An Adaptive Cruise Control System based on Self-Learning Algorithm for Driver Characteristics

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Abstract. An Adaptive Cruise Control system prototype based on self-learning algorithm for driver characteristics is presented. To imitate the driver operations during car-following, a driver model is developed to generate the desired throttle depression and braking pressure. A self-learning algorithm for driver characteristics is proposed based on the Recursive Least Square method with forgetting factor. Using this algorithm, the parameters of the driver model are real-time identified from the data sequences collected during the driver manual operation state, and the identification result is applied during the system automatic control state. The system is verified in a driving assistance system test-bed with electronic throttle and electro-hydraulic brake actuators. The experimental results show that the self-learning algorithm is effective and the system performance is adaptive to driver characteristics.

1 Introduction

With the traffic density increasing rapidly, car-following has become the most frequent driving scenario to the driver. In the vehicle active safety field, several types of driving assistance systems have been actualized for the car-following scenario such as Adaptive Cruise Control (ACC) [1], Stop & Go (S&G) [2] and Forward Collision Warning/Avoidance (FCW/FCA) [3]. The aims of the systems are to facilitate driver to maintain a safe and comfortable car-following state or to mitigate the workload of the driver [4]. Because of the interaction between the driver and the assistance system, the driver behavior and characteristics during car-following have been considered as important issues in system development.

The research on modeling driver behavior in car-following scenario dates back to the 1950s and many types of models were established with different approaches [5]. The classical method is using mathematic functions to represent the relationship between variables like host vehicle speed, acceleration, relative speed and distance headway, such as the Gazis-Herman-Rothery (GHR) model [6], the Gipps model [7] and the linear (Helly) model [8]. These models can be applied to the system control algorithm, but as the required outputs of the models are the desired vehicle motion states, complicated vehicle dynamics model needs to be added. Some models are designed to imitate the driver's throttle and braking operations directly [9]. This method could avoid the vehicle dynamics problem such as the inverse model of vehicle longitudinal

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dynamics. However, the parameters of these models are fixed during system operation and cannot be adaptive to individual driver car-following characteristics.
In this paper, a driver model is proposed to imitate throttle and braking operations of the driver and a self-learning algorithm for driver characteristics is designed based on Recursive Least Square (RLS) method with forgetting factor. Using this algorithm, the parameters of the driver model can be real-time identified from the data sequences collected during manual driving operation state, and the identification result is applied during the system automatic control state. The driver model and the self-learning algorithm are implemented in a driving assistance system test-bed and the functions of the system are validated by tests in real traffic.

2 Driver Behavior Test and Characteristics Analysis

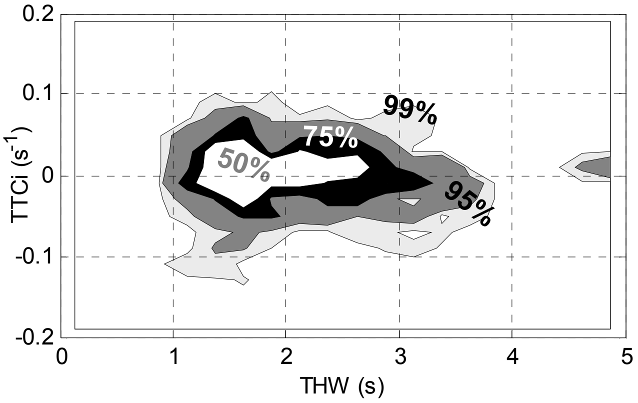
The driver behavior during car-following is a significant factor for the development of driving assistance system. To investigate essential driver characteristics and establish driver behavior database, driver behavior tests in real traffic environment are executed and the signals including host vehicle speed, acceleration, depression of accelerator pedal/throttle, braking pressure, relative distance/speed to leading vehicle, and GPS information are recorded with 10Hz data capture frequency. Thirty drivers are invited as experimental subjects to drive on the city highway for 1 hour per person. The drivers are suggested to drive freely according to their own styles and habits. The data sequences of steady car-following behavior, which corresponds to the ACC function, are extracted from the test data. This behavior is defined as that the driver controls the host vehicle to follow a constant leading vehicle steadily more than 15 seconds without braking and lane-changing. Two common variables are discussed in the data analysis to describe driver characteristics. One is Time Headway (*THW*):

