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TACTICAL LANE CHANGE MODEL WITH SEQUENTIAL MANEUVER PLANNING

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The lane change models used in today's traffic simulators often do not determine lane change actions in terms of the evaluation of sequential plans, but rather in terms of the utility of the very next lane change action. This has the disadvantage of not being able to account for the influence of delayed rewards, such as the simulated vehicle moving across a slow lane to a better-performing non-adjacent lane. This research presents a lane change model which at every simulation time step, builds a tree of potential maneuver sequences, and selects the lane change action according to planning over a time horizon. The model was calibrated using a vehicle trajectory data set and shown to give improved realism of lane change actions of individual vehicles, compared to a lane change model without sequential planning.

KEYWORDS: Microscopic simulation, driver behavior, vehicle trajectory data

1. INTRODUCTION AND BACKGROUND

Microscopic traffic simulation is a useful tool for testing and evaluating infrastructure design, operation, and control policies in a virtual environment, realizing cost savings and flexibility compared to real-world testing or implementation. 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. A comprehensive review of macro-, meso-, and microscopic approaches to traffic modeling has been given in Helbing (2001) and Chowdhury et al. (2000).

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 drivers is that the "decisions 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 taking an exit ramp. Because drivers consider not only the present state of their own and surrounding vehicles, but also the current lane change actions as part of sequential maneuver plans, to leave this out of the driver model would lead to a decrease in realism of the traffic simulator, possibly resulting in less effective policy decisions, inadequate allocation of infrastructure through inferior design, and decreased quality of real time control systems which utilize traffic simulators.

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However, many of today’s traffic simulators use a driver lane change model which does not include planning of lane change sequences, or anticipation of changing conditions of the subject vehicle and surrounding vehicles (Cambridge Systematics, 2004b; Ahmed, 1999; Hidas, 2005; Barcelo and Ferrer, 1997; Liu et al., 1995).

There are a variety of situations in which there is a potential for loss in model realism due to neglecting the sequential planning and anticipation. Aggressive driving (cutting into small gaps) can have disproportionate impacts on the traffic stream, compromising safety, and leading to deterioration of traffic conditions. The representation of the aggressive drivers’ gap acceptance and the maneuver planning leading to these decisions deserves further attention. For example, Figure 1 shows a conceptual example of the effect of a driver cutting into a small gap on the upstream vehicles.

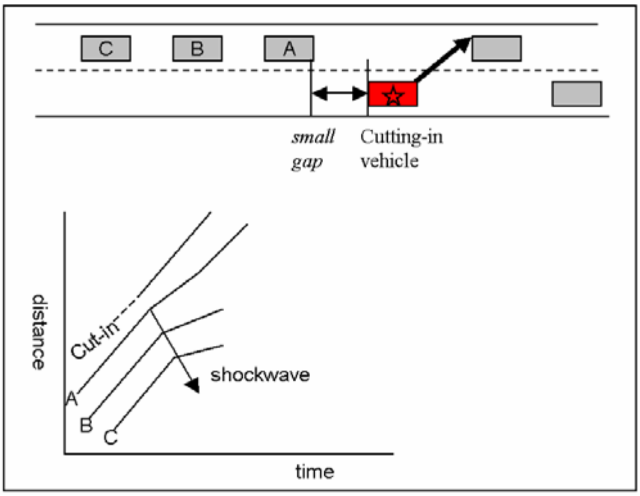

FIGURE 1: Conceptual example of shockwave due to vehicle cutting into small gap

Also, weaving sections are particularly important for consideration of planning and anticipation, because vehicles entering and exiting the freeway must take into account the other vehicles expected course as they plan their own path. This is especially true of vehicles entering a freeway with high-occupancy vehicle (HOV) lane system. The simulated travel time of the qualified vehicles could depend strongly on how their tactical behavior of weaving across the slower-moving middle lanes is modeled.

It should be noted that multilane traffic flow in general (Holland and Woods, 1997) and HOV lanes in particular (Daganzo, 1997; Daganzo et al., 1997) have been treated previously using kinematic wave theory and continuum traffic theory (Huang et al., 2006). Spatio-temporal dynamics and statistical physics have also been applied, considering the effects of blockages and slow vehicles on the traffic flow (Kurata et al., 2003; Nagai et al., 2005). Cellular automata have also been used (Huang, 2002). There have been models which consider longitudinal control and lane changing behavior in an integrated fashion (Tang et al., 2005; Toledo et al., 2005; Tang et al., 2007a-c).

In recent years, advances in traffic data surveillance technologies, computational hardware and algorithmic techniques now allow more realistic driver models to be developed and used.

This paper describes a tactical lane change model for representing the driver behaviors of anticipation and sequential planning of lane change maneuvers in a traffic simulator.

