware" features that can maximize safety, performance, and comfort, while still leave to the driver the full or semi-full control of the vehicle. This presumes well-developed algorithms for perception and learning driver's actions and decision models [1, 2, 3, 4, 5, 6, 7].

In order to implement "driver-ware" features, real-time learning of the preferences (e.g. performance driving for responsiveness vs. eco-driving for fuel economy) and the driver behaviors under various

driving conditions is desired. This task needs to utilize families of models that proactively characterize the driver's actions, instead of fixed single driver model. Such models can be later on used by vehicle control systems, for example, to advise a driver for the most appropriate control actions under specific circumstances, e.g., recommending optimal travel speed, adapting mode of operation (e.g., comfort vs. sporty, performance vs. fuel economy), or adjust the control functions in an anticipation fashion automatically, or override driver erroneous control actions.

In this paper, we focus on an approach for characterizing the driver behavior during car-following drives. The approach learns driver's longitudinal vehicle feedback control structure together with the control parameters in real-time, and uses the learned parameters to deduce driver behavior. The models combine the evolving identification technique [8] with the transitional probabilities of Markov models [9]. The evolving paradigm is based on the concept of evolving (expanding or shrinking in real-time) structure, which adjusts to the changes in the mapping between the conditions and the driver's actions that cannot solely be captured through traditional parameter adaptation techniques. The Markov probabilities here characterize the transitions between the individual models inside the family of models.

The paper is organized as follows. [Section 2](#) provides the mathematical description of driver's car following behavior through a second-order dynamical system, and proposes using two functions of the identified control gains to characterize the driver behavior. [Section 3](#) considers the stochastic evolving model and its application to the determination of driver's car-following behavior. [Section 4](#) shows the results of using the proposed approach for data collected during several car-following test trips. [Section 5](#) concludes the paper.

2. CAR-FOLLOWING DYNAMICS AND DRIVER BEHAVIOR

During a car-following drive, the driver acts as a feedback and feedforward controller that adjusts the vehicle's accelerator and brake pedals in order to regulate the desired relative position and velocity of his vehicle with respect to a leading vehicle. The driver can apply accelerator pedal travel to reduce the relative distance or apply brake pedal travel to increase relative distance, or use both pedals to maintain a constant headway gap or speed with respect to the leading vehicle. In whatever intent, the longitudinal vehicle dynamic responses of the driver-in-the-loop vehicles have certain level of achievable performance. Hence by inverting the car-following model from the driver-in-the-loop system model, the driver's longitudinal control behavior is likely to be identifiable. In the sequel, the inverting process is conducted by reconstructing the driver's driving intents from the closed loop response of the driver-in-the-loop system.

The driver's driving behavior or state during car-following drives can be related to the aforementioned feedback and feedforward controller. Denote the driver state as $b \in B$, where B is the collective set of all the potential driver's states

$$B = \{B_1, B_2, \dots, B_n\}. \quad (1)$$

Considering that drivers usually maintain a rather consistent gaps with leading vehicles at stop and increase the gaps when the travel speeds increase, drivers' headway intent can be characterized as slow time varying functions of the travel speeds and the road conditions, see [9] for detail. Considering the slow time varying nature, the rate change of the desired headway gaps are likely close to zero.

Using a simple PD feedback controller to mimic the car-following control [10], the dynamics desired by the driver can be expressed as in the following discrete time format

$$a_{k+\lambda} = c_s(s_k - \bar{\mu}_k) + c_v(v_k - \bar{\rho}_k) \quad (2)$$

where c_s and c_v are two control gains reflect the driver's distance and speed regulation need. s_k and v_k are the relative distance and velocity between the host vehicle and the leading vehicle. For a vehicle equipped with adaptive cruise control (ACC) system, s_k and v_k are measurable through on-board radar. $\bar{\mu}_k$ and $\bar{\rho}_k$ are the target gap and relative velocity chosen by the driver. λ is the time delay between the instant when the driver initiates the accelerator pedal application to the instant when the vehicle's acceleration starts to build up. a is the vehicle longitudinal acceleration which can be measured through the on-board accelerometer (e.g., equipped for electronic stability control system). μ and ρ are the target headway gap and relative velocity.

