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A LONGITUDINAL HUMAN DRIVING MODEL FOR ADAPTIVE CRUISE CONTROL PERFORMANCE ASSESSMENT

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ABSTRACT

The main goal of this paper is to develop a longitudinal human driving model that is accurate enough for the evaluation of the impact of adaptive cruise control systems on highway traffic. Six driver models were evaluated based on selected data from two vehicle motion databases—The SAVME database and the ICCFOT database, both created at the University of Michigan Transportation Research Institute (UMTRI). Among the models we evaluated, the Gipps' model was found to be most promising and was further analyzed. A modified version of the model was suggested and evaluated. The modified model was implemented in a microscopic traffic simulator and was found to produce results that agree with macroscopic traffic behavior very well.

1 Introduction

Adaptive Cruise Control (ACC) system has been proposed as an enhancement of existing cruise controllers for ground vehicles. It measures the range from the host vehicle to a lead vehicle in its path and controls the velocity/acceleration of the host vehicle properly. Most notably, a safe distance will be maintained between the vehicles, which in most cases takes priority over the goal of maintaining the driver's set speed. Many car companies including DaimlerChrysler, Nissan, BMW and Toyota have introduced adaptive cruise control systems to market as convenience features. As more and more ACC vehicles are put on the road, the interaction between human driven vehicles and ACC vehicles, and among different ACC vehicles become important issues to be studied. String stability, which has significant implication to traffic flow and safety, drew a lot of attentions. In order to benchmark ACC performance, it is important to develop high fidelity human driver models that not only produce microscopic vehicle behaviors that closely mimic those of real human controlled vehicles, but also generates accurate macroscopic traffic pattern, especially traffic flow. More importantly, the models

need to predict these microscopic/macroscopic behaviors at reasonably high traffic density, when string stability becomes a real issue. It is important to point out here that the type of models needed for this purpose is microscopic traffic model. Traditional macroscopic traffic models treat vehicles as homogenous flows that obey simple speed-flow relationships, which is improper for the assessment of the effectiveness of advanced vehicle control systems that requires accurate prediction of the interactions between individual vehicles.

Since the early 1950's, numerous human driving models have been proposed, and many have been used as the basis of microscopic traffic simulation studies. Pipes suggested a linear follow-the-leader model (Pipes, 1953). This model assumes that the driver aims to accelerate the vehicle in proportion to the speed difference between the lead vehicle and the following vehicle. The proportional constant is termed the "sensitivity" of the driver model. This desired acceleration is realized after a neuro-muscular time delay. Chandler (Chandler, 1958) identified the parameters (sensitivity and delay) of the Pipes model based on measured vehicle-following data. Gazis (Gazis, 1961) extends the Pipes' model by assuming that the sensitivity of the follow-the-leader model is proportional to m^{th} power of velocity over l^{th} power of range error. This model is also known to be the GM model because it was developed in the General Motors Research Laboratory. Newell (Newell, 1961) proposed a different model based on the assumption that human driver has a desired speed and a natural tendency to convergence to this desired speed in an exponential fashion. Tyler (Tyler 1964) formulated the human driver as a linear optimal controller, and the cost function being optimized is a quadratic function of range error and range rate error. Later Burnham (Burnham, 1974) modified Tyler's model to include human reaction time and vehicle nonlinearities. Gipps (Gipps 1981) proposed a switching vehicle speed model based on two competing considerations: to keep a safe distance from the lead vehicle and to converge to the desired free flow speed. In order to predict vehicle behavior under both free and congested

traffic with a single equation, Bando (1995) devised a model named “optimal velocity model” which assumes a special basis function to describe human behavior. She also identified these parameters from highway traffic data.

Various mathematical representations of human action were proposed in the models referred above. However, few of them have been validated against real, vehicle level (microscopic) data. For those that have been validated, they were mostly validated against a handful of maneuvers generated by a few numbers of human drivers. This is perhaps due to the fact that high quality vehicle driving data is hard to get until recently. In this paper, we will investigate many of the driver models discussed above and identify one that is flexible enough (i.e., with the most adaptable basis functions) to describe real human driving data most accurately. The driving data will be based on two databases recently constructed at the University of Michigan Transportation Research Institute (UMTRI): The SAVME database (Ervin et al. 2000) and the ICC FOT database (Fancher et al. 1998). The identified driver model will then be implemented in a microscopic traffic simulator (UM ACCSIM) also developed at the University of Michigan (Liang and Peng 2000).