In addition, a method of assessing the performance of lane change models is proposed. The method is used to compare the performance of the tactical lane change model to a *straw man* algorithm (hereafter called the basic lane change model), which is similar to those in today's traffic simulators. The basic lane change model does not include driver planning for sequential lane change maneuvers or anticipation of changing conditions.

2. MODELING APPROACH

This lane changing model is developed in order to more realistically represent the lane change actions of individual vehicles. In order to realize this, a traffic simulator was developed to serve as the testing environment. The traffic simulator, longitudinal control model, basic and tactical lane change models are described in the following subsections. The tactical model represents the original contribution of this work, while the other driver models (longitudinal control model, basic lane change model) serve to support the model performance evaluation described here.

2.1 Traffic simulator testbed

A time-step based simulator was developed. It is capable of representing the vehicle management, network geometry, animation, and data I/O processes. It contains the driver behavior models for longitudinal control, and either the Basic or Tactical lane change models as specified by the user. The longitudinal control model is used with either type of lane change model, and the basic lane change model is used for the performance comparison.

2.2 Longitudinal control model

The Gipps longitudinal control model (Gipps, 1981) was used in this analysis. A detailed investigation into the Gipps model including its use in a simulation of signalized junctions is described in (Spyropoulous, 2007). Other leading longitudinal models which were not used in this work include *stimulus-response*-type models (Gazis et al., 1961), *optimal velocity* (OV) model (Bando et al., 1995), *generalized force* (GF) model (Helbing and Tilch, 1998), and *full velocity difference* (FVD) model (Jiang and Wu, 2006). Although a particular model was selected for the analysis described in this research, there is no reason to rule out use of a different longitudinal control model in further works.

The longitudinal model which was used contains both a free driving 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 model has relatively few parameters: a given vehicle's longitudinal control behavior can be specified by just four parameters: reaction time τ_n, maximum acceleration and deceleration, and desired speed $v_{des|n}$. This allows a best-fit calibration of the model to an individual vehicle to be easily achieved due to the small parameter search space. This form of the Gipps longitudinal control model is used as given in the original 1981 paper (Gipps, 1981).

$$v_{trg|n}\left(t+\tau_n\right)=\min\left\{v_n\left(t\right)+2.5a\tau_n\left(1-\frac{v_n\left(t\right)}{v_{des|n}}\right)\sqrt{0.025+\frac{v_n\left(t\right)}{v_{des|n}}},\right.$$
$$\left.b\tau_n+\sqrt{b^2{\tau_n}^2-b\left[2\left[x_{n-1}\left(t\right)-s_{n-1}-x_n\left(t\right)\right]-v_n\left(t\right)\tau_n-\frac{v_{n-1}\left(t\right)^2}{b}\right]}\right\} \quad (1)$$

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

The model gives the target velocity selected by the vehicle over the simulation time step Δt. The vehicle performance limits of acceleration and deceleration are reflected internally in the equation. The first term inside is the free drive constraint, which allows influence of the vehicle performance limits on acceleration as well as the desired speed on the subject vehicle's target velocity. The second term contains the influence of following the lead vehicle to allow a safe stopping distance.

2.3 Basic lane change model

The basic lane change model serves as a *straw man*, to represent models used in present-day traffic simulators, inasmuch as it does not contain planning of sequential lane change maneuvers. It uses a form of the Gipps (1986) lane change model. The framework, shown in Figure 2, is to first check if a lane change to the adjacent lane is feasible, that is, whether both lead and rear gaps are large enough to allow a safe completion of the lane change maneuver. If so, the second step is to check if the lane change is desirable. This is done by comparing the allowable safe speeds in the current lane and candidate lanes, and if the candidate lane offers a more favorable speed, within the limits of the vehicle's desired speed, then the model initiates a lane change to the candidate lane. In determining the gap safety and desired speed, the Gipps longitudinal control model is used.

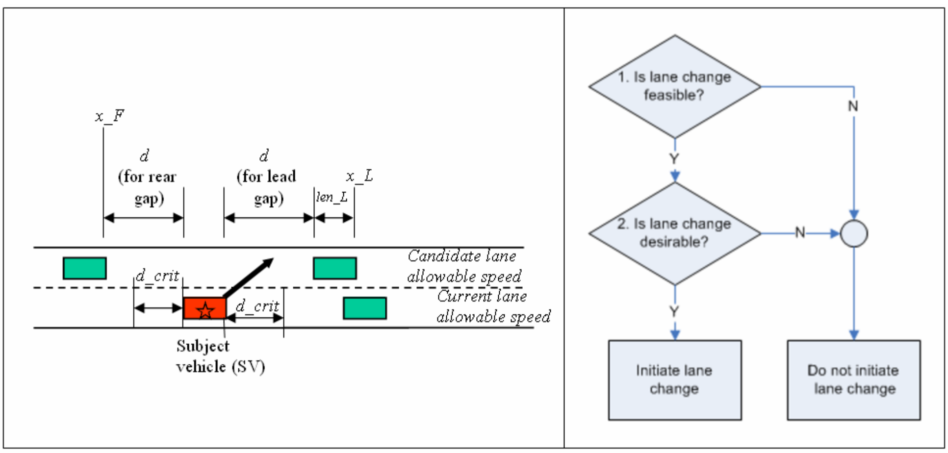

FIGURE 2: Basic lane change model

In this basic lane change model, at every time step the subject vehicle first checks if a lane change to either adjacent lane is possible, in terms of gap availability. The gap availability is judged in terms of both lead and rear gaps, calculated according to the Gipps Car Following Model criteria for safe speed and following distance.

