

TRB 07-0378

Tactical Driver Lane Change Model Using Forward Search

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submission date

11/10/2006

word count

total number of words: 5962 (abstract: 199)

number of figures & tables: 6

total: $5962 + 6 \times 250 = 7462$

ABSTRACT

This paper describes the development and evaluation of a tactical lane change model using the forward search algorithm, for use in a traffic simulator. The tactical lane change model constructs a set of possible choices of near-term maneuver sequences available to the driver and selects the lane change action at the present time to realize the best maneuver plan. Including near term maneuver planning in the driver behavior model can allow a better representation of the complex interactions in situations such as a weaving section and high-occupancy vehicle (HOV) lane systems where drivers must weave across several lanes in order to access the HOV lanes.

To support the investigation, a longitudinal control model and a basic lane change model were also analyzed. The basic lane change model is similar to those used by today's commonly-used traffic simulators. Parameters in all models were best-fit estimated for selected vehicles from a real-world freeway vehicle trajectory data set. The best-fit estimation procedure minimizes the discrepancy between the model vehicle and real vehicle's trajectories. With the best fit parameters, the proposed tactical lane change model gave a better overall performance for a greater number of cases than the basic lane change model.

KEYWORDS

Traffic Simulation, Driver Behavior, Vehicle Trajectory Data

INTRODUCTION

Microscopic traffic simulation is used to test and evaluate infrastructure design, operation, and control policies in a virtual environment, realizing cost savings and flexibility compared to testing or implementing in the real world. In this approach, the motion of each vehicle is reproduced, and the mutual interactions can allow a richer, more accurate model of the overall system, compared with non-simulation based approaches. However, if the motion of the individual vehicles is unrealistic, then the accuracy of the overall simulation results may suffer.

A driver behavior model determines both longitudinal and lateral control actions. Longitudinal control is the acceleration or deceleration, either to follow the lead vehicle or to attain desired speed if there is no lead vehicle. A lateral control action is the determination of whether and in what direction to make a lane change.

Considering the vehicle's response to its environment, driver-vehicle behavior can be classified into three categories. In order of increasing detail, these are: strategic (route planning), tactical, and operational (accelerator / brake pedal, steering). Tactical driver behavior is considered as the development, evaluation, and execution of near-term maneuvers, to realize short-term goals. (Michon, 1985)

A particular feature of human drivers is that the "decisions that we make in our vehicle are largely based on our assumptions about the behavior of other vehicles." Schlenoff et al (2006) It seems that we do not simply consider the present state information of the surrounding vehicles, but follow our expectations about how they will move when making our driving maneuvers such as merging in a weave section, overtaking a slow vehicle, or take an exit ramp.

However, most of today's traffic simulators do not include such anticipatory and planning behavior. In a meeting of the Federal Highway Administration's NGSIM program, the traffic simulation model user committee identified "Complex weaving situations under heavy volumes" and "Modeling freeway flow rates before breakdown" as situations in which present day traffic simulation models don't represent the situation very well, and gave them high priority as research topics to improve the state-of-the-art in traffic modeling. (NGSIM, 2003)

To better represent driver lane changing in such complex situations, this research proposes applying the forward search algorithm to represent driver anticipation and maneuver planning behavior. At each step in the simulation, for each modeled vehicle, the forward search algorithm generates a branching tree of sequential actions, taking into account the changes in the state of the subject vehicle and surrounding vehicles. The sequence of actions leading to the best outcome is then selected and the subject vehicle applies the first action of that sequence. This allows the driver to decide to select a current action for which the payoff is delayed.

For example, consider the situation of a high occupancy vehicle (HOV) deciding to move across

several slow and crowded general purpose lanes to reach a free-flowing HOV lane. Today's traffic simulators which typically consider only the very next action would have the subject vehicle reject the initial lane change and not reach the HOV lane. The proposed model would look further ahead and see the longer-term benefit of reaching the HOV lane and make the initial lane change into the more crowded lane. Even considering the error in prediction of the other vehicles' movements, the inclusion of the sequential maneuver planning in the proposed model at least has the potential to give more realistic representation of the driver lane change actions in the traffic simulator.

This paper describes the development and evaluation of the proposed tactical driver behavior model and its implementation in a traffic simulator. The developed prototype is capable of explicitly representing discretionary but not mandatory lane change behavior, which has been left for further works. A status quo basic lane change model and longitudinal control model were also analyzed.

In addition, these driver behavior models were calibrated to conform to the driver behavior of individual vehicles from a real-world vehicle trajectory data set, which was obtained from a public source and was extracted from video using video image processing. Using the estimated parameters from the calibration, the performance of the proposed sequential planning tactical lane change model relative to the status quo "basic lane change model" is assessed, in terms of realism in representation of individual driver behavior.

LITERATURE REVIEW

In this section, previous works relating various types of longitudinal and lateral control models, tactical driver behavior models, and calibration are presented.

Longitudinal Control Models

Longitudinal control is a vehicle's action of acceleration or braking in order to follow a lead car or else drive alone to attain the desired free travel speed.

Research into car following behavior has been carried out for at least 5 decades, with an overall interest in development of driver assistance functions, development of traffic simulation models, and study of microscopic and macroscopic traffic phenomena. The longitudinal control models, which include both car following and free driving behavior, have been classified into major categories including: stimulus-response models, desired measures models, psycho-physical models, multi-regime models, and more. A thorough review of the various models for longitudinal control (car following and free driving) has been conducted (Cambridge Systematics, 2005) (Miska, 2006). The reader is directed to these or other sources.

Lateral Control Models

The Gipps (1986) lane change model is one of the most commonly used lane change models. (Liu et al 1995, Barcelo and Ferrer 1997) It is a hierarchical decision model which first checks if a lane change is possible, then selects the best destination lane including the current lane, based on clear area ahead or other factors.