The remainder of this paper is organized as follows: The two database systems and the driving data extraction procedure are described in Section 2. The six human driving models investigated in this paper are described and model correlation results are presented in Section 3. The UM ACCSIM and simulation results are described in Section 4. The steady state characteristics of the Gipps model are analyzed in Section 5, which motivate the development of a modified Gipps model. The simulation results of the modified model are subsequently presented. Finally, conclusions are drawn in Section 6.

2 Vehicle Motion Data Extraction

The data used to select and verify the driving models in Section 3 are obtained from two sources: The SAVME database and the ICC FOT database. These two database systems are described in section 2.1 and 2.2, respectively. The data selection criteria and procedure are described in section 2.3.

2.1 SAVME database

The SAVME (System for Assessment of the Vehicle Motion Environment, Ervin et al. 2000) project aimed to document how human controlled vehicles move and position themselves in proximity to others during normal driving. A major deliverable from this project is an archival record of the behavior of drivers on public roads, i.e., an authoritative form of “truth data” documenting the conventional driving process. This database contains extremely valuable information for human model research such as the work reported in this paper.

The SAVME system collects digital video images from two roadside cameras at a 10 Hz sampling rate. The images are then processed to produce 10-Hz data for each vehicle that passes through the selected road site. Both absolute and relative

variables such as vehicle forward speed, position (longitudinal and lateral), range, range-rate, and azimuth angles are then computed. Through Kalman filtering, the dataset is then augmented with additional variables such as longitudinal acceleration, yaw rate, front wheel angle, lateral velocity, and heading angle.

Two batches of data (1996 and 1999) are available from roadside measurement of about 30,000 vehicles operating on a 5-lane arterial street in Ann Arbor, Michigan. These results are in the form of Microsoft ACCESS database of about 600MB each. Validation results show that spatial accuracies are within 2 ft (0.6m) and the accuracy of velocity components is typically within 2 ft/sec (0.6m/s). This error level is slightly worse than, but comparable to that from other sensors such as radar, differential GPS, etc.

2.2 ICC FOT database

To observe the operability of the intelligent cruise control system in naturalistic use, the University of Michigan Transportation Research Institute performed an Intelligent Cruise Control Field Operational Test (Fancher et al. 1998). 108 volunteer drivers participated in the test for two to five weeks each with their driving behavior and vehicle motion faithfully recorded throughout the period of the operation (1-2 weeks each). Infrared laser sensors with a steered 2°-wide-133m-long sweep beam and 7°-wide-32m-long “cut-in” beam were used to measure the range and range rate from the lead vehicle when one is present. The variables recorded include time, date, range, range rate, velocity, lead vehicle speed, throttle level, and ICC operation mode. The ICC could be set to either off, standby, conventional or intelligent modes. The results are a collection of more than 100 CDs of data. In this paper, a small subset of the data in off or standby mode (i.e., human driving mode) were extracted and used.

2.3 Data Selection

Originally, both SAVME and ICC FOT data were stored in the Microsoft Access database format. MS Access query commands, Visual Basic programs and MATLAB scripts were used to extract vehicle interaction data and prepare them in the suitable form for the driver model simulations (see Figure 1). Due to the difference in the nature of the variables of these two databases, the data selection and processing procedures are different. The procedure and criteria are described separately below.

Figure 1 Data processing block diagram

2.3.1 SAVME

(i) Vehicle (leader-follower) pair extraction

In the SAVME database, absolute x-y locations of all the vehicles passing through the sight of the camera are recorded. Since we focus on the car-following cases, leader-follower pairs in the same lane are identified and all relevant variables (range, range rate, etc.) are calculated and stored in a database. We also eliminate all cases when the leader or the follower executes a lane change.

The above criteria are all realized by set proper query commands. To give an example on how these data-selection criteria can be realized, we will describe the “no-lane-change” criterion below. To find the vehicle pairs without any lane change, maximum and minimum of lane number of each vehicle was calculated. If the maximum and minimum lane number are different, that indicates a lane change has occurred and thus the data will not be selected.

(ii) Data quality calculation

A Visual Basic program was written to calculate the raw data quality for each vehicle: root-mean-square error between the numerical differentiation of un-filtered position and filtered velocity and root-mean-square error between the numerical differentiation of filtered position and filtered velocity. Data from vehicles whose first RMS error was larger than 6 m/sec or second RMS error larger than 0.3 m/sec were rejected.