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

The other one is Time-to-Collision (*TTC*, and its inverse *TTCi*):

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

Where: D is the distance between the host vehicle and the leading vehicle; v is the host speed vehicle; and v_r is the host vehicle's relative speed to the leading vehicle. The frequency contour of *THW* and *TTCi* of one driver's steady car-following behavior is shown in Fig 1. The number on each area border (50%, 75%, 95% and 99%) in this figure means the percentage of the data points falling inside this border. It is clear that 50% of *THW* and *TTCi* data distribute in a relatively concentrated area where *THW* is around 1.2s to 2.6s and *TTCi* is around -0.05 to 0.05s^{-1}. This phenomenon indicates that the driver prefers to keep *THW* and *TTCi* in specific ranges, and these two variables can be considered as the driver control targets during car-following for the driver model design.


0.2
0.1
0
-0.1
-0.2
TTCi (s^{-1})
0
1
2
3
4
5
THW (s)
99%
75%
50%
95%

this analysis, a driver model is proposed:

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

Where: $P_{des}(t)$ is generalized depression at time t; $Th_{ss}(t)$ is steady throttle depression to keep the current host vehicle speed $v(t)$; THW_d is the driver's desired time headway; K_{THW} and C_{TTCi} are error gains of THW and $TTCi$ respectively.

Interpolation method is used for Th_{ss} calculation based on the experimental calibration. The desired control variables, Th_{des} and Pb_{des}, are calculated according to the value of the generalized depression p_{des}. The throttle depression for idle-speed is 15. When $p_{des}(t)$ >15:

$$\begin{cases} Th_{des}(t) = p_{des}(t) \\ Pb_{des}(t) = 0 \end{cases} \tag{4}$$

Considering the driver's operation delay at the switching between accelerator and brake pedal, the braking control is not activated immediately when $p_{des}(t)$ falls below the idle-speed depression 15. When 15>= $p_{des}(t)$ >10:

$$\begin{cases} Th_{des}(t) = 15 \\ Pb_{des}(t) = 0 \end{cases} \tag{5}$$

When $p_{des}(t)$ <=10:

$$\begin{cases} Th_{des}(t) = 15 \\ Pb_{des}(t) = B_{pb} \cdot [p_{des}(t) - 10] \end{cases} \tag{6}$$

Where: B_{pb} is the gain from p_{des} to Pb_{des}, whose value is set as -0.1, and the unit of the desired brake pressure Pb_{des} is MPa. The maximal value of Pb_{des} is set as 10MPa.

4 Self -Learning Algorithm for Driver Characteristics

The driver model could describe the driver characteristics and present the individual differences during car-following. The parameter THW_d presents the driver's preferred following distance at same vehicle speed level and reflect his/her aggressive degree. The parameters K_{THW} and C_{TTCi} present the driver's sensitivity of THW error and $TTCi$ error. To improve the system's adaptability of individual driver characteristics, a self-learning algorithm based on Recursive Least Square (RLS) method is proposed. The core idea of this algorithm is to identify the model parameters from the driver manual car-following drive state on-line and apply the identification result to the model during system automatic driver state. Because of the time-variability of the driver, it is supposed that the latest data of driver operation will describe the driver characteristics more accurately and therefore, forgetting factor is brought into the algorithm. The flow chart of this self-learning algorithm is shown in Fig 3.