The distinction between mandatory and discretionary lane changes has also been considered. Mandatory lane changes are those which must be made in order to complete the desired route, while discretionary lane changes are those made in order to overtake a slower vehicle. Ahmed (1999) developed a lane change model which captures both mandatory and discretionary lane changing behavior, using a discrete choice decision model framework. The model also follows a hierarchical decision structure, and takes into account time delay since the lane change opportunity first arose.

However, the above lane change models base the driver actions only on the current situation, and do not include any maneuver planning or anticipation of the surrounding vehicles' actions.

Tactical Driver Behavior Models

Toledo (2003) developed a driver model which selects the target lane and a particular gap in that lane as a goal and then determines a sequence of acceleration, deceleration, and lateral motion actions in order to move into the target gap, even if the gap is not directly alongside. He formulated a discrete choice decision model to determine target lane and target gap. The model consists of a set of logit equations with coefficients calculated based on a calibration data set using maximum likelihood estimation techniques. He also specified three different longitudinal control (acceleration) models applied to the following cases: (a) when the subject vehicle has chosen to stay in the current lane, (b) when the subject vehicle is making a lane change, and (c) when the subject vehicle is accelerating or decelerating in order to move into a target gap in the adjacent lane which is not directly alongside. He applied the developed model to a test case using a real-world vehicle trajectory data set, and compared the performance of his model to a status quo model which did not include the short-term plan of target gap and found that his model better represented the actual measured traffic conditions.

Hidas (2005) has developed a lane changing and car following model based loosely on Gipps' (1986). The model accounts for cooperativeness when determining mandatory lane changes (lane changes where the vehicle can be in a particular lane to make a downstream turn). However, it only considers the vehicles located directly ahead or behind, and does not take into additional nearby vehicles which might have an influence. In the car following model, the driver tries to reach his desired spacing, with a reaction time lag. Detailed flowcharts are provided describing the driver's action in a variety of situations. Hidas explains about a lane change planning model, but the scope of the plan is only the very next lane change, not several lane changes in the near-term.

Thus for both Toledo's and Hidas' models, the scope of the short-term plan they describe is only to the very next lane change action, and not over a sequence of maneuvers beyond that. Although this is an improvement over the simple reactive models, they do not account for the driver's recognition of a delayed reward which can only be realized when considering a plan over a sequence of several maneuvers.

Sukthankar (1997) allowed for the resolution of decision making of sometimes conflicting directives using an arbiter of votes from independent internal components responsible for various tasks, such as lane keeping, reaching target lane for exit, and staying on the road. The possible actions include the steering and acceleration to reach the desired goal (lane and target velocity). Response is represented in terms of a choice from a finite set of acceleration / deceleration and lateral shift maneuvers as a 3x3 action space: {longitudinal (acceleration, steady, deceleration) x lateral (shift left, center, shift right) }. However this model did not construct action scenarios or consider planning behavior.

Schlenoff et al (2006) developed a control algorithm for automated driving which selects a vehicle control action by taking into account the probability distribution of maneuvers of surrounding vehicles, so as to avoid collisions. The model contains both an estimation-theoretic short-term prediction and situation-based long-term prediction component. The short-term model applies the Kalman Filter method to make a state prediction based on the surrounding vehicles' recent state information. The long-term model assumes the surrounding vehicles will move so as to maximize an objective function of several variables, such as proximity to other objects, desired speed, number of lane changes, crossing the center line into opposing traffic, and costs associated with various types of acceleration profiles (constant velocity, slowly accelerating and decelerating, rapidly accelerating or decelerating). This objective function uses coefficients selected by the analysts' judgment only and not based on observed data. The authors explain a simulation example for a two-way street (one lane per direction) in which there is an obstacle in the road. However, real data were not used in this study, it is for urban streets and not freeways, and it is developed for the purpose of autonomous vehicle control, in which the best driver action is desired, and not driver behavior modeling, in which the most realistic representation of human driver behavior is desired.

The tactical driver behavior model proposed in this paper will work to overcome the limitations mentioned above.

Calibration

There have also been many works involving the calibration of car following models to a real-world driver behavior data set.

Ossen et al. (2006) examined the performance of seven different car following models compared to a real driver behavior vehicle trajectory data set. The approach taken was to calibrate each model for each individual vehicle in the data set, comprising 229 triplets of vehicles driving in real traffic. In the

calibration, parameter vectors, consisting of reaction time lag and various other parameters, were used and the resulting trajectory was compared to the actual vehicle trajectory data in terms of following distance and following vehicle speed. The optimal parameter set and error function value for each model were calculated for each individual driver using the simplex method in an iterative approach. The performance of each of the various models was compared based on a cumulative distribution function of the performance error over the entire vehicle population. An interesting finding was that the simpler models examined did not adequately capture driver behavior. The Gipps model gave the best overall performance. For some drivers, however, other models offered a better representation. Thus, not only the parameters, but the model form, can vary by driver.

TRAFFIC SIMULATOR

In this research, a traffic simulator has been developed which represents the driver's longitudinal control and lane change behavior. This is a discrete time simulator where each vehicle's action is determined at each time step. For a selected vehicle from the vehicle trajectory data, the surrounding vehicles are represented as they actually traveled, and the subject vehicle is started at the initial position and velocity, and then control is turned over to the driver behavior models. The simulation cycle is shown in FIGURE 1.

The simulator contains two separate lateral control models have been developed: (a) a basic lateral control model, which does not include sequential lane change planning, and (b) a tactical driver behavior model, which includes sequential lane change planning. These have been calibrated to match the behavior of several individual vehicles. The evaluation of the performance of the best-fit models will be described in a later section.

Longitudinal Control Model

The model by Gipps (1981) was selected for use as the longitudinal control model because it contains both a free drive model and a car following model, and allows a smooth transition between the two. In addition, by its design it prevents the collisions between vehicles from occurring in the simulator. The Gipps model has relatively few parameters, so it is practical for calibration; a given vehicle's longitudinal control behavior can be specified by just four parameters: reaction time τ , maximum acceleration and deceleration, and desired speed.

