An Adaptive Longitudinal Driving Assistance System Based on Driver Characteristics

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An Adaptive Longitudinal Driving Assistance System Based on Driver Characteristics

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***Abstract*—A prototype of a longitudinal driving-assistance system, which is adaptive to driver behavior, is developed. Its functions include adaptive cruise control and forward collision warning/avoidance. The research data came from driver car-following tests in real traffic environments. Based on the data analysis, a driver model imitating the driver's operation is established to generate the desired throttle depression and braking pressure. Algorithms for collision warning and automatic braking activation are designed based on the driver's pedal deflection timing during approach (gap closing). A self-learning algorithm for driver characteristics is proposed based on the recursive least-square method with a forgetting factor. Using this algorithm, the parameters of the driver model can be identified from the data in the manual operation phase, and the identification result is applied during the automatic control phase in real time. A test bed with an electronic throttle and an electrohydraulic brake actuator is developed for system validation. The experimental results show that the self-learning algorithm is effective and that the system can, to some extent, adapt to individual characteristics.**

***Index Terms*—Car following, driver characteristics, driving-assistance systems, self-learning algorithm.**

I. Introduction

WITH THE rapid increase in traffic, car following has become the most frequent driving scenario. In the vehicle active safety field, several types of driving assistance systems have been developed for the car-following scenario, such as Adaptive Cruise Control (ACC) [1], Stop & Go (S&G) [2], [3], and Forward Collision Warning/Avoidance (FCW/FCA) [4]–[6]. The objectives are to assist the driver to maintain a safe and comfortable car-following state, to mitigate his/her workload, to reduce traffic accidents, and to increase traffic flow. Although some of these assistance systems are available on the market [7], [8], their performance is still not good enough. The development of new driving-assistance systems needs to face some crucial technical problems, as well as the consequences of the interaction with driver activity [9]. One reason is that driver characteristics vary, which are reflected in the desired distance (time) headway (from very conservative to very aggressive) [10]. The type of assistance that a driver needs in different traffic situations largely depends on the driver. In addition, transferring advanced driving-assistance system (ADAS) technology from one culture to another can be problematic. It is important that the systems take into account local information, particularly infrastructure and driving behavior [11]. Because of the disharmony or adverse interaction between the driver and assistance systems in some situations, the driver has poor acceptance of the systems [12]. To achieve the best interaction of the human driver and the ADAS, longitudinal driving behavior modeling during car following is essential for system development.

Since the pioneering theoretical study in human driver behaviors by Gibson and Crooks in 1938 [13], many researchers have contributed to driver behavior modeling [14]–[17]. The classical methods use mathematical models to represent the relationships between the state variables of the host vehicle (speed, acceleration, relative speed, and distance headway), such as the Gazis Herman Rothery [18] or Gipps models [19]. Michon critically reviewed driver behavior models of the past 20 years [20]. The author pointed out that driver behavior modeling had not kept up with the rather drastic and fundamental change that psychological research had undergone. The model developed before was weak in one or more of the following respects: they were generally bottom-up, incapable of learning, or, if they contained top-down elements, they did not specify the processes involved and, consequently, could not be validated. They also did not specify the structure of the internal models that drivers must hold in their minds or their feedback circuits, or, if they did, they tended to be simplistic. Those models can be used in vehicle system control, but as the required outputs of the models are the desired vehicle motion states, complicated vehicle dynamics are necessary to calculate the desired throttle fuel rate and braking pressure. Simpler vehicle dynamics models were proposed by Fong and Smith [21] to imitate the driver's throttle and braking operations. However, most parameters of the models were fixed for reflecting the average driver characteristics, and they cannot automatically adapt to different drivers. Therefore, driver models should be improved to adapt to different driver characteristics.

During 1990s, this topic was extensively studied. Neural network learning and fuzzy reasoning were applied in driver behavior modeling as in the survey paper by Ghazi Zadeh *et al.* [22]. The driver models reviewed included automatic lateral and longitudinal guidance and control. Several driver models

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in the survey were for autonomous vehicle following. For example, Germann and Isermann proposed intelligent cruise control based on fuzzy logic and neural networks with a three-layer structure [23]. Kehtarnavaz *et al.* presented a neural-network module for autonomous vehicle following without vehicle dynamics involved [24]. Brackstone and McDonald made a historical review of car-following models and their validations. The review briefly assessed the options in the choice of car-following models and their complications [25]. Those artificial intelligence methods (with capabilities of approximation, generalization, and self-learning) were suitable for modeling driver behavior with nonlinear characteristics. The research showed that artificial intelligence could offer some potential advantages in driver behavior analysis and modeling. However, those algorithms were generally complex, requiring much computational load and processor time. In addition, system stability needed further evaluation.

Entering the 21st century, more and more research on driver behavior has been conducted, and new results have been obtained. Toledo proposed an integrated driving behavior model with both lane changing and acceleration based on the concepts of short-term goal and plan [26]. Information on the longitudinal distance and the lateral displacement between cars, and the yaw angle of the car played central roles in the determination of the threat threshold [27]. Li *et al.* built a car-following model with vehicle speed-dependent control gains. To more accurately and concisely model the driver characteristics, a sensitivity-to-velocity-error/sensitivity-to-distance-error-based linear car-following model was built, and a nonlinear optimization algorithm was adopted to identify the model parameters [28]. Raksincharoensak *et al.* described an integrated driver behavior model, particularly in longitudinal driver–vehicle dynamics, for an ADAS design embedded with individual adaptation technology. Statistical machine learning of an integrated driver–vehicle–environment system model based on the driving database was conducted by a discriminative modeling approach [29].

In recent years, several FCW/CA and ACC algorithms considering driver behavior have been developed. Fancher *et al.* developed an assistance system with both ACC and FCW functions, which was knowledge, rule, and skill based and was related to driver psychological behaviors [30]. The conceptual, theoretical, and experimental results illustrated how ideas from psychology of human factors, vehicle dynamics, and control technologies could be melded into the design of human-centered driver assistance systems. However, the warning thresholds were fixed and adjusted by the driver. The parameters of driver behavior were identified based on lump sum experimental data, which could not be obtained online. Nakaoka *et al.* [31] proposed an FCW algorithm, which was based on road friction coefficients and driver characteristics. The warning threshold was determined from time to collision. The authors pointed out that the individual driver parameters in a future model would be determined from the analysis of normal driving data. The effectiveness of such a situation-adaptive forward collision avoidance system would be verified by real-world driving experiments. Simonelli *et al.* [32] proposed an ACC model with humanlike driving capabilities based on a neural network approach that was intended to assist drivers under safe car-following conditions by providing feasibility indications. The trajectory-based estimation required significant computational time (several minutes), which was not suitable for real-time learning. Although the efforts of improving ADAS performance and acceptability are being carried on by many researchers [33], [34], challenges in adapting to individual driver behavior remain.