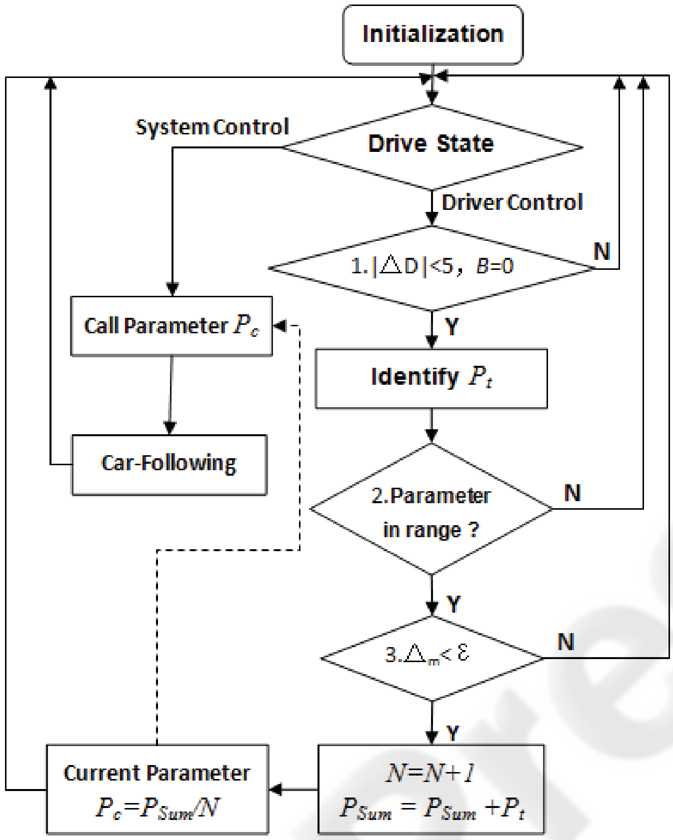


Fig. 3. The flow chart of self-learning algorithm.

After the system initialization, the signal collection of distance D, relative speed v_r, host vehicle speed v and throttle depression Th is enabled. The driver selects the drive states. During the driver manual control process, the algorithm starts the cycle to judge the car-following state and identify the parameters step-by-step. The system step length is 0.1s. The parameters THW_d, K_{THW} and C_{TTCi} are identified from steady car-following data sequence.

The first condition is that the leading vehicle should be a constant target (i.e. no target changing such as cut-in and cut-out scenarios) and this condition is judged according to the variation of the distance signal. Furthermore, the driver is not controlling the brake system. At step k:

$$\begin{cases} \Delta D = |D(k) - D(k-1)| < 5 \\ B(k) = 0 \end{cases} \tag{7}$$

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 LRS method.

The observation vector of the iteration process is $\boldsymbol{h}^T(k)$:

$$\boldsymbol{h}^T(k) = [\frac{D(k)}{v(k)} \quad \text{-1} \quad \frac{v_r(k)}{D(k)}] \tag{8}$$

The output of the process is $z(k)$:

$$z(k) = Th(k) - Th_{ss}(k) \tag{9}$$

Where: $Th_{ss}(k)$ is the current steady throttle which can be interpolated with $v(k)$. According to the standard linear square form, the parameter vector $\hat{\boldsymbol{\theta}}(k)$ to identify in this process can be derived from Equation (**1**):

$$\hat{\boldsymbol{\theta}}(k) = [\hat{\theta}_1(k)\ \hat{\theta}_2(k)\ \hat{\theta}_3(k)]^T = [K_{THW}(k)\ \ K_{THW}(k) \cdot THW_d(k)\ \ C_{TTCi}(k)]^T \tag{10}$$

The iteration algorithm of LRS method with forgetting factor is [10]:

$$\begin{gathered} \hat{\boldsymbol{\theta}}(k) = [\hat{\theta}_1(k)\ \hat{\theta}_2(k)\ \hat{\theta}_3(k)]^T = [K_{THW}(k)\ \ K_{THW}(k) \cdot THW_d(k)\ \ C_{TTCi}(k)]^T \\ \boldsymbol{K}(k) = \boldsymbol{Q}(k-1)\boldsymbol{h}(k)[\boldsymbol{h}^T(k)\boldsymbol{Q}(k-1)\boldsymbol{h}(k) + \mu]^{-1} \\ \boldsymbol{Q}(k) = \frac{1}{\mu}[\boldsymbol{I} - \boldsymbol{K}(k)\boldsymbol{h}^T(k)]\boldsymbol{Q}(k-1) \end{gathered} \tag{11}$$

Where: $\boldsymbol{K}(k)$ and $\boldsymbol{Q}(k)$ are process matrices and μ is forgetting factor with value 0.9. The identified parameter vector of the driver model in this step is $P_t(k)$:

$$\begin{aligned} \boldsymbol{P}_t(k) &= [THW_d(k)\ \ K_{THW}(k)\ \ C_{TTCi}(k)]^T \\ &= [\hat{\theta}_2(k)/\hat{\theta}_1(k)\ \hat{\theta}_1(k)\ \hat{\theta}_3(k)]^T \end{aligned} \tag{12}$$

After obtaining $\boldsymbol{P}_t(k)$, the second condition is that the parameters should be in proper ranges. These ranges are provided by the off-line parameter identification results of the driver real traffic steady car-following data sequences with linear square method, which are shown in Table 1. The proper range of each parameter is selected as its 25% to 75% accumulation frequency.