In this research, the form of the Gipps longitudinal control model is exactly the same as in the original 1981 paper.

$$v_{trg}(t + \tau) = \min \left\{ \begin{array}{l} v_n(t) + 2.5a\tau \left(1 - \frac{v_n(t)}{V_n} \right) \sqrt{0.025 + \frac{v_n(t)}{V_n}} \\ b\tau + \sqrt{b^2\tau^2 - b \left[2[x_{n-1}(t) - s_{n-1} - x_n(t)] - v_n(t)\tau - \frac{v_{n-1}(t)^2}{b} \right]} \end{array} \right. \quad (1)$$

where:

τ_n	=	reaction time lag parameter for vehicle n
a_n	=	driver's acceleration
b_n	=	driver's deceleration
s_n	=	effective length of vehicle n
V_n	=	driver's desired speed
$x_n(t)$	=	location of vehicle n at time t
$v_n(t)$	=	speed of vehicle n at time t
$v_{trg n}(t)$	=	the target speed to be applied over the time interval $[t, \Delta t]$
Δt	=	simulation time step

Lane Change Models

In this research, as explained above, two types of lane change (lateral control) models have been developed: (1) a basic lateral control model and (2) the proposed tactical lane change model based on sequential maneuver planning. These are explained below.

The models developed in this research, both basic and tactical, allow overtaking in the slow lane, consistent with the behavior observed in the calibration data set. It should be noted that the regulatory and compliance situations regarding overtaking in the slow lane may vary by country or region, and to transfer to another region, the analyst should adjust the lane changing models so as to reflect local conditions.

As in the longitudinal control model, the lane change models include a response time lag equal to τ (from eq. 1). Technical details will be described in forthcoming works.

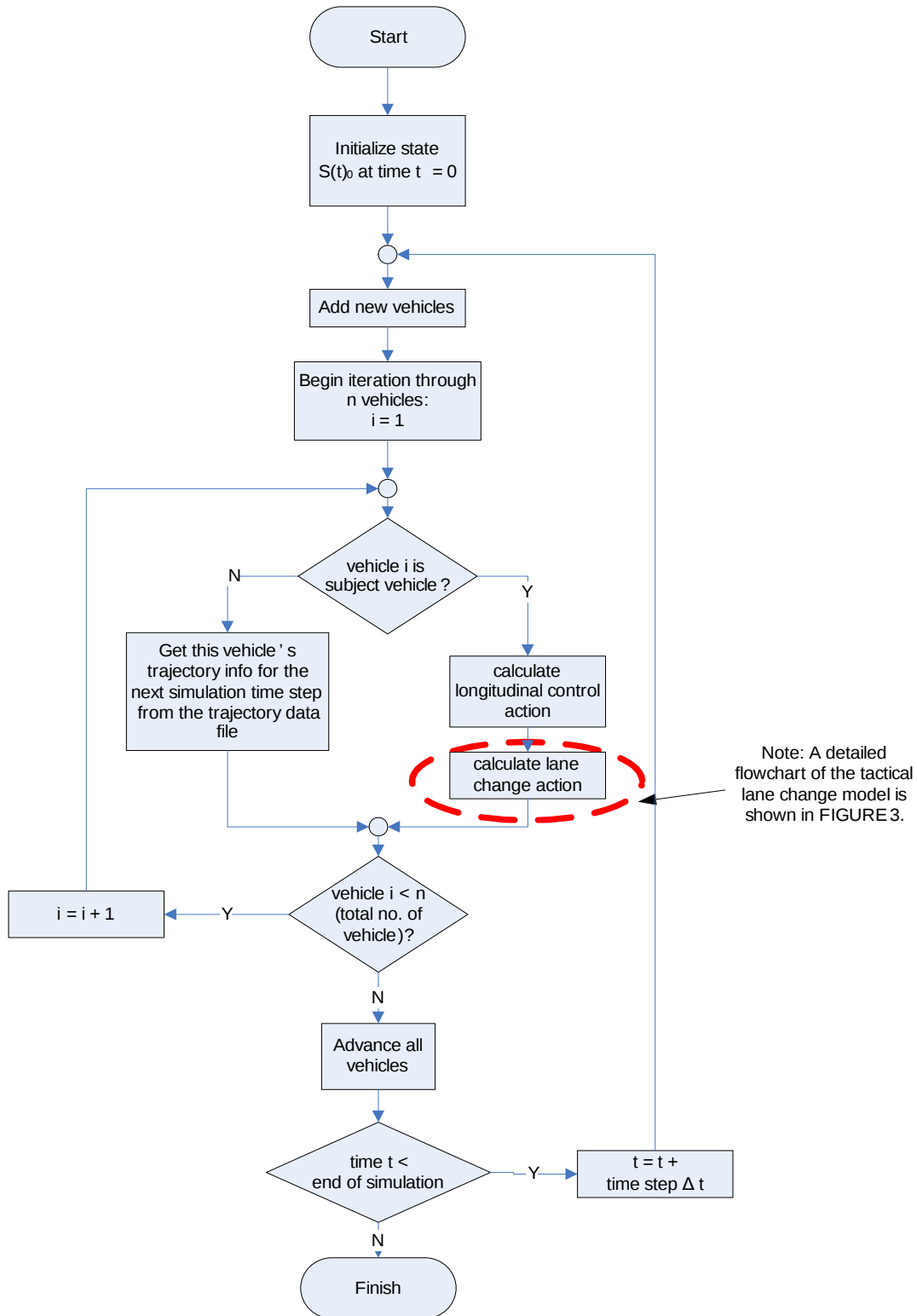


FIGURE 1 Simulation cycle.