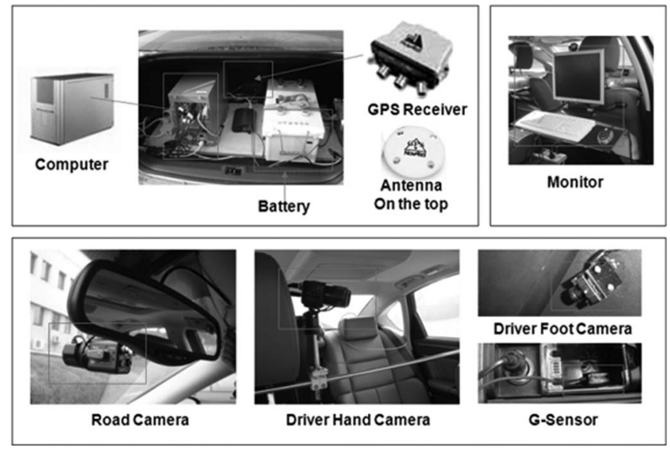

Fig. 1. Installation of data collection system.

Several studies on longitudinal ADAS performance testing and evaluation have been conducted with simulations and field operational tests (FOTs) [35]–[37]. Studies showed that ACC could have a positive impact on traffic safety [38] and flow [39]. However, there are potential problems since the task of driving an ordinary vehicle changes when handling a partially automated vehicle. Other studies showed the negative effects of ACC with changes in driving performance such as increased lane position variability [40] and delay in braking [41]. Therefore, *how* to minimize the potential for "negative" behavioral adaptation and how to maximize system usability and user acceptance [42] were recognized as increasingly important. There is still large space for system performance improvement in driver behavior learning and adaptation [43].

In this paper, a driver model is proposed to imitate the throttle and braking operations based on results from driver test data in traffic. A generic model has been established with a set of parameters to capture individual driver characteristics. A recursive least-square (RLS) self-learning algorithm has been developed for determining the model parameters. Using this algorithm, the parameters can be identified in real time from the data sequences collected during the manual driving mode. The identified model can then be fed into the control in automatic driving mode. The driver model and the self-learning algorithm are implemented in a driving simulation platform [44] and an instrumented vehicle test bed [45]. System functionality has been validated by tests in real traffic.

This paper is organized as follows. Section II presents driver behavior test and characteristics analysis, Section III is for control strategy design based on driver behavior, Section IV presents the self-learning algorithm for online model identification, Section V presents algorithm validation and system verification with the test bed, and Sections VI and VII are devoted to discussions and conclusions, respectively.

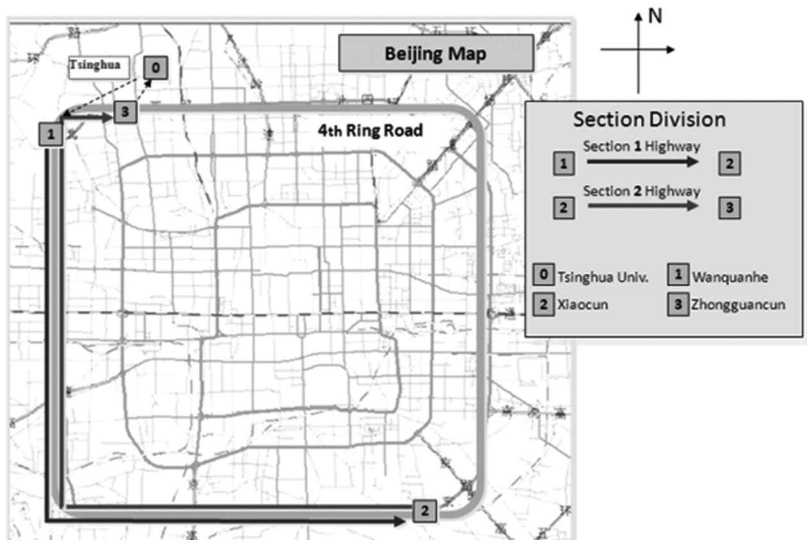

Fig. 2. Map of experimental route.

TABLE I
AGE AND YEARS OF DRIVING EXPERIENCE STATISTICS

Parameters	Age	Years of driving experience
Mean	44.78	17.25
Std. Dev.	9.49	7.67
Max	63.00	38.00
Min	27.00	4.00

II. DRIVER BEHAVIOR TEST AND CHARACTERISTICS ANALYSIS

A. Driver Behavior Test in Real Traffic

To investigate essential driver characteristics and establish a relevant database, driver behavior tests in real traffic environments have been conducted. A data collection system was developed and installed on a passenger car to collect signals, which included vehicle speed, acceleration, accelerator pedal/throttle depression, brake pressure, relative distance/speed to lead vehicle, and Global Positioning System information. The data collection frequency is 10 Hz. The data collection system is shown in Fig. 1. Thirty three drivers were invited, with each driving on an urban four-lane highway for more than 60 km. Fig. 2 shows the experimental route.

Table I shows the statistics of age and the years of driving experience. The recruited drivers included 26 males and seven females. For each new participant, the staff gave instructions on the operation procedures and the route. The drivers then took a trial of the instrumented vehicle on the roads for about 30 min. All the tests started at the same time of day with clear weather. During the experiment, the drivers were directed to drive according to their own styles and habits. The highest traffic volume was about 2400 vehicle/h. Even though traffic conditions differed for the participants, car following was always the most frequent scenario (with 90% on average) in those tests.

B. Driver Characteristics Analysis

The data sequences of two major types of driver behaviors were extracted from the test data: steady car following and approaching. The former corresponds to the ACC function, which is defined as the host vehicle following a fixed leading vehicle for more than 15 s without changing lanes. The total time of steady car-following data sequences is 14 116 s, with an average speed of 18.37 m/s and a standard deviation at 2.83 m/s. The latter corresponds to the FCW/FCA function, which is defined as the host speed to be larger than the leading vehicle for more than 5 s. The total number of times that drivers released the accelerator pedal and braked in approaching scenarios was 395 and 169, respectively.

Time headway (THW) and time to collision (TTC) are regarded as two critical variables to reflect the relative motion between the host vehicle and the leading vehicle, which have been used in the analysis of driving behavior and longitudinal driver assistance system control [30], [33]. These two variables are also used similarly in the data analysis in this paper: THW and TTC, with its inverse $TTCi$, are defined as

$$THW = \frac{D}{v} \tag{1}$$

$$TTC = \frac{D}{v_r}, \quad TTCi = \frac{v_r}{D}. \tag{2}$$

Here, D is the relative distance between the host vehicle and the leading vehicle, v is the speed of the host vehicle, and v_r is the host vehicle's relative speed to the leading vehicle.

Fig. 3 shows an example of THW frequency and $TTCi$ contour for one of the drivers in the car-following scenario on the highway. It can be observed that the THW and $TTCi$ concentrate in a certain area but vary with respect to time during driving.

In practice, noise and error for sensor measurement of speed and distance always exist. The Kalman filter is used to process the signals, and Fig. 4 shows some of the results before and after filtering.

The scale and errors of necessary parameters are listed in Table II. It is illuminated in [46] and [47] how to get those signals.