Figure 2 shows an example of the subject vehicle checking for available gaps in the lane to the left. For a given adjacent lane, both the lead and rear gap must satisfy the criteria of being no less than the adjusted critical gap size, as described in equations (2), (3), and (4). Note that equations (2) and (3) are derived directly by solving for $x_{n-1}(t) - s_{n-1} - x_n(t)$ from equation (1) for the case in which the second of the two arguments in the *min* function on the right-hand-side is governing.

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

$$d = x_L - len_L - x_F \tag{3}$$

$$\text{acceptable gap if: } d \geq F\, d_{crit} \tag{4}$$

where x_L and x_F are the lead and following vehicle longitudinal positions (m), v_L and v_F are the lead and following vehicle speeds (m/s), len_L is the lead vehicle's length (m), b is the vehicle maximum deceleration (m/s^2) (assumed identical for all vehicles and known by all drivers), τ is the car following sensitivity parameter (s), d_{crit} is the distance below which the car following would be unsafe (m), d is the actual car following distance if the vehicle moved into the gap (m), and F (= smallest acceptable gap / d_{crit}), is the gap adjustment factor (unitless), unique for each vehicle.

Each vehicle has its own value of F, which specifies 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 d_{crit}, 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. It should be noted that this approach differs from that of the original Gipps model (Gipps, 1981, 1986) which did not contain an vehicle-specific gap adjustment parameter, effectively applying $F=1.0$ for all vehicles in equation (4) above.

If the lane change is feasible, that is, the lead and lag gaps in the adjacent lane are acceptable, then the next check is if it is desirable. This is the case where the allowable speed can be improved up to the desired speed, compared to the present lane. If several lanes receive the same allowable speed, the target lane is chosen according to the lane discipline rule. The formula for allowable speed, v_{allow}, is given in equation (5). The case in which the first argument in the *min* function on the right-hand-side governs, has been derived from equation (2). This can easily be verified by solving equation (5) for $x_{n-1}(t) - s_{n-1} - x_n(t)$ which will give equation (2).

$$v_{allow} = \min\left\{\frac{3}{2}b\tau \pm \sqrt{{v_L}^2 - 2b(x_L - len_L - x_F) + \frac{9}{4}b^2\tau^2}, v_{des}\right\}, \tag{5}$$

where v_{des} is the subject vehicle's desired free driving speed.

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.

2.4 Tactical lane change model

The tactical lane change model provides a framework for representing the act of planning in the human driver's lane change decision process. In the model, the driver considers all maneuver sequences unfolding over a planning time horizon, and selects the action sequence which best satisfies his or her goals.

Like the basic lane change model, it also follows the same two-step decision process: (1) checking the feasibility of lane change to the candidate adjacent lane feasible in terms of safe gap availability and (2) checking the desirability to change lanes. However, the Tactical Lane Change Model decides the desirability not by considering the current conditions, but rather by predicting the resultant states of the subject and surrounding vehicles for various sequences of subject vehicle lane change maneuver choices over the planning time horizon t_h, which is a model parameter on the order of 10 s or less.

A Forward Search Tree is constructed starting at the present time, and projecting forward each planning time step until the time horizon. The maneuver sequences to be considered must allow safe following and lane changes into safe gaps under the same gap acceptance criteria of the basic lane change model. The structure of the Forward Search Tree is shown in Figure 3; it represents the enumeration of possible maneuver sequences. Like the basic lane change model, the sequential planning lane change model is executed every simulation time step, and returns an integer representing the lane change control action to be executed at the current time step: -1 for *left*, +1 for *right*, and 0 for *no lane change*.