Basic Lane Change Model

The basic lateral control model has been developed using a form of the Gipps (1986) lane change model. In this basic lane change model, at every time step the subject vehicle first checks if a lane change is possible, by checking if the lead and rear gaps in the adjacent lane are available, where the lead and rear gaps are calculated according to the Gipps Car Following Model criteria for safe speed and following distance.

$$d_{crit} = \frac{v_L^2 - v_F^2 + 3v_F b \tau}{2b} \quad (2)$$

$$d = x_L - len_L - x_F \quad (3)$$

$$\text{acceptable gap if: } d > F d_{crit} \quad (4)$$

where:

x_L, x_F = the lead and following vehicle longitudinal positions

v_L, v_F = the lead and following vehicle speeds

len_L = the lead vehicle's length

b = the max. decel. (Assumed identical for all vehicles and known by all drivers)

τ = the car following sensitivity parameter

d_{crit} = the distance below which the car following would be unsafe

d = the actual car following distance if the vehicle moved into the gap

F = gap adjustment factor, unique for each vehicle

$$= \frac{\text{smallest acceptable gap}}{\text{gap size which would allow safe stopping}}$$

Each vehicle has its own value of F , which shows the vehicle's smallest acceptable gap size compared to the safe stopping gap size d_{crit} given by the equation (2) above. For example, if a vehicle has a smallest acceptable gap which is exactly equal to the gap size which would allow safe stopping, then the value of F would be 1.0. If the vehicle has a smallest acceptable gap one half the size then F would be 0.5.

If a lane change is possible, then the target lane is selected as the lane with the greatest allowable speed according to the car following model safe car following criteria. In this simulator, lane changes are assumed to take place over a time interval of length equal to the vehicle's reaction time lag, τ , and once a lane change occurs, no new lane changes are permitted until this time interval elapses.

Tactical Lane Change Model

The tactical lane change model uses the same gap acceptance criteria as the basic lane change model, but the lane change decision is made using knowledge from the Forward Search Tree, which is constructed each time step in which the subject vehicle has an available gap in either adjacent lane. The structure of the Forward Search Tree is shown in FIGURE 2, and it represents the enumeration of the possible maneuver sequences as part of the tactical lane change model shown in FIGURE 3. The model is executed every simulation time step, and represents the area in FIGURE 1 enclosed by the dashed red circle.

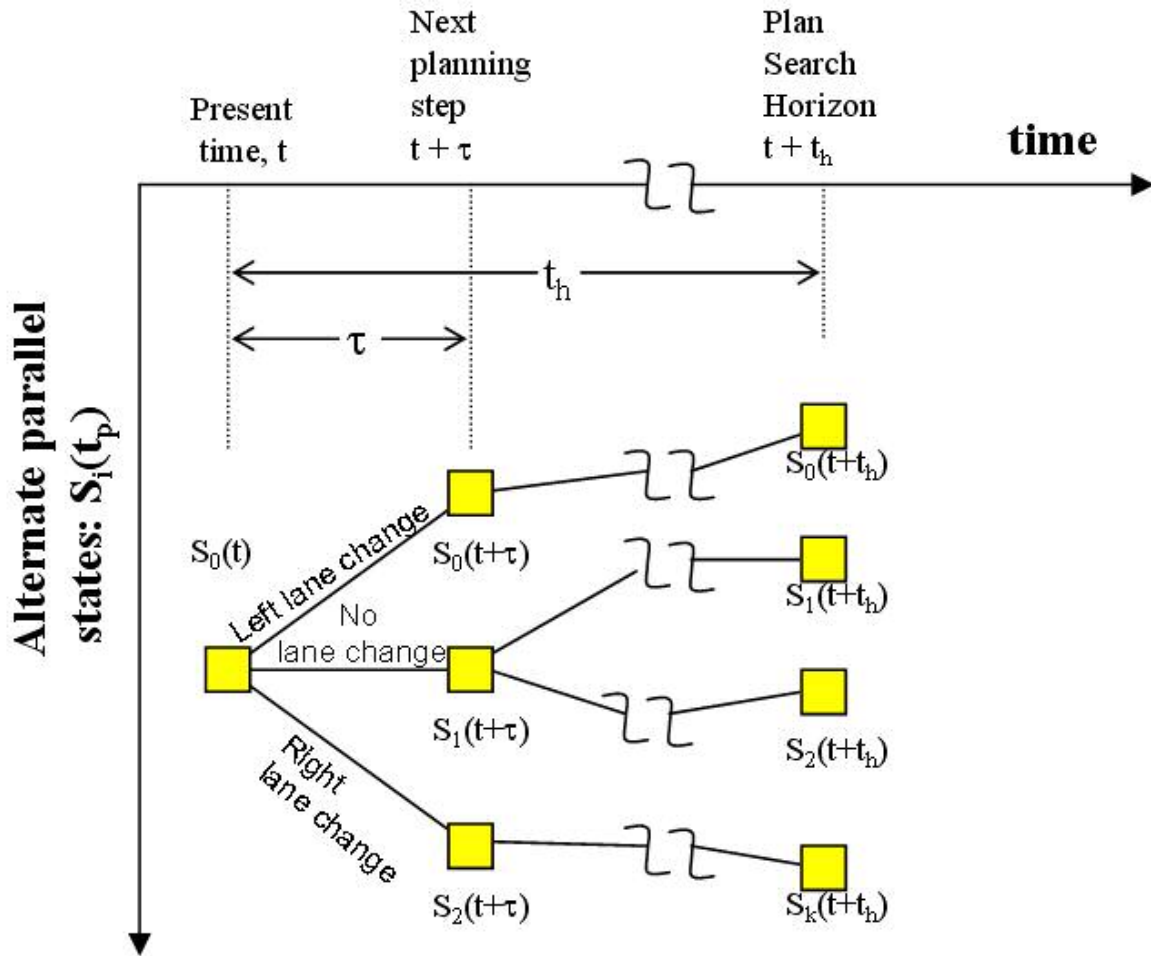


FIGURE 2 Forward Search Tree.