(iii) Select cases of interest

Of the entire vehicle pairs that satisfy the error criteria stated above, data points with time to impact less than 11 seconds were extracted. These data are judged to be “interesting” because they are the closing in cases representing the safety critical interaction between the lead vehicle and the host vehicle. In the future, they may be used for collision warning and collision control system calibration and verification. Among all the eligible data, the 100 longest cases were selected for the driver model evaluations to be described in Section 3.

2.3.2 ICC-FOT

A Visual Basic program was written to extract data from the ICC-FOT database that satisfy the following conditions:

- The ICC mode is either off or standby. (Human driving)
- A lead-vehicle was within the sensor range.
- Vehicle speed is always larger than 0.

- The same lead-vehicle throughout the vehicle interaction.

The eligible data were sorted and the 4000 longest car-following cases were identified and used to represent “driver population” under normal driving conditions. This driver population will be used in the traffic simulator as “background traffic” for future ACC studies. The selected SAVME and ICCFOT data are plotted in Figure 2.

Figure 2 Range rate, range and velocity traces, SAVME & ICCFOT data

3 Driving Models Evaluation

3.1 Correlation Study

The real human driving data extracted from the two database systems can be used to evaluate existing driving models to see whether they use “basis functions” or templates that are rich enough and “degrees of freedom” that are flexible enough to describe most of the real driving datasets with acceptable accuracy. In the evaluation, we will allow all the “degrees of freedom” of the models (free parameters) to change from one dataset to the next, as long as the variations are allowed in the proposed model. All the models evaluated in this section have been reviewed in Section 1, with key references. Interested readers can find out the details from those publications. The model equations and degree of freedoms (DOF) are summarized in Table 1. It can be seen that the DOF of these models vary between 2 to 5, and thus the comparison between them may not be completely fair (and is not the purpose of this study). The purpose of this evaluation study is to see whether any model is flexible enough, and if so, to build a look-up table detailing the distribution of its parameters, which can then be used to build a vehicle population in traffic simulators to represent real “drivers”.

Table 1 Summary of longitudinal driver models

Model	DOF	Equation
Linear follow-the-leader	K, τ	$\dot{V}_F(t + \tau) = a_c(t + \tau) = K[V_L(t) - V_F(t)]$
Newell	$V_{j0}, \lambda_j, d_j, \Delta$	$v_j(t) = V_j \left[1 - \exp \left\{ -\lambda_j V_j^{-1} [x_{j-1}(t - \Delta) - x_j(t - \Delta) - d_j] \right\} \right]$
Nonlinear follow-the-leader	C, l, m, τ	$\ddot{x}_{n+1}(t + \tau) = \frac{c \dot{x}_{n+1}(t + \tau)^l}{[x_n(t) - x_{n+1}(t)]^m} [\dot{x}_n(t) - \dot{x}_{n+1}(t)]$
Linear optimal control	C_V, C_S, C_C	$u(t) = C_V(V_L(t) - V_F(t)) + C_S[(S_L(t) - S_F(t)) - C_C \cdot V_F(t)]$
Gipps	a_n, V_n	$v_n(t + \tau) = \min \left\{ \begin{aligned} &v_n(t) + 2.5 a_n \tau \left(1 - \frac{v_n(t)}{V_n} \right) \sqrt{0.025 + \frac{v_n(t)}{V_n}} \\ &b_c \tau + \sqrt{b_c^2 \tau^2 - b_c \left[2[x_{n-1}(t) - s_{n+1} - x_n(t)] - v_n(t) \tau - \frac{v_{n+1}(t)^2}{b} \right]} \end{aligned} \right.$
Optimal velocity	a, V_0, m, b_c, b_f	$\ddot{x}_n = a[V(\Delta x) - \dot{x}_n] = 2.0[V(\Delta x) - \dot{x}_n]$ $V(\Delta x) = V_0 \left[\tanh m(\Delta x - b_f) - \tanh m(b_c - b_f) \right]$