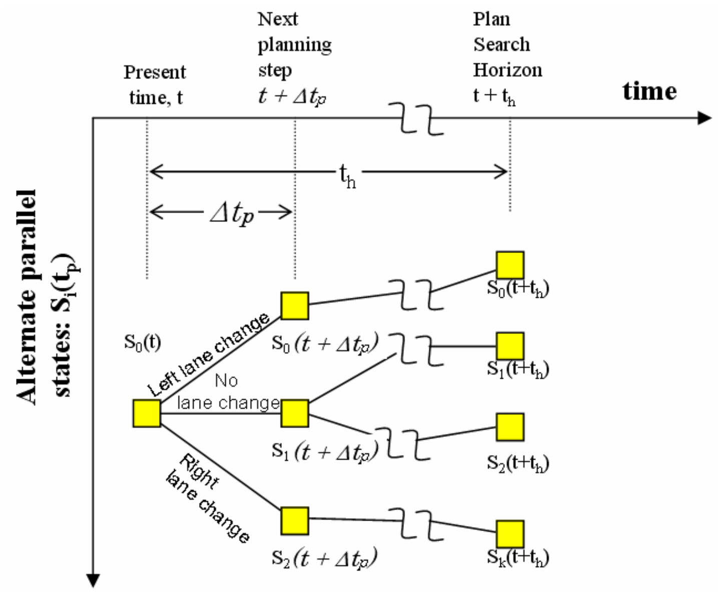

FIGURE 3: Forward search tree

The nodes in the Forward Search Tree 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 of each of the surrounding vehicles, represented collectively as state $S_j(t_p)$ (yellow square in Figure 3). For a given planning time t_p there will be one or more unique states $S_j(t_p)$ with index j.

$$S_j(t_p) = \{\hat{x}_n(t_p), \hat{l}_n(t_p), \hat{v}_n(t_p) \mid n = 1, 2, \ldots\ldots, N\}, \tag{6}$$

where t_p is the planning time point, $S_j(t_p)$ is the state j at time planning time t_p, which includes the position and speed of all vehicles, n is the index number of subject vehicle or nearby non-subject vehicle, N is the last in the list of subject vehicles, $\hat{x}_n(t_p)$ is the predicted longitudinal position of vehicle n at planning time t_p, $\hat{l}_n(t_p)$ is the predicted lane of vehicle n at planning time t_p, and $\hat{v}_n(t_p)$ is the predicted speed of vehicle n at planning time t_p.

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 $S_j(t+\Delta t_p)$ ($i \neq j$). In the proposed model, the planning time step size is set equal to a user-specified parameter, Δt_p. In this analysis, Δt_p is set to 1.0 s. Note that the planning step size Δt_p should not be confused with the simulation time step size Δt. Also, in the proposed model, Δt_p is necessarily a multiple of Δt. This is not a problem when Δt is very small (e.g. $\Delta t < 0.2$ s) as is the case for the data set analyzed, in which $\Delta t = 0.0667$ s. Thus any errors due to rounding of Δt_p are very small and can be ignored. Also, there are no restrictions on Δt_p with regards to the longitudinal control model time lag parameter τ.

The Tactical Lane Change Model's computational complexity greatly depends on the time resolution used. For this analysis, with $\Delta t_p = 1.0$ s, the computations for a single vehicle were possible on a desktop computer. Other factors which can affect the computation time are the length of time horizon t_h, the number of lanes, and level of traffic (moderate traffic density gives the most non-redundant choices of maneuvers). That said, the Tactical model has a much higher computational cost than the Basic lane change model, which makes only a few computations at each simulation time step.

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. 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 s x 30 m/s = 180 m < 200 m view distance) Next, all possible states $S_j(t_p)$ are successively estimated for each planning time t_p at planning increments Δt_p until the time horizon, $t + t_h$, as shown in Figure 4.

This is a *breadth-first* search. A contrasting approach would be *depth-first* search, see Russell and Norvig (2003), Chapter 3. To estimate one or more resulting states $S_j(t_p)$ from the previous planning state $S_i(t_p – \Delta t_p)$, the surrounding vehicles (non-subject vehicles) are simply advanced in the same lane at their current speed, constrained by safe car following. Subject vehicle longitudinal control actions are represented as maximum achievable velocity allowed by the vehicle's performance, constrained by safe car following and the driver's desired speed. For the subject vehicle, every state $S_i(t_p – \Delta t_p)$ 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 $S_j+(t_p)$ and $S_j+2(t_p)$ may be added, thus making a branch in the Forward Search Tree.