Table 1. Data Statistics of Driver Model Parameters.

	Mean	Std	Max	Min	25%	75%
THW_d	1.80	3.18	56.51	0.15	0.9	2.3
K_{THW}	44.26	50.68	408.35	0.10	6	95
C_{TTCi}	-157.3	129.4	-0.96	-842.7	-20	-300

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 correspondingly:

$$\Delta_m = \max(\Delta_{THW}(k), \Delta_K(k), \Delta_C(k)) < \varepsilon \tag{13}$$

Where:

$$\Delta_{THW}(k) = \left| \frac{THW_d(k) - THW_d(k-1)}{THW_d(k)} \right| \tag{14}$$

$$\Delta_K(k) = \left| \frac{K_{THW}(k) - K_{THW}(k-1)}{K_{THW}(k)} \right| \tag{15}$$

$$\Delta_C(k) = \left| \frac{C_{TTCi}(k) - C_{TTCi}(k-1)}{C_{TTCi}(k)} \right| \tag{16}$$

ε is the threshold, which is 0.5% in this algorithm.

Because that the driver state is time-varied, the identified parameters are always fluctuating. In order to find the parameters describing the driver characteristics as precisely as possible, an accumulation method is used:

$$\boldsymbol{P}_{sum} = \boldsymbol{P}_{sum} + \boldsymbol{P}_t(k) \tag{17}$$

All parameters satisfied the conditions are accumulated to $\boldsymbol{P}_{sum}$ and when the drive state switches to system automatic driving, the current parameter vector $\boldsymbol{P}_c$ is called by the driver model:

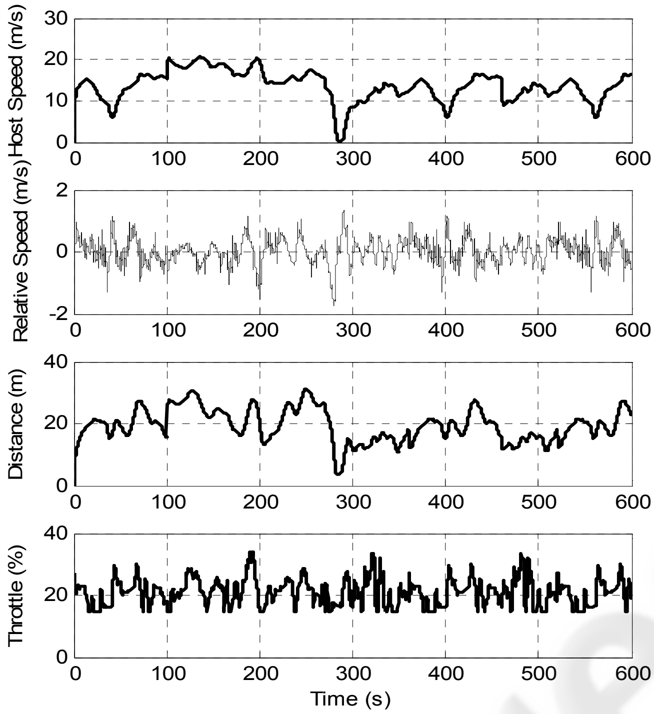
$$\boldsymbol{P}_c = \frac{\boldsymbol{P}_{sum}}{N} \tag{18}$$

Where: N is the counter of the parameters.

With the running time increasing, the algorithm will accumulate more identified results from driver manual operation and the learning effect will be improved. The driver model will be closer to the driver average characteristics. During the algorithm running process, if any of the three conditions are not satisfied, the iteration will be stopped and the current $\boldsymbol{P}_{sum}$ and N will be held. Until new proper parameters are identified, the accumulation will be continued.