The evaluation procedure is as follows: First, we use the MATLAB command `fminsearch()` to identify the values of all the free parameters of a model that results in smallest **sum square** error between the predicted vehicle speed and the true vehicle speed as indicated by the SAVME and ICC FOT results. More than one initial condition were tried to prevent numerical trap at local minimum. We repeat this optimization procedure throughout the 100 approaching cases extracted from the SAVME database and the 100 car-following cases extracted from the ICC FOT datasets, allowing a new set of values for the free parameters for each new maneuver (new driver or new engagement). Once all the optimal model parameters were identified, we calculate the correlation between the predicted and true vehicle speed. If the model is rich enough and flexible enough to accommodate a particular dataset, it will be able to find a set of values for the free parameters that achieves high correlation with the dataset. It is important to remember that in many cases the driver may not have focused on the driving task with full attention and thus it might be hard to make any sense out of the demonstrated driving behavior. Therefore, we did not expect to achieve extremely high correlation. It is also important to point out that several of the models predicted vehicle acceleration rather than speed. For those models, we will add an integrator to convert the model output to vehicle speed. This universal model output is important to ensure a fair comparison. The correlation results for the six driving models are shown in Figure 3 and Figure 4. For example, regarding the Linear optimal control model of Figure 3, more than 70% of cases among selected data showed

the correlation between velocity data and estimated velocity between 0.9 and 1.0.

Figure 3 Correlation results for six driving models (ICC FOT data)

Figure 4 Correlation results for six driving models (SAVME data)

Figure 5 Correlation calculation

It can be seen that among the six models studied, the Gipps model demonstrated the highest flexibility. It has high (>0.9) correlation with 90% of the datasets from both databases. We have no basis to judge the percentage of the datasets that represent “good” data, in the sense that the vehicle reflects the

behavior of safety-conscious driver. For the ICC FOT data, many of the selected datasets last for 100 seconds or longer. Therefore, the human drivers may not be fully engaged in the driving task throughout the whole maneuver. The SAVME data, on the other hand, last for no more than 15 seconds for most of the cases, and are pretty much in the approaching phase. Furthermore, the SAVME data are manually selected from a very large population (100 out of 30,000), and thus are almost always “good” data. We conclude from the correlation study that most models can do a reasonable job in fitting the “good” data, but only the Gipps model survives the “torture test”, which might include some “bad” data. The Gipps model is selected because of this higher level of robustness, as well as the fact that it has only two DOF, and thus is easier to implement. In addition, when the model parameters are selected from the ICCFOT database, the behavior of the vehicle are mostly cruising and thus could be used to represent “background traffic”, for the purpose of evaluation of safety of longitudinal vehicle control systems including Adaptive Cruise Control systems. We will discuss the Gipps model and its identified model parameters in details below.

3.2 Gipps model

The mathematical form of the Gipps model was summarized earlier in Table 1. The physical interpretation of the parameters is shown in Table 2. The model output switches between two equations. The first equation represents the driver’s tendency to converge back to a desired (free-flow) speed. The second equation estimates the safe speed that needs to be maintained under possible hard-braking by the lead-vehicle, which is strongly influenced by the range variable. We follow the original Gipps proposition and do not treat b_n , $\hat{b}$ and τ as free parameters. Rather, they are constrained by the following equations: $b_n = -2.0 a_n$, $\hat{b} = \min(-3.0, (b_n - 3.0)/2)$ and $\tau = 2/3$ second. We further assume that the effective vehicle size $s_n = 4\text{m}$ and thus is not a free variable.

Table 2 Parameters of the Gipps model

a_n	The vehicle/driver’s acceleration level
b_n	The vehicle/driver’s deceleration level
$\hat{b}$	Estimated value for b_{n-1}
s_n	The effective size of vehicle n . Actual size plus a margin
V_n	The vehicle/driver’s natural flow speed
$x_n(t)$	The location of vehicle n at time t
$v_n(t)$	The speed of vehicle n at time t
τ	The apparent reaction time

When only a_n and V_n are treated as free parameters, and the simplex method is used to fit the data from the ICC FOT database (with about 50 hours worth of driving data), the distribution of parameters were found to be those shown in Figure 6, which represents about 100 drivers and will be used in the next section to generate vehicles with different “personalities”.

Figure 6 Gipps model parameter distributions from selected ICCFOT data

4 Microscopic Traffic Simulation

In recent years, the number of microscopic models and simulation tools has increased dramatically. These models, as oppose to their macroscopic counterparts, keep track of the motion of individual vehicles and are more suitable for the study of active vehicle control devices such as ACC systems. Examples of recent microscopic models include AIMSUN, SmartAHS, TRANSIMS, CORSIM, [SISTM](#), [NEMIS](#), etc.