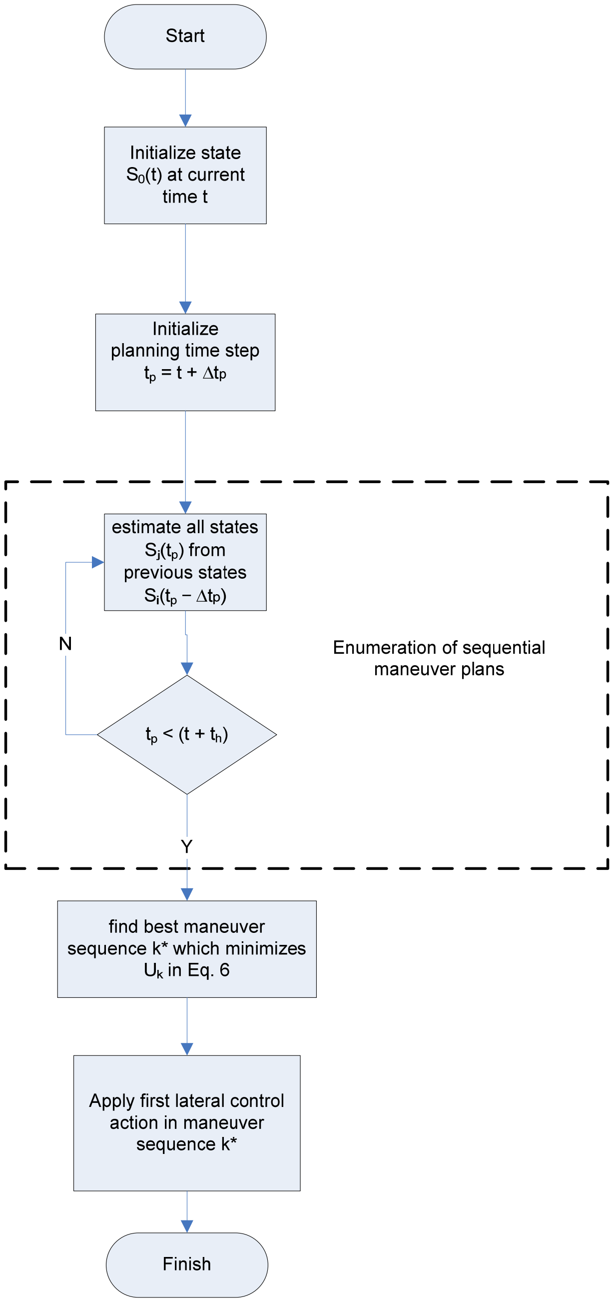

FIGURE 4: Tactical lane change model using Forward Search Tree

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.

It should also be noted that the tactical maneuver plan does not consider potential lane changes by the surrounding vehicles. To account for complex interactive situations such as in Figure 5, in which the drivers of vehicles A and B are both considering moving into the middle lane, further model development would be needed. However, even in the current model, if called for every vehicle in a traffic simulator, it would simultaneously determine the tactical decision for every vehicle over a short time interval and thus could be expected to reproduce traffic always simultaneously responding to surrounding vehicles. Also it should be mentioned that in any simulator implementation, measures for dealing with the special case of A and B initiating the lane change at the exact same time, would be necessary.

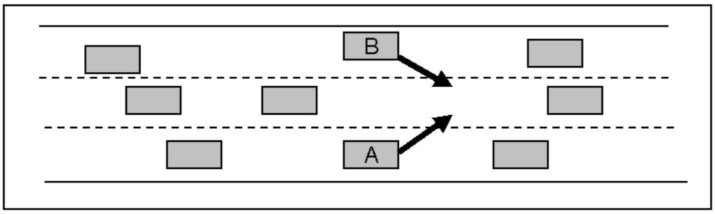

FIGURE 5: Example situation with anticipation of other vehicle lane changes, not included in model

Regarding the length of the time horizon, t_h, it is possible 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 on a basic roadway section.

The completed Forward Search Tree enumerates a set of subject vehicle maneuver sequences. The subject vehicle selects one maneuver sequence from this set. The lane change action (or no action) initiated over the upcoming simulation times step is first action in this selected plan. The maneuver sequence which gives the maximum utility based on distance gained for the subject vehicle over the planning time horizon is selected (equation (7)). Note that the model presented here is capable of representing discretionary lane changes, but not mandatory lane changes, which would require additional variables in the utility function to account for the advantage of being in a destination lane to achieve the desired route.

$$U_{SV}^{k} = \hat{x}_{SV}^{k}(t+t_h) - x_{SV}(t)\,, \tag{7}$$

where U_{SV}^{k} is the utility of maneuver sequence k for the subject vehicle, $x_{SV}(t)$ is the subject vehicle's current longitudinal position, and $\hat{x}_{SV}^{k}(t+t_h)$ is the longitudinal position of the subject vehicle at the planning time horizon if using maneuver sequence k.

In Figure 6, the subject vehicle generates four maneuver sequences in the Forward Search Tree, {P1, P2, P3, P4}. Over the time horizon, each plan allows a certain distance to be gained. Because the distance gained by plan P4 is the longest, this plan gets the maximum utility in the objective function and is selected as the best maneuver plan. It is shown in red in the figure. The current action in this plan is to make a left lane change, so that left lane change is selected as the lane change action which is the tactical lane change model's result.

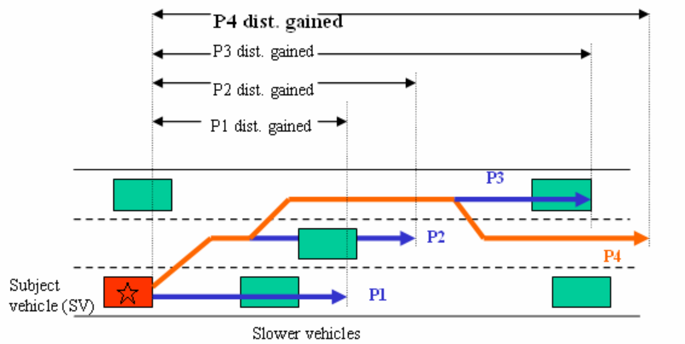

FIGURE 6: Selection of lane change action, example

In cases of equal value of U for several movement plans, the plan will be selected according to the lane discipline user setting. For example, if the lane discipline setting is set to “free lane” then the plan among the tied best-scoring plans which has an initial “no lane change” action would be selected.