5 System Verification in Driving Assistance System Test-bed

A test-bed on a passenger car is developed to verify the system functions including driver characteristics self-learning algorithm and ACC. During the self-learning algorithm verification experiment, a driver subject drives the test-bed vehicle in real traffic and the self-learning algorithm runs online synchronously to identify the model parameters. The parameter identification test continues for 600 seconds to make the results closer to the driver average characteristics, Fig 4 gives the driver manual operation data sequence when following a specified leading vehicle. Fig 5 shows the parameter identification process from this data sequence. It is indicated that the algorithm is effective and the parameters tend to be stable gradually after some fluctuation at the beginning. At the end of the test, the final identification results are: THW_d = 1.84, K_{THW} = 33.5, C_{TTCi} = -109.5.


Host Speed (m/s)
Relative Speed (m/s)
Distance (m)
Throttle (%)
Time (s)
0
100
200
300
400
500
600

Using these identified parameters, the system is switched to ACC mode and Fig 6 shows a data sequence of system automatic car-following. The system can track the leading vehicle's speed steadily and keep safety distance. The control performances of the upper and lower controllers are both favorable.

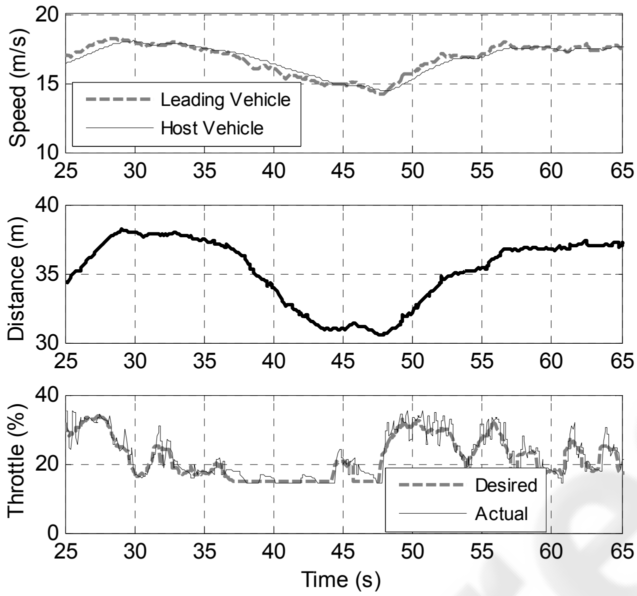


Fig. 6. The performance of the system ACC function.

More experiments of ACC verification are carried out in real traffic and the system performance is analyzed with *THW-TTCi* frequency contour, which is shown in Fig 7.

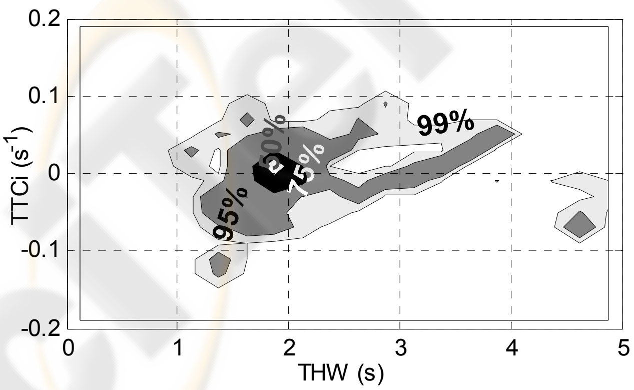


Fig. 7. Frequency contour of *THW* and *TTCi* during system control.

Comparing with Fig.1, it is indicated that the overall data distributions (99% percentage) of the system and the driver are similar. Based on the parameter identified from the driver behavior, the system performance is adaptive to the driver characteristics and gives the driver comfortable riding experience. 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 the system is more stable than the driver.

6 Conclusions

In this paper, an Adaptive Cruise Control system prototype with self-learning functions is developed on a passenger car test-bed.
(1) Driver real traffic tests are carried out and the driver behavior database for the system upper controller design is established. The data analysis of steady car-following show that the driver prefers to keep *THW* and *TTCi* in specific ranges, and a driver model is designed based on this result.
(2) The Recursive Least Square method with forgetting factor can identify the driver model parameters online from data sequence of driver manual operation state, and the self-learning algorithm for driver characteristics is proposed with this method.
(3) The experimental results show that the ACC system can be adaptive to the driver characteristics automatically with the learned parameters. The system has similar performance with the driver manual operation and favorable acceptability of driver.

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