One of the key benefits of these microscopic models over fluid-based macroscopic models is the possibility to recognize each vehicle/driver’s “personality”. Therefore, more accurate evaluation of individual vehicle’s response under realistic traffic environment is possible. Drivers’ behavior can be described either by certain car-following/lane change models or by a set of if-then rules. These models or rules dictate the lane location, forward speed or acceleration of each vehicle at each sampling time, based on a distribution of driver and vehicle parameters.

A microscopic simulator (UM-ACCSIM) was developed at the University of Michigan to evaluate the performance of ACC systems (Liang and Peng 2000). This software simulates and records the motions of each vehicle operating on a 2-lane circular track, and can produce many important microscopic and macroscopic outputs. The car-following, headway, desired speed and lane change models were all constructed based on the statistical analysis of human drivers’ characteristics from field measurement work (Fancher 1998).

Due to the existence of two lanes, frequent lane changes and thus lead-vehicle speed perturbations occur. Therefore, it provides a naturalistic environment for the analysis of vehicles equipped with ACC systems.

A major drawback of this simulator (Liang and Peng 2000) was the fact it uses Pipes model for vehicle speed regulation, and that all vehicles have the same model parameters (personalities) in terms of its speed control behavior. By introducing the Gipps model into this simulator, all aspects of human driving models used in controlling individual vehicle motions are now based on statistical driver behavior data, thus completing its status of being an empirical data-based simulator. If all the behavior models describe human-controlled vehicles with high enough fidelity, we expect the overall simulator to demonstrate many characteristics exhibited by human controlled vehicles/traffic, such as shock wave, traffic flow/density relationship, etc.

In the following, simulations of the enhanced UM-ACCSIM software were performed at controlled traffic density. The traffic density is said to be 100% if on the averaged sense the vehicles are allowed to drive at their desired speed (mean ~ 23 m/sec) and keep their desired time headway (mean ~ 1.5 sec) but otherwise fully occupy both lanes of the roadway. If the vehicle population is lower (higher), the vehicle density is said to be less (more) than 100%. When the traffic density is low, no shock wave is observed in the simulations, probably because the denser traffic built up behind the shockwave can be relieved through lane changes. When the traffic density is high, lane changes become rare because empty spots are harder to come by. Therefore, the behavior is closer to that of a single-lane. In this case, shockwaves, i.e., propagation of slow-traveling traffic pocket upstream of the highway, becomes quite noticeable (Figure 7). This figure also points out a potential need for future improvement: when the shockwave occurs at very low vehicle speed, usually vehicles will exhibit stop-and-go behavior, and the shockwave grew in size. The shockwaves observed in the simulations, however, smooth out a little with time. It seems the vehicle characteristics we observed at higher speed in the ICCFOT database cannot describe behavior at low vehicle speed accurately. If the intent is to use this simulator for simulations down to very low speed, additional factors need to be introduced to reflect the fact vehicle are more sluggish at lower speed.

Figure 7 Observed shockwave behavior from UM-ACCSIM simulations

When we start from lower traffic density and keep adding vehicles for subsequent simulations, and calculate overall traffic flow (over a period of 60 minutes), it can be seen from Figure 8 and Figure 9 that the traffic flow peaks at about **3000 vehicles/lane/hr**. The average speed reduces when density increases. In both figures, we have shown both simulated results, as well as observed traffic data (Gartner, 1997). The boundaries of the so-called “aggressive drivers” and “conservative drivers” shown in Figure 8 were imagined upper and lower limits from the observed traffic data reported in [Kockelman, 2000]. It is clear that the simulated results are qualitatively similar to observed traffic data. Again, at high density and low speed (> 70 vehicles/km), the simulated results are more aggressive than observed traffic. Additional factors to increase the sluggishness of vehicles might be needed.

Figure 8 Flow rate vs. density

Figure 9 Average speed vs. density

5 Modified Gipps model

5.1 Estimated steady state time headway

The microscopic simulation results shown in the previous section agree with the data qualitative but the flow rate is noticeably overestimated. We conducted a steady state traffic flow analysis to identify the reasons. When traffic density is high, the vehicle behavior is dominated by the second equation (safe speed) of the Gipps model, where the safe speed at steady-state can be calculated as follows.

$$V_{ss} = b_n \tau + \sqrt{b_n^2 \tau^2 - b_n \left[2R_{ss} - V_{ss} \tau - \frac{V_{ss}^2}{\hat{b}} \right]} \quad (1)$$

Here, V_{ss} is the steady state velocity. Solving for R_{ss} gives the steady state time headway T_{ss} , which is defined to be the ratio between R_{ss} and V_{ss} , as follows:

$$T_{ss} = \frac{3}{2} \tau + \frac{1}{2} \left(\frac{1}{\hat{b}} - \frac{1}{b_n} \right) V_{ss} \quad (2)$$

Considering Gipps suggested τ to be 2/3 seconds, if $|b_n| > |\hat{b}|$ the steady state time headway might be smaller than 1 second, which results in a flow rate higher than 3600 vehicles/lane/hr. This analysis suggests that the original Gipps model tends to over-estimate flow which needs to be corrected.