3. BEST-FIT MODEL ESTIMATION AND PERFORMANCE COMPARISON

A comparison of the realism performance in representing the lane change behavior of individual vehicles from a trajectory set was conducted, for the tactical and basic lane change models. The best-fit tactical and basic lane change models were compared. These models were used in conjunction with the longitudinal control model which was also best-fit estimated for each analyzed vehicle. First the data set is described, next the techniques used for driver model parameter best-fit estimation, and finally the basic and tactical lane change models are compared in terms of realism in modeled lane change actions of the individual analyzed vehicles.

3.1 Real-world vehicle trajectory data set

The NGSIM project (Cambridge Systematics, 2004a) is a research project led by the US Department of Transportation 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 community. The data set consists of a 900 m long 6-lane section of the I-80 freeway in Oakland, California. The data set was collected from 2:35 to 3:05 p.m. on April 22, 2004. The traffic conditions range from moderate to congested flow conditions. The section contains an upstream single-lane entry ramp, and a downstream single-lane exit ramp. The data has a spatial resolution within 1.0 meters, 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 (Ni and Leonard, 2006).

3.2 Longitudinal control model best-fitting technique

The longitudinal control model is calibrated by finding the set of model parameters which gives the most similar trajectory for the simulated vehicle, compared to the actually-traveled trajectory. This approach was also used by Ossen et al. (2006).

The objective function $U_{ordLong}(\tau,v_{des})$ is computed over a range of values and estimate (τ,v^*_{des}) which minimizes $U_{ordLong}$. To evaluate each $U_{ordLong}(\tau,v_{des})$ is computed over a range of values and estimate (τ,v^*_{des}) which minimizes $U_{ordLong}$. To evaluate each $U_{ordLong}(\tau,v_{des})$, the simulator is executed with the selected parameters as input arguments, in an automated fashion. The traffic simulator is run using the real vehicle trajectories for the surrounding vehicles and only the subject vehicle under the simulator model control. The lane change action is disabled for the subject vehicle. For each time step in the simulation, if the subject vehicle has a different lead vehicle than the real analyzed vehicle, then the subject vehicle is reset to the real vehicle's position and velocity. The simulator writes the trajectory of all simulated vehicles to an output data file, which is then read and the root-mean-squared (RMS) difference of the subject vehicle's longitudinal position to the actual position in the real data is calculated for every time step in which the simulated vehicle and real vehicle are both present.

The objective function is as follows:

$$U_{ordLong} = RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}[x_{sim}(i) - x_{realData}(i)]^2} \ , \tag{8}$$

where $U_{ordLong}$ is the objective function based on longitudinal difference between simulated subject vehicle and its real course, i is the index number of time step over the duration of the simulation, n is the total number of time steps, $x_{sim}(i)$ is the position of the simulated subject vehicle at time step i, and $x_{realData}(i)$ is the position of the real vehicle in the trajectory data at time step i.

In Figure 7, the longitudinal course is shown for the vehicle running in the simulation according to its optimized longitudinal control parameters $\{\tau^*, v^*_{des}\}$, together with the actual vehicle trajectory.

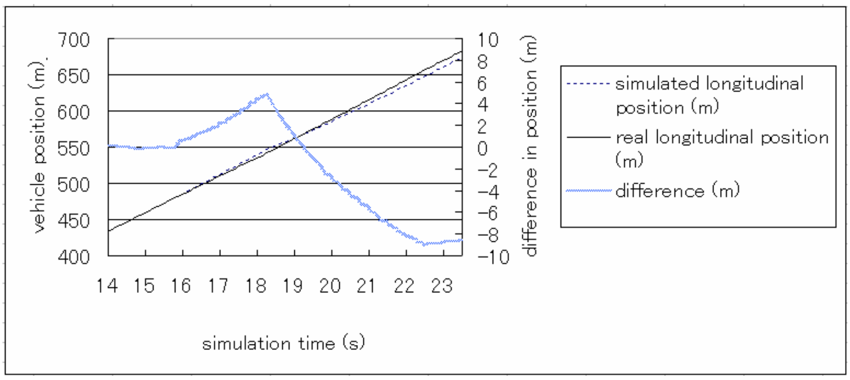

FIGURE 7: Example of the optimized longitudinal control simulated trajectory compared to the real vehicle trajectory

3.3 Lane change model best-fitting technique

The lane change model performance function U_{LC} is computed separately for each vehicle to be analyzed, as described in this section. First, the traveled course of the real vehicle is divided into units known as gap sessions.