Based on the reasoning in [9], the driver's car-following model can be depicted as in the following:

$$a_{k+\lambda} = c_{si}(s_k - \bar{\mu}_k) + c_{vi}(v_k - \bar{\rho}_k) \quad (3)$$

where c_{si} and c_{vi} are the control gains corresponding to the i th driver behavior.

Fig. 1 and Fig. 2 show the vehicle's relative gap and velocity with respect to the leading vehicles together with the vehicle longitudinal acceleration for two test trips.

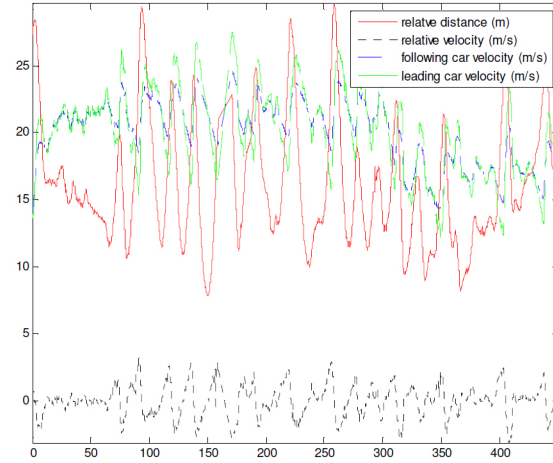


Fig. 1. The sensor measurements for the car-following test trip where the driver shows aggressive driving behavior

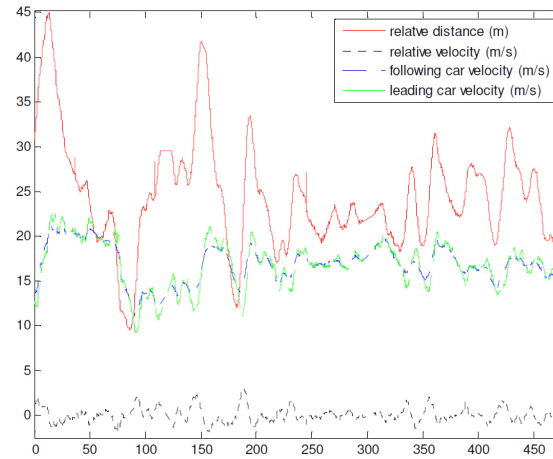


Fig. 2. The sensor measurements for the car-following test trip where the driver shows cautious driving behavior

One way for characterizing the driver state is to treat (3) as a 2nd order dynamical system. The response time t_p and the damping ratio ζ of this 2nd order dynamical system are functions of the two control gains as in the following:

$$t_p = f(c_s, c_v) = \frac{2\pi c_s}{\sqrt{4c_s - c_v^2}} \quad (3)$$

$$\zeta = g(c_s, c_v) = \frac{c_v}{2\sqrt{c_s}}$$

We can know define various driver behavior based on the two functions in (3). Let B_1 depict the normal driving behavior, where it is desired that the transient response of the driver-in-the-loop system in (2) is fast enough but with a bounded damping ratio ζ , i.e.,

$$B_1 = \{(c_s, c_v) \mid t_{\min} \leq f(c_s, c_v) \leq t_{\max} \\ \zeta_{\min} \leq g(c_s, c_v) \leq \zeta_{\max}\} \quad (4)$$

where the involved parameters can be specified as, for example, in the following

$$\begin{aligned} \zeta_{\min} &= 0.5 \\ \zeta_{\max} &= 0.7 \\ t_{\min} &= 0.5 \text{ sec,} \\ t_{\max} &= 1.5 \text{ sec} \end{aligned}$$

Let B_2 depict the aggressive driver behavior, where it is desired that the transient response of the driver-in-the-loop system in (2) is very fast (small t_p) and under-damped such that the system response yields excessive overshoot, i.e.:

$$B_2 = \{(c_s, c_v) \mid f(c_s, c_v) \leq t_{\min} \\ g(c_s, c_v) \leq \zeta_{\min}\} \quad (5)$$

Let B_3 depict the cautious driver behavior, ζ is likely to show a reasonably large value (e.g., greater than 0.7) and a reasonable response time, i.e.:

$$B_3 = \{(c_s, c_v) \mid t_{\max} \leq f(c_s, c_v) \leq \kappa t_{\max} \\ \zeta_{\max} \leq g(c_s, c_v) \leq \kappa \zeta_{\max}\} \quad (6)$$

with a safety factor $\kappa > 1$ (e.g., $\kappa = 2$).