5.2 Modified Gipps model

Figure 10 depicts the braking scenario based on which an improved “safe speed” equation for the Gipps model can be constructed. The lead vehicle and the host vehicle both apply a constant level of deceleration. It is hypothesized that the host vehicle driver will take some time to observe the deceleration of the lead vehicle and then initiate his/her own braking. The total delay is assumed to be $\tau + \theta$ where τ is the execution (neuro/muscular/vehicle) time delay and θ is the observation/decision time delay. Area under each speed curve is the distance traveled by the vehicle. For the host vehicle to stop

safely, the initial range between the lead vehicle and the host vehicle should be larger than or equal to the area enclosed by the two speed profiles. This situation could be express as follows.

$$R_h = \left[\frac{1}{2} (\tau + \theta) (V + V_h^*) + \frac{V_h^{*2}}{(-2b_h)} \right] - \left(\frac{V_p^2}{(-2\hat{b})} \right) \quad (3)$$

velocity

Figure 10 Speed profiles of lead & host vehicles both engaging severest braking

Solving for V_h^* and assuming the decision delay θ to be about the same as the execution delay τ gives the following result.

$$V_h^* = b_h \tau + \sqrt{[b_h \tau]^2 - b_h \left[2R_h - 2\tau V_n - \frac{V_p^2}{\hat{b}} \right]} \quad (4)$$

which is slightly different from the original Gipps model. The steady state time headway for this new equation was found to be

$$T_h = 2\tau + \frac{1}{2} \left(\frac{1}{\hat{b}} - \frac{1}{b_n} \right) V_{ss} \quad (5)$$

Therefore, lower traffic flow is expected from this new model.

5.3 Parameter optimization

Since we have decided to depart from the original Gipps model, we decided to start with a clean slate for all model

parameters. Here, instead of using the relations suggested by Gipps, all 6 parameters (all those shown in Table 2, excluding the position and velocity variables) were optimized as follows:

First, parameters related to the “safe speed” (b_n , τ , s_{n-1} , $\hat{b}$) minimizing the error between the estimated safe speed and the test data were identified. Fixing the delay τ found in the previous step, a_n and V_n were then optimized based on the “free speed” equation. The distributions of the identified parameters are shown in Figure 11.

Figure 11 The distributions of optimized parameter for modified Gipps model

5.4 Microscopic simulation result

The flow characteristics of the modified Gipps model are presented in Figure 12 and Figure 13. The new results fall within the range observed in real traffic. Another important difference is that the new model exhibits stop-and-go behavior (see Figure 14) while the original Gipps model was found to be extremely string stable.

Figure 12 Flow rate vs. density (modified Gipps model)

Figure 13 Average speed vs. density (modified Gipps model)

Figure 14 Velocity history of a selected vehicle (Modified model, density = 36 vehicles/lane/km)

6 Conclusions

In this paper, a longitudinal driver model that is suitable for the design and evaluation of Adaptive Cruise Control systems is developed. Many of the existing driver models can do a reasonable job when they are evaluated only for the “approaching” cases, i.e., when the host vehicle is slowing down from behind a slower lead-vehicle. When the vehicle is in general car-following mode, the driver may not be paying full attention to the driving task. For these more general, and possibly lower-quality data (human behavior less consistent), only the Gipps model works satisfactorily, with more than 90% of the test data accurately fitted. We implemented the Gipps model and found that the simulated traffic exhibits many of the microscopic and macroscopic characteristics observed in real traffic, but the predicted traffic flow was too high and the vehicles are string stable. The steady state characteristics of Gipps model including time headway estimation were analyzed and a modified version of Gipps model was derived. A modified Gipps model was proposed and its parameters

identified. Both issues reported above (over-estimated flow and string stability) were adequately addressed by the new model.

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