A gap session is a time period over which the subject vehicle has the same set of vehicles in the relative positions around it, specifically the {*lead, rear, left lead, left rear, right lead, right rear*} positions, and the same gap availability. The concept of gap session is illustrated in an example in Figure 8 which shows how one gap session transitions into another.

The gap session shown at the top of Figure 8 has lead vehicle D, rear vehicle C, a left gap with lead vehicle B and rear vehicle A, and right gap with lead vehicle F and rear vehicle E. The spatial size of this gap session is the length in meters from the back bumper of Vehicle D to the front bumper of Vehicle C. This gap session transitions to that shown at the bottom of Figure 8, when vehicle A in the left lane pulls alongside the subject vehicle, ending the availability of a left gap.

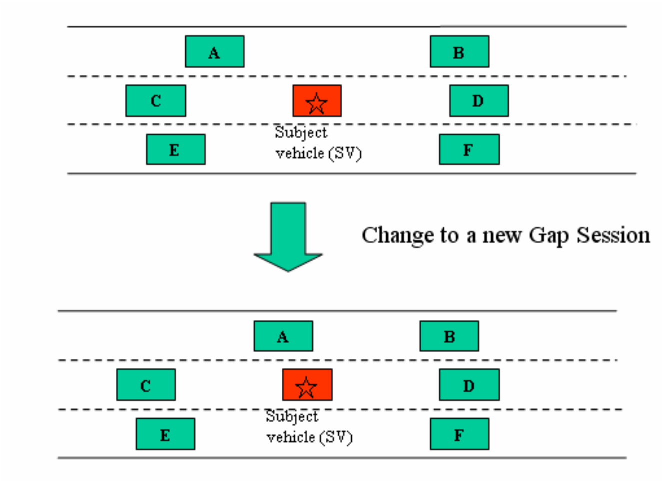

FIGURE 8: Transition between gap sessions

For each driver model considered, the U_{LC} is computed for each point in the parameter search space: $\{F, t_h\}$ for the tactical model, $\{F\}$ for the basic model. The best-fit parameters are those which minimize the fitness value U_{LC}. The overall performance of the model is the minimum score obtained for U_{LC}. In the simulation the longitudinal control model is given the best-fit parameter values which have been already determined as described in Section 3.2.

The simulated subject vehicle (SV) is set at initial conditions and history of the real vehicle for the beginning of each gap session. Then the SV is simulated until the end of the gap session using the best-fit longitudinal control model parameters τ and v_{des}. If, during the simulated gap session i, the SV performed the same lane change as the real vehicle, then δ_i is 0; otherwise it is 1. At each gap session, the lane change action resulting from the simulator given the selected vector of parameters, is used to compute the objective function score U_{LC}.

$$U_{LC} = \frac{\sum_{\forall i} w_i \delta_i}{\sum_{\forall i} w_i}, \tag{9}$$

where U_{LC} is the performance evaluation of lane change model (0 is best possible, and 1 is the worst), i is the index number of Gap Session i, w_i is the weight of Gap Session i, $L_{x|i}$ is the spatial size of Gap Session i when it begins, $L_{t|i}$ is the time duration of Gap

Session i, and δ_i equals 1 if the SV has a different lane change action from the real vehicle in Gap Session i, and 0 otherwise.

The contribution of each gap session i is given by its weight:

$$w_i = (L_{x|i})*(L_{t|i}). \tag{10}$$

This weighting strategy allows gap sessions which have a bigger size and a longer duration to get a greater influence on the computation of the measure of correctness U_{LC}. This is important to prevent gap sessions which are very small or of short duration from having a disproportionate influence on the measure of correctness.

The range and grid search interval of longitudinal control and lane change model parameters are shown in Table 1. These values were selected so as to provide an adequate range as well as coverage density of appropriate values. The search range of reaction time lag τ was selected to adequately cover the range of this value, as reported in a number of studies on driver reaction time reviewed in Koppa (2002). The desired speed v_{des} search range was selected to adequately cover a range of speeds from well below to well above the average time-mean speed in non-congested flow (100 km/h) found in the reference describing the data set (Cambridge Systematics, 2004a).

TABLE 1: Parameter search range and grid spacing

Parameter	Description	Minimum	Maximum	Interval
τ	Reaction time lag (s)	0.2	2.0	0.2
v_{des}	Desired speed (m/s)	25.0 (90 km/h)	40.0 (144 km/h)	2.5 (9 km/h)
F	Gap adjustment factor	0.4	1.6	0.2
t_h	Planning time horizon (s)	1.0	8.0	1.0

The minimum value in the search range for the planning time horizon parameter t_h was 1.0 seconds. This is because the Tactical Lane Change Model is based on distance gained over the time horizon, so a parameter value $t_h = 0$ would be meaningless as there would be no plans generated, and no difference in their distance in terms of which to compare their utilities.