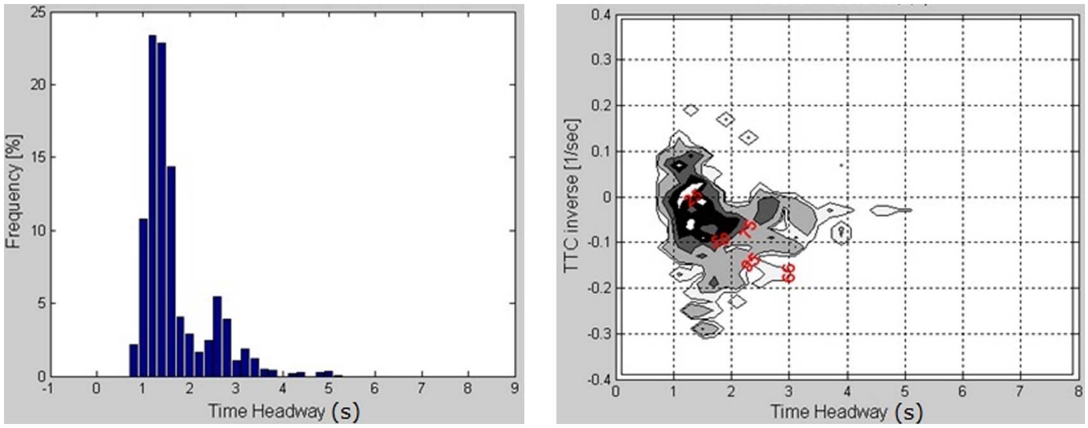

Fig. 3. (Left) THW frequency distribution. (Right) THW frequency contour and $TTCi$.

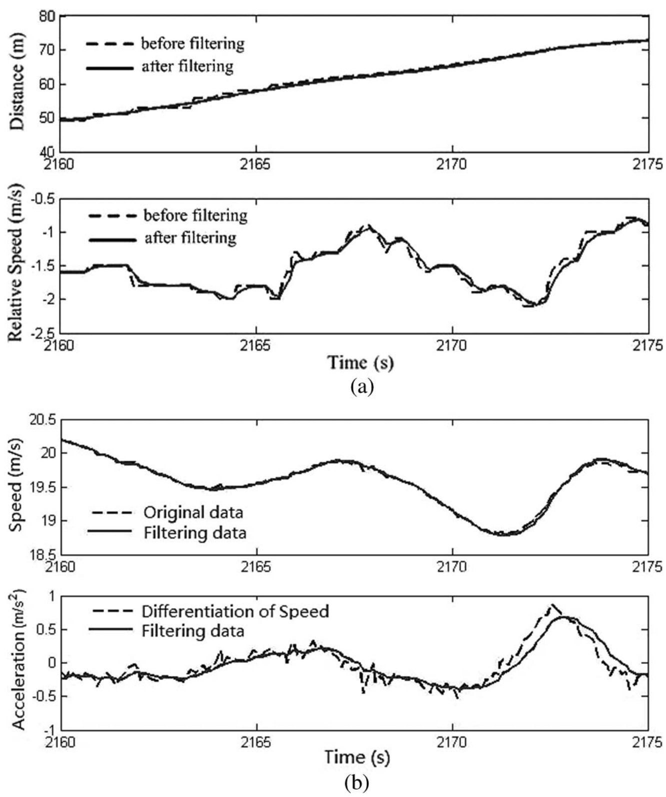

Fig. 4. Experimental data before and after processing. (a) Distance and relative speed. (b) Speed and acceleration.

TABLE II
DATA STATISTICS OF DRIVER MODEL PARAMETERS

Signal	Distance	Relative Speed	Vehicle Speed	Brake Pressure	Throttle Angle
Scale	2-180 (m)	-56-28 (m/s)	0-58 (m/s)	0-20 (MPa)	0-100 (%)
Error	0.5 (m)	0.3 (m/s)	0.3 (m/s)	1 (%)	0.5 (%)

The frequency contour [45] of steady car following THW and $TTCi$ was used to indicate the driver's car-following characteristics, and the statistical results of all drivers are shown in Fig. 5. The numbers on area borders (25%, 50%, 75%, 95%, and 99%) represent the percentages of the data points inside relevant borders. It is clear that 50% of the data distribute in

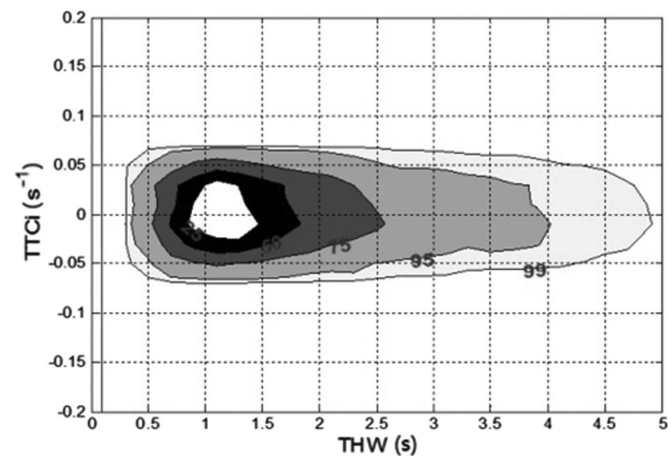

Fig. 5. Frequency contour of THW and $TTCi$ during steady car following.

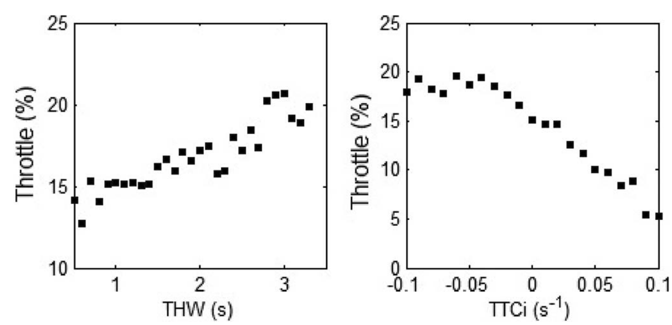

Fig. 6. Relationships between throttle and vehicle states.

a relatively concentrated area. According to this phenomenon, one could draw the conclusion that drivers prefer to keep THW and $TTCi$ around some specific values and that those two variables could be considered as the driver control targets in driver modeling for the car-following scenarios. More analysis results of driver behavior were presented by Wang *et al.* [49], [50].

Based on this observation, the mean values of THW and $TTCi$ (1.43 s and 0 s^{-1}) during steady car following are considered as the preferred control targets. The throttle depression (mean value) at different THW levels (or $TTCi$) when $TTCi$ (or THW) reaches the target value are shown in Fig. 6. The results indicate that the relationships between driver operation and vehicle states are linearly correlated.

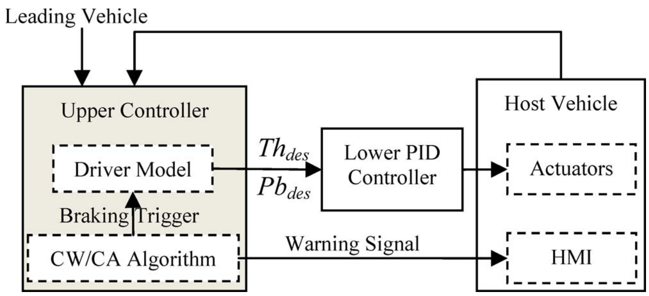

Fig. 7. Control strategy of the driving-assistance system.