The Forward Search Tree contains nodes and links, which represent the possible sequences of states of subject vehicle and nearby vehicles at each planning time t_p . During the sequential planning from the present time t until the planning horizon $t + t_h$, the subject vehicle will predict not only its own position and velocity, but that for each of the surrounding vehicles, represented as state $S_j(t_p)$ (yellow square in FIGURE 2). For a given planning time t_p there will be one or more unique states $S_j(t_p)$ with index j .

$$S_j(t_p) = \{\hat{x}_n(t_p), \hat{l}_n(t_p), \hat{v}_n(t_p)\}, \forall n \quad (5)$$

where:

$S_j(t_p)$	=	The state j at time planning time t_p which includes the position and speed of all vehicles
n	=	Index number of subject vehicle or nearby non-subject vehicle
$\hat{x}_n(t_p)$	=	Predicted longitudinal position of vehicle n
$\hat{l}_n(t_p)$	=	Predicted lane of vehicle n
$\hat{v}_n(t_p)$	=	Predicted speed of vehicle n

The lines connecting the squares in the figure represent the subject vehicle lane change actions {left lane change, no lane change, or right lane change} at a given planning time. A given state $S_i(t_p)$ may connect to one or more succeeding states $S_j(t + \tau)$ (different values of j). In the proposed model, the planning time step size is set equal to the reaction time lag τ (see longitudinal control model, Eq. 1), which is unique for each subject vehicle. Note that the reaction time lag value τ should not be confused with the simulation time step size Δt in FIGURE 1. Also, in the proposed model, τ is necessarily a multiple of Δt . This is not a problem when Δt is very small (e.g. $\Delta t \leq 0.2$ s) as is the case for the analysis described in this paper ($\Delta t = 0.0667$ s). Thus any errors due to rounding of τ are very small and can be ignored.

The Forward Search Tree is built starting at initial state $S_0(t)$, which consists of the speed and position of all nearby vehicles upstream or downstream of the subject vehicle within a *view distance* specified as a model parameter. In the prototype model, a view distance of 200 m in each direction was assumed, being able to recognize the first vehicle ahead or behind with a following time of 6 seconds at free flow speed of 30 m/s. ($6 \text{ s} \times 30 \text{ m/s} = 180 \text{ m} \leq 200 \text{ m view distance}$) Next, all possible states $S_j(t_p)$ are estimated for each planning time t_p at planning increments τ until the time horizon, $t + t_h$, as shown in FIGURE 3. This is a *breadth-first* search. To estimate one or more resulting states $S_j(t_p)$ from the previous

planning state $S_i(t_p - \tau)$, the surrounding vehicles (non-subject vehicles) are simply advanced in the same lane at their current speed, constrained by car following. Subject vehicle longitudinal control actions are represented as maximum acceleration, constrained by safe car following and the driver's desired speed. For the subject vehicle, every state $S_i(t_p - \tau)$ will have at least the no-lane-change result state $S_j(t_p)$, and if a new gap is available on one or both of the adjacent lanes, then additional result states $S_{j+1}(t_p)$ and $S_{j+2}(t_p)$ may be added, thus making a branch in the Forward Search Tree.

Note that because the car following behavior is included in the vehicle state prediction, the proposed model can not only predict motion at constant speeds, but also capture the driver behavior in response to changing conditions, such as lane changing to avoid a downstream backward propagating congestion front, provided that the *view distance* reaches far enough ahead to the congestion front.

Regarding the length of the time horizon, t_h , it is thought that a driver's planning time horizon may vary depending on the complexity of the situation: maneuvering a weaving section may require a longer planning horizon than ordinary driving in a basic roadway section. However, for the analysis described in this paper, $t_h = 4$ seconds was used, based on a preliminary investigation of the simulation performance of a several t_h values for a small number of selected vehicles.

It should be noted that in the currently implemented version, several heuristics have been applied which, although serving to reduce computation time and software algorithm complexity, may also reduce the realistic representation of the subject vehicle's tactical lane change decision. (1) In the Forward Search Tree, the surrounding vehicles do not make lane changes. Indeed, a more realistic (and computationally intensive) model could include each non-subject vehicle's plan behavior nested inside the subject vehicle's plan, cycling through one or more recursions. (2) In the Forward Search Tree, subject vehicle lane change decisions are restricted to situations when an acceptable gap in the adjacent lane first comes available, and reversals of previous lane changes are not allowed until the surrounding vehicle state has changed. Without these restrictions, after several planning steps the possible subject vehicle lane change choices could skyrocket, generating plans with the subject vehicle hopping back and forth between lanes at each planning time step.