Let B_4 depict an aged driver or a driver with physical limitation, where the transient response of the driver-in-the-loop system (2) is likely to be slow, i.e., t_p might be very large

$$B_4 = \{(c_s, c_v) \mid f(c_s, c_v) > \kappa t_{\max}\} \quad (7)$$

B_1, B_2, B_3 and B_4 can be used to partition the 2-dimensional space of the driver's control gains (c_s, c_v) into different regions. Fig. 3 shows such a partition.

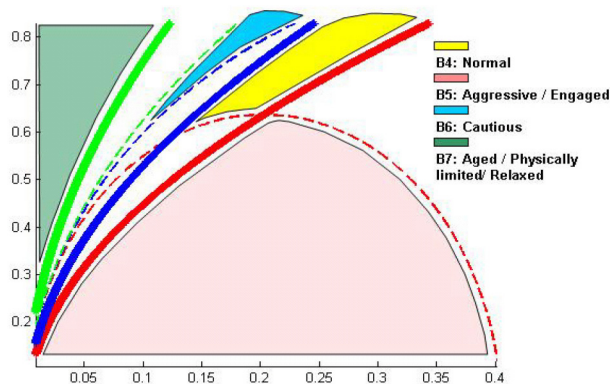


Fig.3. The driver behaviors are defined through partitioned regions in the (c_s, c_v) parameter space

Based on the aforementioned driver behavior characterization that uses the response time and the damping ratio of the driver-in-the-loop vehicle dynamics, the driver behavior identification boils down to the determination of the control gains c_{si} and c_{vi} in real-time.

Let's use the moving averages of the relative distance and velocity as the desired ones, then the target variables. $\bar{\mu}_k$ and $\bar{\rho}_k$ in (2) and (3) can be approximated as in the following

$$\begin{bmatrix} \mu_k \\ \rho_k \end{bmatrix} = (1 - \alpha) \begin{bmatrix} \mu_{k-1} \\ \rho_{k-1} \end{bmatrix} + \alpha \begin{bmatrix} s_k \\ v_k \end{bmatrix} \quad (8)$$

where α is a positive parameter less than 1 which reflects the low-pass filtering structure that can determine the moving averages of the involved relative gap and velocity with respect to the leading vehicle. α is usually varying with driver or driver behavior, but in this paper, its value is pre-defined. In the future, α is learned with the driver behavior.

We should note that the identification of the two control gains c_{si} and c_{vi} cannot be separated from the estimation of the time delay λ , hence the simultaneous estimation of those 3 parameters from the following equation:

$$a_{k+\lambda} = c_{si}(s_k - \mu_k) + c_{vi}(v_k - \rho_k) \quad (9)$$

is assumed. This estimation task can be formulated as the following nonlinear simultaneous delay and parameter identification problem.

Given N_a measurements $y_k(\lambda) = a_{k+\lambda}$ ($k=1, 2, \dots, N_a$) from the delayed a_k with unknown time delay λ bounded by $\lambda_{\max}$, N_a measured signals s_k and v_k ($k=1, 2, \dots, N_a$), find the scalars λ^* , c_{si}^* , and c_{vi}^* such that the following cost function is minimized:

$$J(\lambda, c_s, c_v) = \frac{1}{N_a - \lambda_{\max}} \sum_{k=1}^{N_a - \lambda_{\max}} [y_k(\lambda) - c_s(s_k - \mu_k) + c_v(v_k - \rho_k)]^2 \quad (10)$$

There is no generic approach to find the global minimum to minimize $J(\lambda, c_s, c_v)$ defined in (10). Considering

$$\min_{\lambda, c_s, c_v} J(\lambda, c_s, c_v) \leq \min_{\lambda} \min_{c_s, c_v} J(\lambda, c_s, c_v) \quad (11)$$

the original problem in (10) can be solved for a local minimum through 2 consecutive minimization problems on the right hand side of (11).

For a given fixed λ , the solutions of the modified optimization Problem

$$\min_{c_s, c_v} J(\lambda, c_s, c_v)$$