III. System Control Strategy

A. Overall Structure of Control Strategy

The overall structure of the control strategy for the ADAS is shown in Fig. 7. The upper controller imitates the driver's operation and comprises two parts: 1) a driver model for desired control variable generation and 2) an FCW/FCA algorithm for system warning and automatic braking activation. The inputs of the upper controller are the motion states of the leading vehicle and the host vehicle, and the outputs include the desired throttle depression Th_{des}, desired brake pressure Pb_{des}, and warning signal. The lower controller makes the actuators follow the desired control variables with a proportion–integral–differential control algorithm. The human–machine interface (HMI) sends acoustic and visual warning signals to the driver.

B. Driver Model

According to the analysis of steady car-following behavior, it is recognized that the driver desires to obtain THW in his/her preferred range and $TTCi$ around zero. This control target is observed as a linear function of throttle/brake pedal deflection. Furthermore, if THW and $TTCi$ reach the desired values and the leading vehicle is in constant speed, the driver will maintain the current speed. Based on this analysis, a driver model is proposed as follows:

$$P_{\text{des}}(t) = Th_{\text{ss}}(t) + K_{\text{THW}} \cdot [THW(t) - THW_d] + C_{TTCi} \cdot TTCi(t) \quad (3)$$

where $P_{\text{des}}(t)$ is the generalized depression at time t (in percentage); $Th_{\text{ss}}(t)$ is the steady throttle depression to keep the current host vehicle speed $v(t)$ (in percentage); THW_d is the desired time headway; and K_{THW} and C_{TTCi} are the error gains of THW and $TTCi$, respectively.

The nonlinear relationship between Th_{ss} and v is described as a lookup table. An interpolation method is used for Th_{ss} calculation based on the experimental calibration. The desired control variables Th_{des} (in percentage) and Pb_{des} (in megapascals) are calculated according to the value of the generalized depression P_{des}. When $P_{\text{des}}(t) > P_{\max}$,

$$Th_{\text{des}}(t) = P_{\max}, \quad Pb_{\text{des}}(t) = 0. \quad (4)$$

If $P_{\max} \geq P_{\text{des}}(t) > P_{\text{idle}}$, then

$$Th_{\text{des}}(t) = P_{\text{des}}(t), \quad Pb_{\text{des}}(t) = 0. \quad (5)$$

Considering the operation delay in switching between the accelerator and brake pedals, the braking control is not immediately activated when $P_{\text{des}}(t)$ falls below the idle-speed depression P_{idle}. When $P_{\text{idle}} \geq P_{\text{des}}(t) > P_{\min}$, the engine speed drops to idle and stays there. Meanwhile, the braking is not activated, i.e.,

$$Th_{\text{des}}(t) = P_{\text{idle}}, \quad Pb_{\text{des}}(t) = 0. \quad (6)$$

When $P_{\text{des}}(t) \leq P_{\min}$, the system will activate braking, i.e.,

$$Th_{\text{des}}(t) = P_{\text{idle}}, \quad Pb_{\text{des}}(t) = B_{pb} \cdot [P_{\text{des}}(t) - P_{\min}]. \quad (7)$$

$P_{\max}$ is set to 60%, $P_{\min}$ to 10%, and P_{idle} to 15%. B_{pb} is the gain from P_{des} to Pb_{des}, and the maximal value of Pb_{des} is 10 MPa.

According to this driver model, the desired throttle depression and desired brake pressure can be obtained by directly imitating the driver's operation, without considering the complicated vehicle dynamics.

C. FCW/FCA Algorithm

The FCW/FCA algorithm of this system is designed based on TTC and the output Pb_{des} of the driver model. During the manual mode, the system estimates real-time TTC and the desired brake pressure Pb_{des} and collects the driver's brake pedal action B ($B = 1$: brake on; $B = 0$: brake off). Based on these signals, four warning/braking logics are designed.

1) ***No warning and no automatic braking***. In this case, TTC is larger than threshold W_0, or the driver is braking, i.e.,

$$\text{IF } TTC > W_0 \text{ or } B = 1, \text{ THEN } C_W = 0 \,\&\, C_B = 0 \quad (8)$$

where C_w is the warning level, and C_B is the braking level.

2) ***System warning at level 1 without automatic braking.*** In this case, TTC is between W_0 and W_1, and the driver is not braking, i.e.,

$$\text{IF } W_0 \geq TTC > W_1 \,\&\, B = 0, \text{ THEN } C_W = 1 \,\&\, C_B = 0. \quad (9)$$

3) ***System warning at level 2 without automatic braking***. This is the case when TTC decreases, the collision risk increases, and the system generates an emergency warning signal (warning level 2), but the automatic braking is not activated if the desired brake pressure is zero. That is

$$\text{IF } TTC \leq W_1 \,\&\, B = 0 \,\&\, Pb_{\text{des}} = 0 \quad \text{THEN } C_W = 2 \,\&\, C_B = 0. \quad (10)$$

4) ***System warning at level 2 with automatic braking***. If the driver does not respond to the warning $(B = 0)$ and the system decides to brake $(Pb_{\text{des}} > 0)$, automatic braking will be activated, i.e.,

$$\text{IF } TTC \leq W_1 \,\&\, B = 0 \,\&\, Pb_{\text{des}} > 0 \quad \text{THEN } C_W = 2 \,\&\, C_B = 1. \quad (11)$$

During the system's warning or automatic braking, if the driver recognizes the system's action and starts to manually

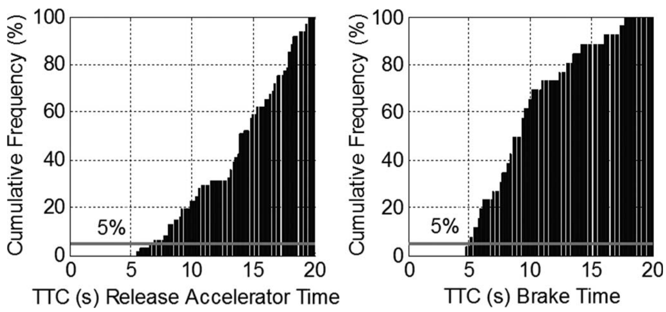

Fig. 8. Cumulative frequency of TTC values for driver operation.

brake, the system will return to state 1. That is

$$\text{IF } B = 1, \text{ THEN } C_W = 0 \,\&\, C_B = 0. \tag{12}$$

Thresholds W_0 and W_1 were obtained from the statistics of the driver's accelerator pedal release and brake pedal activation during approach, respectively.

Fig. 8 shows the cumulative frequency of TTC values for driver operation. The data are collected from all driver-approaching behaviors. The TTC values at a frequency of 5% are selected as the thresholds because the FCW/FCA system is used mostly in emergency situations. Threshold W_0 of warning level 1 is 6.6 s, and W_1 of warning level 2 is 5.1 s.