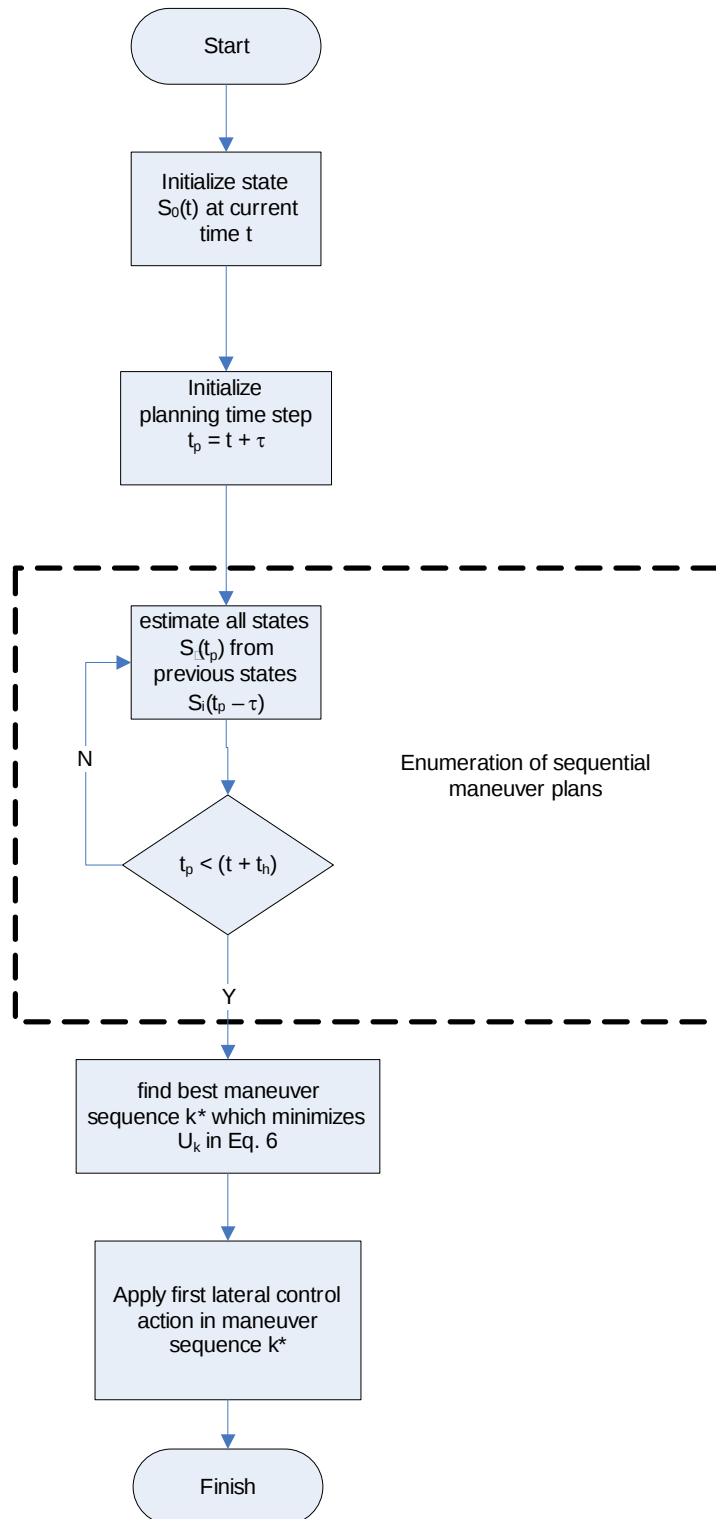


FIGURE 3 Tactical lane change model using Forward Search Tree.

The completed Forward Search Tree enumerates a complete set of subject vehicle maneuver sequences, and each sequence can be evaluated in terms of how it improves the situation for the driver. The current version of the proposed model evaluates each maneuver sequence in terms of the distance gained over the search horizon. The best maneuver sequence k^* gives the maximum of all enumerated maneuver sequences according to the following utility function:

$$U_k = d_x(S_k(t + t_h), S_0(t)) \quad (6)$$

where:

U_k	=	The utility of maneuver sequence which results with state $S_k(t + t_h)$ at the time horizon
$S_0(t)$	=	The state at the present time, with the current longitudinal position of the subject vehicle
$S_k(t + t_h)$	=	The final state of maneuver sequence k , at the time horizon
$d_x(a, b)$	=	The difference in longitudinal position of the subject vehicle in states a and b . A large value will give better performance of the objective function.

Finally the lane change (or no lane change) action leading to the selected lane change sequence k^* is acted on for the current time step.

In later work, other information could be included in the utility function, such as mandatory lane changes or avoidance of delaying faster rear vehicles.

The proposed sequential planning model addresses limitations of the driver behavior models used in existing simulators: the ability to consider the motion of the surrounding vehicles rather than only their current state, the ability to make a maneuver which leads to a longer-term gain when there is no short-term advantage, such as weaving across several crowded lanes of traffic to a less-crowded lane.

The next section describes the calibration of driver behavior model parameters to match driver behavior of individual vehicles in a real-world data set.

CALIBRATION

This section describes the calibration on of the basic and tactical driver behavior models, using real vehicle trajectory data. In this calibration effort, best-fit driver behavior parameters were estimated for selected vehicles from the vehicle trajectory data set. First, the data set is described, and the calibration procedures are explained.

Vehicle Trajectory Data

The NGSIM project (Cambridge Systematics, 2004) is a research project led by the US DOT to provide a core set of driver behavior data and algorithms for verification and validation purposes. Vehicle trajectory data from video image processing is provided free to the research user community. The data set consists of a 900 m long 6-lane section of the I-80 freeway in Oakland, California. The section contains an upstream single-lane entry ramp, and a downstream single-lane exit ramp. The space resolution (precision) is within one meter, and the time resolution is 1/15 s. The time duration of the data set is approximately 30 minutes. This data set has been treated in detail by other researchers such as Ni and Leonard (2006). Vehicles to be used for the calibration were selected at random from the passenger cars or small trucks both beginning and ending on the mainline.

Calibration Approach

In this research, the estimation of these model parameters is described as follows. In order to keep the number of search parameters to a minimum, and recognizing that extreme values of acceleration and deceleration are unlikely to be observed in the ordinary driving found in the vehicle trajectory data, the acceleration and deceleration values were assumed constant for all vehicles and appropriate values were taken from the literature references (Koppa, 2002):

- a , max acceleration (m/s^2): 3.0 m/s^2
- b , max deceleration (m/s^2): -4.6 m/s^2

The following driver behavior parameters were estimated for each vehicle:

- τ , reaction time (s)
- v_{des} , desired speed (m/s)
- F , critical gap adjustment factor (unitless):

In the simulator, all vehicles were assigned to their actually-traveled trajectories except for the subject vehicle, which was put under the control of the selected driver behavior models. The estimation of the parameter values $\{\tau, v_{des}, F\}$ was decomposed into longitudinal and lateral steps as described below. It should be noted that there is some degree of interaction between the longitudinal and lateral control actions (Toledo, 2003), and therefore the longitudinal and lateral parameter calibration should ideally be performed simultaneously, in a single step. However, in this research, in order to simplify the parameter search problem, the longitudinal and lateral calibrations are performed in separate steps.