3.4 Performance comparison

From the trajectory data, a set of 36 vehicles was selected which performed a relatively large number of lane changes, and had an overall high travel speed in comparison to the surrounding vehicles. The performance of both the Basic and Tactical lane change models was measured for each vehicle. The summary statistics of the estimated parameters: $\{\tau^*, v^*_{des}, F^*_{basic}, F^*_{seqPl}, t^*_{h,seqPl}\}$ as well as the lane change model performance values $\{U_{LC|basic}, U_{LC|seqPl}\}$ are shown in Table 2.

TABLE 2: Summary statistics of vehicle parameter estimation

	τ^* (s)	v^*_{des} (m/s)	F^*_{basic}	$U_{LC\|basic}$	F^*_{seqPl}	$t^*_{h,seqPl}$	$U_{LC\|seqPl}$
Mean	0.81	32.4	1.12	0.24	0.98	2.00	0.14
Std. dev.	0.42	5.9	0.32	0.22	0.19	1.49	0.11
Median	0.70	31.0	1.00	0.19	1.00	1.00	0.11
Min.	0.20	25.0	0.40	0.00	0.40	1.00	0.00
Max.	1.90	40.0	1.60	0.91	1.60	6.00	0.44

Over the set of vehicles analyzed, the overall performance of the two lane change models can be judged by the number of vehicles in which the performance was better by either model. Figure 9 shows the improvement in performance by using the Tactical Lane Change Model, compared to the Basic Lane Change Model, for each analyzed vehicle. It can be seen that in the majority of vehicles considered (64%), the Tactical Lane Change Model resulted in an improvement in the performance.

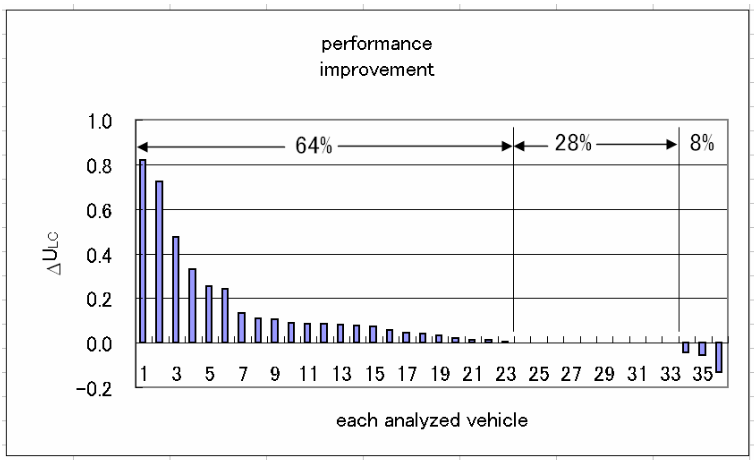

FIGURE 9: Comparison of performance of lane change models

It should be noted that in 8% of the cases, the Tactical Lane Change Model gave inferior performance compared to the basic lane change model. This may reflect the cases where drivers make choices of lane change action that are influenced by factors not included in the model. It is also possible that for these cases, the Basic Lane Change Model simply gives a better representation of their driver behavior, in that they may select their lane change actions in terms of the allowable speed by lane at the current time and not make a plan.

It should be noted that although this comparison has shown a superior performance for a subset of the vehicles in the traffic stream, that these vehicles may likely exert a disproportionate effect on the traffic stream as a whole through shockwaves due to their frequent lane changes. Further, in simulation travel time studies of a subset of the traffic stream, such as the HOV vehicles entering the freeway in the example mentioned earlier in this paper, such a difference in lane change behavior will influence the travel time of this subset of the vehicles.

4. CONCLUSIONS

In this paper, a Tactical Lane Change Model was described, which determines the simulated vehicle lane change action by selecting from maneuver sequences over a planning time horizon. The model parameters were best-fit for selected individual vehicles from a trajectory data set. The model was compared to a Basic Lane Change model which did not contain sequential maneuver planning, and it was found that the Tactical Lane Change Model gave more realistic representation of lane change actions for a greater number of analyzed vehicles.

In this work, the potential for improving lane change model realism was shown. However, other tasks have been left for further research. An interesting topic for further research is the effect of the use of the Tactical Lane Change Model (rather than the Basic model), on the realism performance of the traffic stream as a whole, rather than in terms of the individual vehicle, as was done here.

To fully implement traffic simulation for transportation management and operations applications requires the simulation of all the vehicles concurrently in the traffic stream. And the model itself could be further improved by expansion of the model functions to include mandatory lane changes, longitudinal control action planning, cooperative behavior and others. Additionally, the computational efficiency should be addressed, which would be essential in its application to a traffic simulator. The benefit of potential improvement in realism, shown in this paper, must be balanced with computational costs, especially when simulating many vehicles.

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