IV. Self-Learning Algorithm of Driver Behavior

In this driver model, parameter THW_d represents the driver's preferred following distance at a specific vehicle speed and reflects his/her degree of aggression. Parameters K_{THW} and C_{TTCi} represent the driver's sensitivity to THW error and $TTCi$ error. To improve the system's adaptability to individual driver characteristics, a self-learning algorithm based on the RLS method is proposed. The core idea of this algorithm is to identify the model parameters from car following in manual mode and to apply the identified model in automatic control mode. It is assumed that the latest data of driver operation more accurately represent the driver characteristics. Therefore, a forgetting factor is introduced in the algorithm.

After the system initialization, data of distance D, relative speed v_r, host vehicle speed v, and throttle depression Th are collected. In manual mode, the algorithm starts the cycle to determine whether the vehicle is in steady car-following state and then identifies the model parameters at each time step with an update rate of 0.1s. Parameters THW_d, K_{THW}, and C_{TTCi} are identified from a steady car-following data sequence similarly.

It is assumed that the lead vehicle remains the only target (no cut-in and cut-out) that is judged from the measured distance signal. Furthermore, the driver is not controlling the brake system. At step k

$$\begin{cases} \Delta D = |D(k) - D(k-1)| < 5 \text{ m} \\ B(k) = 0. \end{cases} \tag{13}$$

If the first condition is satisfied, the algorithm will use the current data $D(k)$, $v_r(k)$, $v(k)$, and $Th(k)$ to start the iteration process of the RLS method.

TABLE III
Data Statistics of Driver Model Parameters

	Mean	Std	Max	Min	25%	75%
THW_d	1.8	3.2	56.5	0.2	0.9	2.3
K_{THW}	44.3	50.7	408.3	0.1	6.0	95.0
C_{TTCi}	-157.3	129.4	-1.0	-842.7	-20.0	-300.0

The observation vector of the process is

$$\mathbf{h}^T(k) = \left[\frac{D(k)}{v(k)}, -1, \frac{v_r(k)}{D(k)}\right]. \tag{14}$$

The output of the process is

$$z(k) = Th(k) - Th_{\text{ss}}(k) \tag{15}$$

where $Th_{\text{ss}}(k)$ is the current steady throttle, which can be interpolated with $v(k)$.

According to the standard linear square form, the parameter vector $\hat{\theta}(k)$ to be identified in this process can be derived from the driver model (3), i.e.,

$$\begin{aligned} \hat{\boldsymbol{\theta}}(k) &= \left[\hat{\theta}_1(k), \hat{\theta}_2(k), \hat{\theta}_3(k)\right]^T \\ &= \left[K_{\text{THW}}(k), K_{\text{THW}}(k) \cdot THW_d(k), C_{TTCi}(k)\right]^T. \end{aligned} \tag{16}$$

The following equations show the iteration algorithm of the RLS method, i.e.,

$$\hat{\boldsymbol{\theta}}(k) = \hat{\boldsymbol{\theta}}(k-1) + \boldsymbol{K}(k)\left(z(k) - \boldsymbol{h}^T(k)\hat{\boldsymbol{\theta}}(k-1)\right) \tag{17}$$

$$\boldsymbol{K}(k) = \boldsymbol{Q}(k-1)\boldsymbol{h}(k)\left(\boldsymbol{h}^T(k)\boldsymbol{Q}(k-1)\boldsymbol{h}(k) + 1\right)^{-1} \tag{18}$$

$$\boldsymbol{Q}(k) = \frac{1}{\mu}\left(\boldsymbol{I} - \boldsymbol{K}(k)\boldsymbol{h}^T(k)\right)\boldsymbol{Q}(k-1) \tag{19}$$

where $\boldsymbol{K}(k)$ and $\boldsymbol{Q}(k)$ are process matrices, and μ is a forgetting factor of value 0.9. The identified parameter vector of the driver model in this step is $\boldsymbol{P}_t(k)$, which is given by

$$\begin{aligned} \boldsymbol{P}_t(k) &= \left[THW_d(k), K_{\text{THW}}(k), C_{TTCi}(k)\right]^T \\ &= \left[\hat{\theta}_2(k)/\hat{\theta}_1(k), \hat{\theta}_1(k), \hat{\theta}_3(k)\right]^T. \end{aligned} \tag{20}$$

After obtaining $\boldsymbol{P}_t(k)$, the second condition is that the parameters should be in proper ranges. These ranges are provided by the statistical results of the driver steady car-following data sequences in real traffic with the linear square method, which is shown in Table III. The proper range of each parameter is selected as its 25%–75% accumulation frequency.

When the identified $\boldsymbol{P}_t(k)$ is in the proper ranges, the parameters will be inspected by the third condition to judge if the identified result tends to be steady, corresponding to the following:

$$\Delta_m = \max\left(\Delta_{\text{THW}}(k), \Delta_K(k), \Delta_C(k)\right) < \varepsilon \tag{21}$$

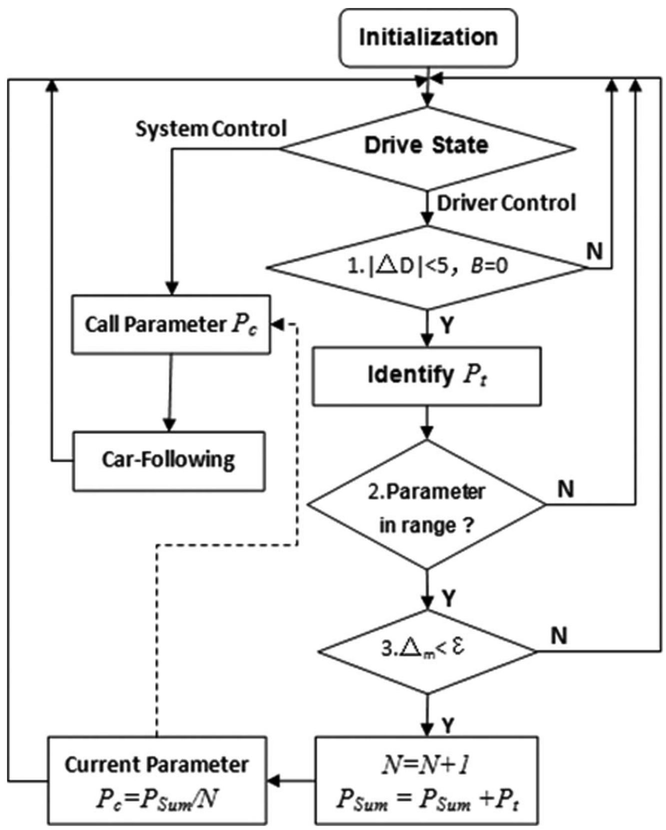

Fig. 9. Flowchart of the self-learning algorithm.

where

$$\Delta_{\mathrm{THW}}(k) = \left|\frac{THW_d(k) - THW_d(k-1)}{THW_d(k)}\right| \tag{22}$$

$$\Delta_K(k) = \left|\frac{K_{\mathrm{THW}}(k) - K_{\mathrm{THW}}(k-1)}{K_{\mathrm{THW}}(k)}\right| \tag{23}$$

$$\Delta_C(k) = \left|\frac{C_{TTCi}(k) - C_{TTCi}(k-1)}{C_{TTCi}(k)}\right|. \tag{24}$$

ε is a threshold, which is set to be 0.5% in this algorithm.