Longitudinal Control Model Parameter Calibration

In the first step, the longitudinal control model parameters $\{\tau, v_{des}\}$ are calibrated. First, the lane change function is disabled and the subject vehicle is simulated under the longitudinal control model using selected values of $\{\tau, v_{des}\}$. If the real vehicle makes a lane change, then the subject vehicle position and speed are reset to that of the real vehicle. The Root Mean Squared Error objective function $U_{ordLong}$ is computed for each candidate search vector, based on the difference in longitudinal position of the simulated vehicle to the actual vehicle position, summed over all time steps. The search is performed to find the vector $\{\tau^*, v_{des}^*\}$ which minimizes this objective function.

$$U_{ordLong} = RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (x_{i|sim} - x_{i|realData})^2} \quad (8)$$

where:

$U_{ordLong}$ = Objective function based on longitudinal difference between simulated subject vehicle and its real course

i = Index number of time step over the duration of the simulation

n = Total number of time steps

In FIGURE 4, an example of the search for minimum of $U_{ordLong}(\tau, v_{des})$ is shown.

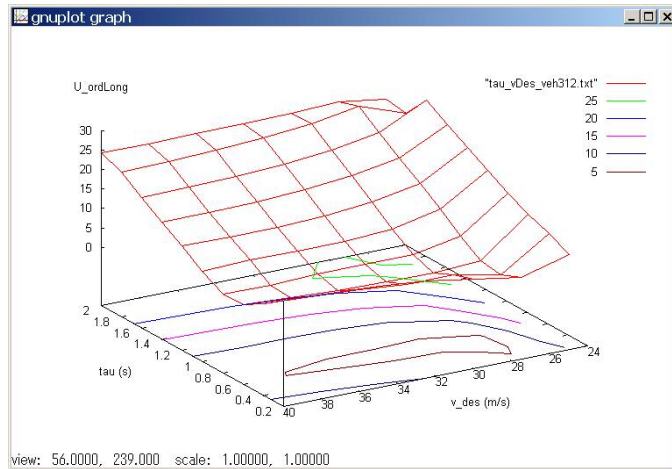


FIGURE 4 Example of the search for the minimum of $U_{ordLong}(\tau, v_{des})$.

Lateral Control Parameter Calibration

In the second step, the lateral control model parameter, gap adjustment factor F is calibrated. As explained above in Eq. 4, F is the adjustment factor to the critical gap, which varies according to the speeds and positions of the subject vehicle and the other vehicles in the adjacent lane. The longitudinal control is disabled and the subject vehicle is simulated with the longitudinal position fixed to the real vehicle's position at every time step. At each time step, the lane change action resulting from the simulator given the selected value of parameter F is used to compute the objective function to be minimized:

$$U_{LC} = \frac{\sum \delta_i}{n} \quad (9)$$

where:

U_{LC} = lane change model performance index

i = Index number of time step over the duration of the simulation

n = Total number of time steps

δ_i = 0 if the simulated lane change action: *{left, right, or no lane change}* equals the real vehicle's lane change action at time step i , 1 otherwise

If the lane change control actions of the simulated vehicle at each time were identical to those of the real vehicle, then the objective function would evaluate to 0. The worst possible score is 1. A range of values of F are searched, $U_{LC}(F)$ is evaluated, and the F^* which minimizes U_{LC} is found. The search of F^* is performed separately for both the basic and sequential planning lane change models.

This procedure was performed for 70 vehicles selected randomly from the trajectory data set. The statistics of the parameters estimated for each vehicle and driver model performance are described in the next section.

RESULTS

For the selected vehicles, the summary statistics of the estimated parameters: $\{\tau^*, v_{des}^*, F_{basic}^*, F_{seqPI}^*\}$ as well as their goodness-of-fit values $\{U_{ordLong}, U_{LC|basic}, U_{LC|seqPI}\}$ are shown in TABLE 1.

TABLE 1 Estimated parameters and goodness-of-fit values: summary statistics (sample size = 70)

	τ^* (s)	v_{des}^* (m/s)	$U_{ordLong}$	F_{basic}^*	$U_{LC basic}$	F_{seqPI}^*	$U_{LC seqPI}$
mean	0.891	32.6	6.111	1.151	0.045	1.103	0.040
st.dev.	0.478	4.8	3.741	0.456	0.093	0.486	0.095
median	0.700	31.0	5.294	1.300	0.010	1.200	0.004
min	0.4	25.0	1.3	0.4	0.0	0.4	0.0
max	2.0	40.0	27.4	1.6	0.6	1.6	0.7

In the model calibration, there are two indicators of the goodness of fit: $U_{ordLong}$ for the longitudinal control model and U_{LC} for the lane change model, as were described previously. If the simulator were to perfectly match the real-world vehicle trajectory, then both of these would be zero. The summary statistics of the goodness-of-fit of the estimated basic and sequential planning lane change model parameters, $U_{LC|basic}$ and $U_{LC|seqPI}$ respectively, are shown in TABLE 1. The median value of U_{LC} is lower for the sequential planning model. Note that the mean values of U_{LC} are much higher than the median, due to a few vehicles receiving very high values of U_{LC} even when the best-fit parameters were used.

The best-fit result of gap acceptance parameter F in TABLE 1 is also of interest. The mean and st. dev. terms $F = 1.15 \pm 0.456$ indicates that many vehicles have a best-fit value of $F < 1.0$. These vehicles would accept gaps which are smaller than would allow a safe stop if the lead vehicle were to brake at maximum deceleration. This implies that the drivers are anticipating that the lead vehicles will not undertake such quick decelerations.

FIGURE 6 shows a performance comparison of the proposed lane changing model to the basic model in terms of the number of individual vehicles for which the proposed lane change model resulted in a better U_{LC} score. It can be seen that among the cases where the performance was different, the number of cases in which the proposed sequential lane change model performed better than the basic lane change model ($U_{LC|seqPI} < U_{LC|basic}$) were greater than the opposite, ($U_{LC|seqPI} > U_{LC|basic}$) by a ratio of at least two-to-one.

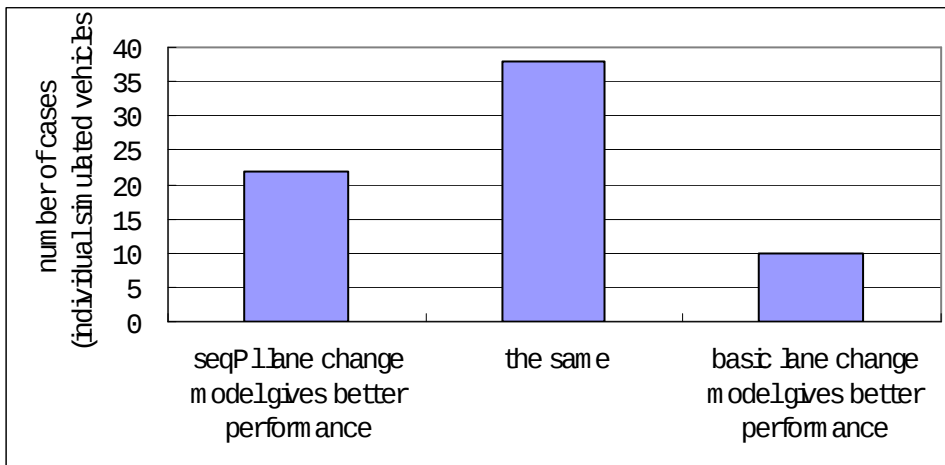


FIGURE 5 Comparison of performance of lane change models.

CONCLUSIONS

This paper presented a lane changing model which allows for driver's sequential planning of near-term maneuvers, using the forward search algorithm. An initial prototype implementation of the model and its validation with a real data set have been described. It was found that the sequential planning model had a better performance in representing the real-world driver lane changing behavior for a greater number of selected vehicles, compared to the basic lane change model.

The following are possible approaches for expansion of the prototype model for further work. By considering a detailed comparison of the simulated and actual lane changes, better model features and performance measures could be developed. For example, the control action choice set enumeration could be expanded to also include longitudinal acceleration and deceleration actions, and the length of the time horizon could be further investigated. The action selection objective function could be expanded to also consider destination lane to allow treatment of mandatory lane changing situations. Approaches for improving the computational efficiency could also be considered.

REFERENCES

1. Ahmed, K.I. *Modeling Drivers' Acceleration and Lane Changing Behaviors*, Ph.D. Thesis, Department of Civil and Environmental Engineering, Massachusetts Institute of Technology, Cambridge, Massachusetts, 1999.
2. Barcelo, J. and Ferrer, J. L. *An Overview of AIMSUN2 Microsimulator*, Department of Statistics and Operations Research, Universitat Politècnica de Catalunya. 1997.
3. Cambridge Systematics. *NGSIM Task E.1-1: Core Algorithms Assessment. Final Report*. Cambridge, Massachusetts, USA, 2004.
4. Gipps, P.G. A Behavioral Car-Following Model for Computer Simulation. *Transportation Research, Part B: Methodological*. v15B, 1981, pp 105-111.
5. Gipps, P.G. A Model for the Structure of Lane-Changing Decisions. *Transportation Research, Part B: Methodological*. 20B, 1986, 107-120.
6. Hidas, P. Modeling vehicle interactions in microscopic simulation of merging and weaving. *Transportation Research Part C*. v13, 2005, 37-62.
7. Koppa, R.J. Chapter 3. Human Factors. *Monograph on Traffic Flow Theory*. Turner-Fairbank Highway Research Center, US Department of Transportation, MacLean Virginia, USA. 2002.
8. Liu R., Van Vliet D., and Watling D.P. DRACULA: Dynamic Route Assignment Combining User Learning and microsimulAtion. *Proc. PTRC European Transport Forum, Seminar E*, 143-152. 1995.
9. Michon, J.A. A critical review of driver behavior models: What do we know, what should we do? In: L.A. Evans & R. Schwing (eds.). *Proceedings of the International Symposium on Driver Behavior and Traffic Safety*. General Motors Research Laboratories. New York: Plenum Press: pp. 485-520. 1985.
10. Miska, M.P. A Driving Behavior Model for Microscopic Online Simulation based on Remote Sensing and Equipped Vehicle Data. *Transportation Research Board Annual Meeting*. 2006. Washington, DC. Conference Proceedings CD-ROM.
11. NGSIM Workshop, *Model User Stakeholder Meeting Notes*. Cambridge Systematics. University of Maryland, College Park – March 2003.
12. Ni, D. and Leonard, J.D. Direct Methods of Determining Traffic Stream Characteristics by Definition. *Transportation Research Board Annual Meeting*. 2006. Washington, DC. Conference Proceedings CD-ROM.
13. Ossen, S., Hoogendoorn, S., Gorte, B. Inter-Driver Differences in Car Following: a Vehicle Trajectory Based Study. *Transportation Research Board Annual Meeting*. 2006. Washington, DC, USA. Conference Proceedings CD-ROM.
14. Schlenoff, C., Madhavan, R., and Kootbally, Z.. PRIDE: A hierarchical, integrated prediction framework for autonomous on-road driving. In: *Proceedings of the IEEE Conference on Robotics and*

Automation, Orlando, Fla. - May 2006

15. Sukthankar, R. *Situation Awareness for Tactical Driving*. Ph.D. Dissertation. Carnegie-Mellon University. 1997.
16. Toledo, T. *Integrated Driving Behavior Modeling*. PhD Dissertaion. MIT. 2003.