Because the driver state is time varying, the identified parameters are always fluctuating. To find the parameters describing the driver characteristics as accurately as possible, the following accumulation method is used:

$$\boldsymbol{P}_{\mathrm{sum}} = \boldsymbol{P}_{\mathrm{sum}} + \boldsymbol{P}_t(k). \tag{25}$$

All available parameter values satisfying the conditions are accumulated to $\boldsymbol{P}_{\mathrm{sum}}$, and when the driving state is switched to automatic mode and the current parameter vector $\boldsymbol{P}_c$ is transferred to the driver model:

$$\boldsymbol{P}_c = \frac{\boldsymbol{P}_{\mathrm{sum}}}{N} \tag{26}$$

where N is the number of available parameter values.

The flowchart of the self-learning algorithm is shown in Fig. 9. The algorithm accumulates more identified results from manual operation, and the learning effect is progressively improving as time evolves. The driver model will approach the average characteristics of the driver. During the learning process, if any of the three conditions are not satisfied, the iteration will be stopped, and the current $\boldsymbol{P}_{\mathrm{sum}}$ and N will be held. Until new proper parameters are identified, the accumulation will continue. Similarly, parameter B_{pb} can be identified from a driver braking data sequence.

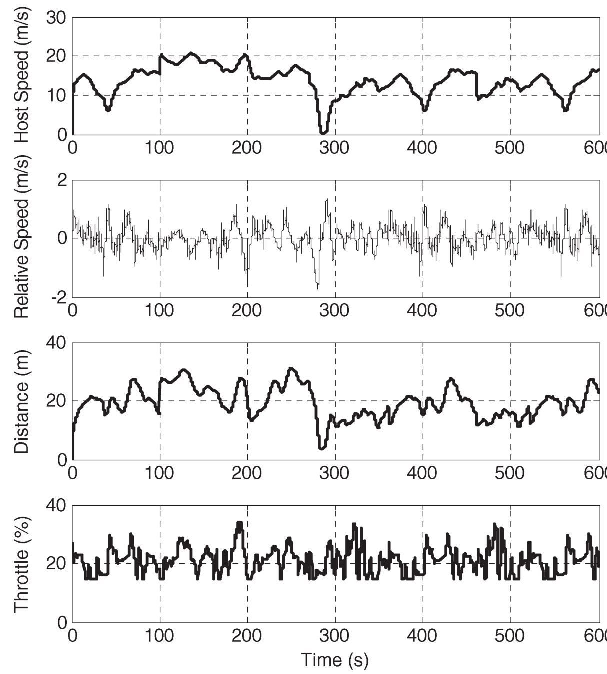

Fig. 10. Data sequence of driver manual car following.

V. DRIVING-ASSISTANCE SYSTEM TEST BED AND SYSTEM VERIFICATION EXPERIMENTS

A. Driving-Assistance System Test Bed

A passenger car test bed is developed to verify that the system functions and includes driver characteristics self-learning, ACC, and FCW/FCA. A millimeter-wave radar with controller area network (CAN) port is used to measure the relative distance and speed with respect to the leading vehicle. The system electronic control unit (ECU) is developed with a 16-bit microcontroller to implement signal collection, controller calculation, and actuator activation. The original electronic throttle system on the vehicle is modified and controlled by the ECU with digital-to-analog output. An electrohydraulic brake (EHB) actuator is added to the original brake system. The ECU also controls the motor and electromagnetic valves of the EHB actuator with pulsewidth modulation interface. A human–machine interface with touch-screen monitor is developed using embedded technology and installed on the cockpit. The radar, ECU and HMI are linked through vehicle CAN bus.

B. System Verification Experiments

During the self-learning algorithm verification experiment, one of the drivers in Fig. 4 drives the test vehicle in real traffic, and the self-learning algorithm runs online to identify the model parameters. The parameter identification test continues for 600 s to make the results closer to the driver's average characteristics as much as possible. Fig. 10 shows the driver manual operation data sequence with a specified lead vehicle followed.

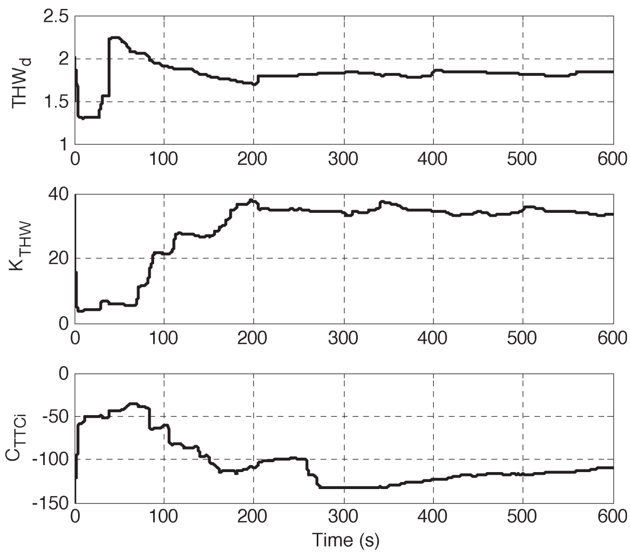

Fig. 11. Driver model parameter online identification result.

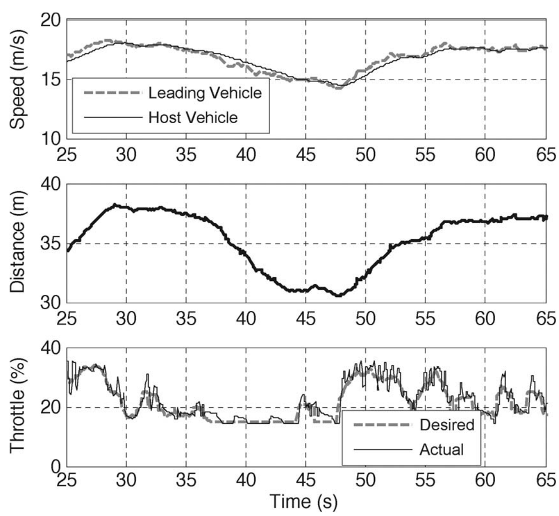

Fig. 12. Performance of the system ACC function.

Fig. 11 shows the parameter identification process from this data sequence. It indicates that the algorithm is effective and that the parameters tend to gradually stabilize after some initial fluctuation. At the end of the test, the final identification results are $THW_d = 1.84$, $K_{\mathrm{THW}} = 33.5$, and $C_{TTCi} = -109.5$.

Fig. 12 shows a data sequence of car following in ACC mode using these identified parameters. The system can steadily track the leading vehicle's speed while keeping a safe distance. The control performances of both upper and lower controllers are favorable.

For further validation of the self-learning algorithm, more experiments of the longitudinal ADAS verification have been conducted in real traffic. The comparison with a typical ACC with fixed-parameter LQ controller (named "Typical ACC") was analyzed. The experimental flow for each driver is given here.

1) The driver freely drove for 1 h with ADAS off, which was used as the baseline for system evaluation.

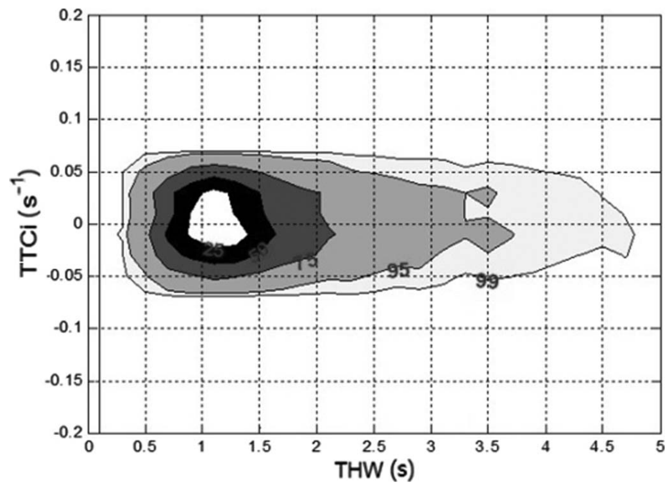

Fig. 13. Frequency contour of THW and $TTCi$ during system control.

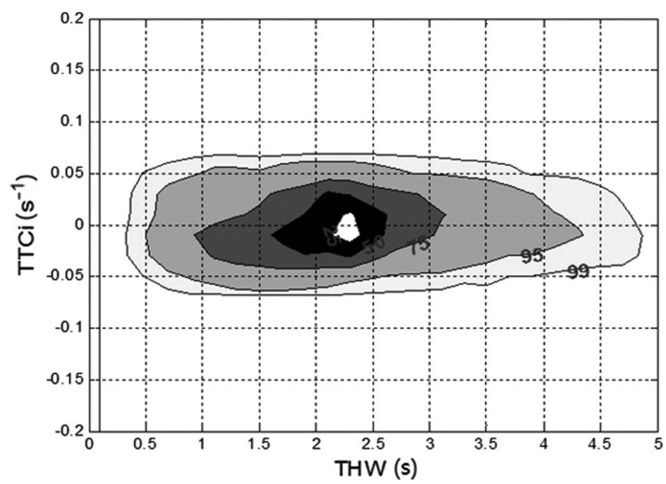

Fig. 14. Frequency contour of THW and $TTCi$ during typical ACC control.

2) The driver drove in ACC mode with both the self-learning algorithm (named "Self-learning ACC") and FCW/FCA on.
3) Finally, every participant would finish a questionnaire after the experiment. The questions included subjective feelings of the systems, attitude toward ADAS functioning, and self-driving style [50].

The system performance is analyzed with $THW - TTCi$ frequency contour. The result of all drivers' average data with self-learning ACC on is shown in Fig. 13. The comparison with Fig. 5 indicates that the overall data distributions (99% percentile) of the system and the driver are similar. Furthermore, the 50% and 75% areas of system performance are more centralized than the driver. This result indicates that the THW and $TTCi$ fluctuations during system control state are much smaller and that the ADAS is more stable than manual control.

Fig. 14 shows the $THW - TTCi$ frequency contour of the Typical ACC system. Compared with Fig. 5, it is observed that the typical distribution of the ACC system is the most concentrated because of fixed system parameters. However, Fig. 13 matches Fig. 5 better than Fig. 14, which indicates that the system presented in this paper is closer to the driver characteristics.

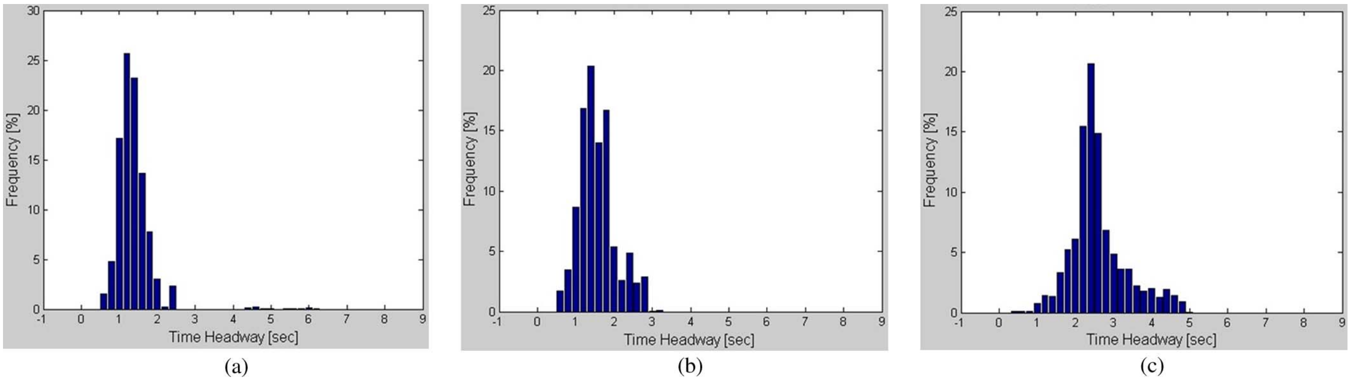

Fig. 15. THW frequency of Driver 1. (a) System off. (b) Self-learning ACC on. (c) Typical ACC on.

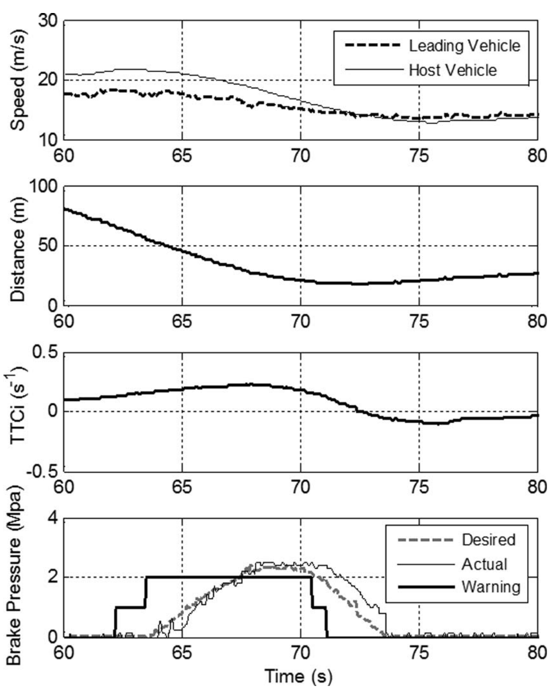

Fig. 16. Performance of the system FCW/FCA function.

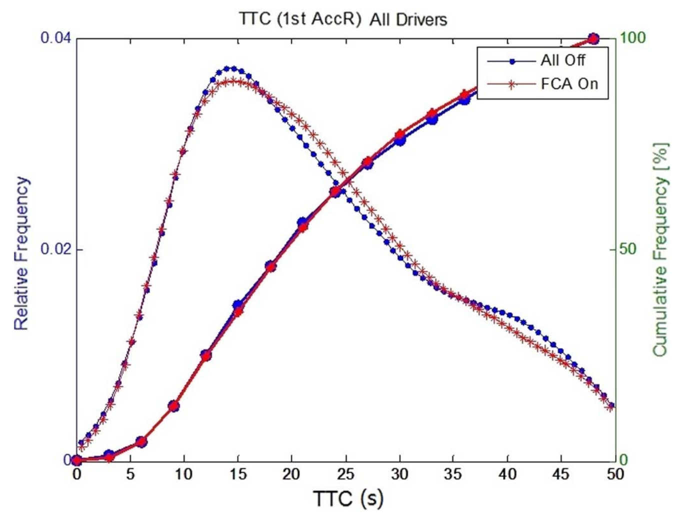

Fig. 17. TTC distributions at acceleration pedal release.

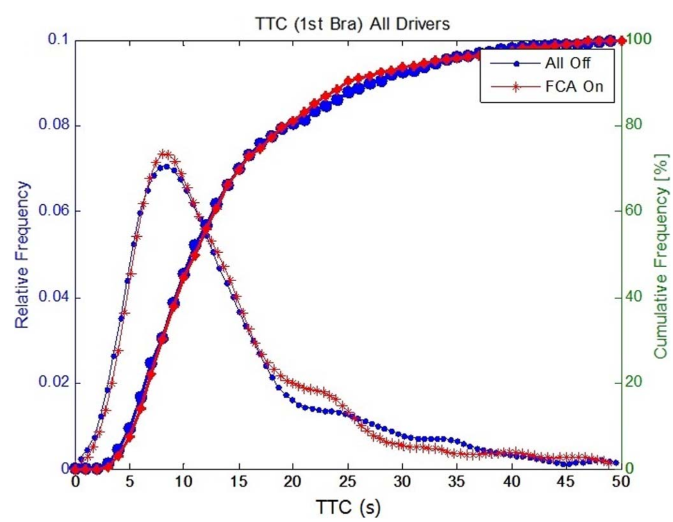

Fig. 18. TTC distributions at brake pedal action.

Fig. 15 shows the comparison of TTC distribution of one driver with ADAS off, Self-learning ACC on, and Typical ACC on. It can be observed that the TTC distribution with Self-learning ACC on matches naturalistic driving better than with Typical ACC on.

The performance of the FCW/FCA system is also verified on this test bed with the results shown in Fig. 16. When the driver controls the host vehicle in approaching the lead vehicle, TTC decreases ($TTCi$ increases), and level-1 and level-2 warning signals and automatic braking are appropriately activated. The level-1 warning signals include beeping and the "Caution" sign on the HMI monitor. The level-2 warning signals include higher frequency beeping and the warning sign on the monitor to attract more driver attention. With $TTCi$ decreasing, the desired brake pressure also drops until the host vehicle safely follows the lead vehicle at the same speed. The actuator timing, magnitude, and rate are all acceptable to the driver. The experimental results have therefore validated the FCW/FCA algorithm.

To understand the influence of ADAS on the driver behavior, the TTC distribution was compared for the event of the first accelerator pedal release (see 1st AccR in Fig. 17) and the first brake pedal action (see 1st Bra in Fig. 18) in vehicle approaching with FCW/FCA on and off, respectively. The figures show that the TTC distributions are similar.

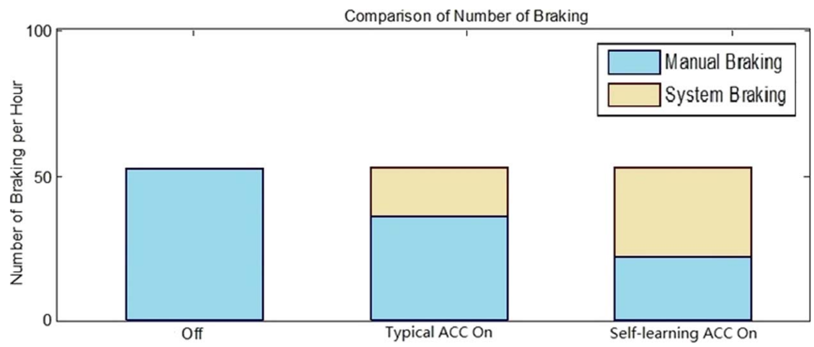

Fig. 19. Comparison of Typical ACC and Self-learning ACC in manual braking.

To evaluate the effectiveness of the new approach, a preliminary comparison has been conducted between Typical ACC and Self-learning ACC using a number of driver interventions. Fig. 19 shows that the number of manual braking over total braking times for Self-learning ACC is less than that for Typical ACC. The acceptability of Self-learning ACC has, therefore, improved to some extent.

VI. Discussion

This paper proposes a self-learning approach to increase driver acceptance of the longitudinal ADAS. The analysis of data from driver tests in real traffic has shown that the expected performance has been improved. However, it is still difficult to accurately and comprehensively mimic or model driver characteristics because of the large variability of drivers' states of mind and the effect of dynamic road and traffic environments. Therefore, for the practical implementation of the proposed algorithm, many questions remain.

1) How could the algorithm accommodate variable driving conditions such as weather and road conditions (rain, snow, or wind)? Driver habits and behaviors vary under different environmental conditions. An important issue is *how to identify* the parameters of driver behavior in real time and make the assistance algorithms adapt to changes in traffic conditions. Possible solutions could include the installation of sensors to detect weather conditions and identify road conditions (such as friction coefficient) and add those parameters to the driver behavior model, so that those factors could be reflected.
2) How much historical data should be used to train the driver model? Because of the difference in driver states of mind and driving conditions, it is difficult to decide how much historical data are appropriate for model training. If the historical data come from the similar driving condition to current, using the data is appropriate. Otherwise, it would be inappropriate. The question is how best to appropriately incorporate historical data in the training process? More experiments and improved modeling may be necessary to address this issue.
3) What is the effect if the ADAS with the self-learning capability is applied in practice? Our experiments were conducted with a small number of drivers to qualitatively validate the algorithm. Experiments with many more drivers in extended periods would be necessary to fully evaluate the system. In particular, it is important to know what positive influences and side effects on driver acceptance, driving comfort, safety, and traffic flow.

VII. Conclusion and Future Work

In this paper, driver tests in real traffic have been conducted, which provide a database for driver behavior analysis and adaptive ADAS design. Based on the analysis of steady car following, THW and $TTCi$ of the driver distribute in a relatively concentrated area. This indicated that these two parameters can be considered as the driver control targets. A linear relationship between the driver operation and vehicle states has been adopted to establish a driver model to imitate driver operations in different modes and the transition in between. With the RLS method, the self-learning ACC and FCW/FCA algorithms for driver characteristics have been proposed to identify the model parameters online from a data sequence of manual operation, which are then used in automatic driving mode. The functions of ACC and FCW/FCA are verified on the test bed, and the results show that the performance of this ADAS with the self-learning approach is, to some extent, capable of adapting to the driver characteristics and has favorable driver acceptance.

Due to the complicated nature of human beings, longitudinal driving behavior is affected by many factors such as driver physical and mental characteristics, vehicle types, and road environment (including road geometry, weather conditions, traffic information, and real-time traffic flow). To further enhance the driver acceptance of ADAS, further research into different vehicle types under different road and traffic conditions will be conducted in the future.

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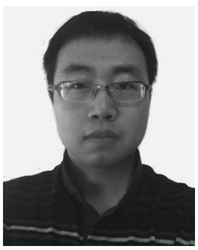

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