TACTICAL DRIVER LANE CHANGING HEURISTIC USING FORWARD SEARCH

by Nathan Webster*, Masao Kuwahara**, and Edward Chung***

1. Introduction

Traffic simulators are 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.[1] In a microscopic traffic simulator, the state and motion of every vehicle as well as other elements (such as a traffic signal) are represented dynamically in the simulation. The vehicle motion is based on the vehicle's internal characteristics (e.g. vehicle type, desired speed, driver aggressiveness, etc.), as well as the conditions of nearby vehicles.

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.[2]

In a simulator, representation of short-term planning is important for simulated maneuvers in which the reward for performing the action is slightly delayed. For example if from a crowded lane, a driver sees past an even more crowded adjacent lane to an open lane two lanes away (such as a high-occupancy vehicle (HOV) exclusive use lane), he would never move into that lane if he considers each lane change one at a time.

However, the current (state of the art) simulator does exactly this, considering only the very next action, neglecting the near-term plan made by the driver, possibly leading to an overestimation of the traffic congestion, compared to that in the real world.[3] In this paper, the existing approaches to driver tactical models are surveyed, and a heuristic to represent driver tactical driver lane changing behavior in a simulator is proposed.

2. Review of the State-of-the-art

In general, driver behavior models perform a mapping of environmental conditions to a corresponding driver response. For example, a mapping could contain a rule such as: "if a driver is following behind a very slow car, and there is a gap available in the lane to his right, then his action is to make a lane change to the right". These are represented as if-then rules in flowcharts or pseudo code. Gipps[4] enumerated such a mapping in 1986.

Additionally, each traffic simulator addresses several issues. First, the representation of the vehicle and driver can be as a single entity, the "driver-vehicle unit"; or else as two separate models, such as the "driver model" which determines driver control action values on the steering, accelerator, and brake, and the "vehicle dynamics model" which determines the exact vehicle motion, including the internal parts of the vehicle and the wheels, based on a set of driver control actions.

Another consideration is the variation of driver behavior by individual. One person may drive aggressively and follow closely, accepting very small gaps for lane changing, while another may act more carefully or conservatively. In general there are as many driver types as there are drivers; just as each person has a unique fingerprint pattern,

Key words: traffic simulation, artificial intelligence, driver model
* PhD Student, Institute of Industrial Science, University of Tokyo, 4-6-1 Komaba, Meguro-ku, Tokyo 153-8505, Japan., Tel: 03-5452-6419, Fax: 03-5452-6420, Email: nwebster@iis.u-tokyo.ac.jp
**Professor, Institute of Industrial Science, University of Tokyo, 4-6-1 Komaba, Meguro-ku, Tokyo 153-8505, Japan., Tel: 03-5452-6419, Fax: 03-5452-6420, Email: kuwahara@iis.u-tokyo.ac.jp
***Adjunct Professor, Collaborative Research Center for Advanced Mobility, University of Tokyo, 4-6-1 Komaba, Meguro-ku, Tokyo 153-8904, Japan., Tel: 03-5452-6529, Fax: 03-5452-6420, Email: edward@iis.u-tokyo.ac.jp

each person may have a unique (different even if very slightly) mapping of environmental conditions to response actions, compared to any other driver. However for practical implementation in a simulator, similar drivers can be aggregated into a finite set of archetypes. Commercial software often allows the user to configure several driver types with customized settings of the parameters. There have been studies using instrumented vehicles to measure and characterize driving patterns of many individuals and then to aggregate them into groups of drivers with similar behavior.[5)]

Toledo[3)] 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 decision model using a set of logit equations with coefficients calculated based on a test data set using maximum likelihood estimation techniques. He applied the developed model to a test case and compared it to a 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[6)] has developed a lane changing and car following model based loosely on Gipps 1986 model[4)]. The model accounts for cooperativeness when determining mandatory lane changes (lane changes where the vehicle be in a particular lane to make a downstream turn). However, it only considers the immediate lead and rear vehicles. 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. In 2005, Hidas[7)] 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 short-term plan they describe is simply the very next lane change. Although this is an improvement over the simple reactive models which only consider the immediate effect of each action in the very next time step, it does not account for the driver performing actions as part of a plan over the short term, such as where there is a delayed reward for a sequence of actions. In the next section, I propose a method to represent this near-term planning element in the modeling of driver tactical lane changing behavior.

3. Tactical Modeling Approach

The Forward Search Algorithm[8)] is used in a variety of applications such as robot control and computer chess playing. At each time instant, a player considers the possible choices he can make now and in the near future, and their outcomes, visualized as a branching tree as shown in Figure 1.

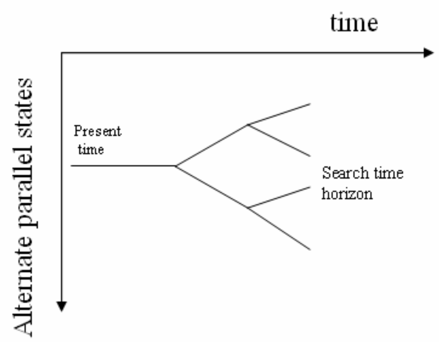

Figure 1. Forward Search Tree

Each branch represents a particular choice of actions by the player (and those of other players), and the events which are expected to occur due to this set of choices. Such a prediction, which takes place in the mind of the player, is projected until the time horizon. During model development, the length of the time horizon should be considered in detail, based on the time required for completing, say, at least two lane changes. At each moment when deciding what action to take, a player builds the forward search tree, and selects the current action which leads to the best outcome, e.g. the outcome which has the player in the best situation at the time horizon.

When applying the forward search heuristic, in order to restrict the number of possible control actions (and thus branches in the forward search tree) to a computationally feasible number, the subject vehicle maneuver control is to limited lane changing (or not) at the first opportunity only. Longitudinal actions are represented as maximum acceleration, constrained by safe car following and the driver's desired speed. In the conceptual framework proposed in this paper, tactical planning of longitudinal acceleration and deceleration, which accompanies lane changing maneuvers, is left for further research. The latter has been addressed in detail in Toledo's dissertation.[3)] The surrounding vehicles are assumed to not make any lane changes and to simply continue at their current speeds, performing car following when necessary. Note that this differs from the case of computer chess in which the opponent player may also make several possible moves in a given situation, causing further branching of the search tree.

When the driver finds a choice of lane change, the tree splits into two branches. At the time horizon, each action plan can be evaluated in terms of how it improves the situation for the driver, such as minimizing travel time or returning to the shoulder lane. Thus for each plan a numeric score can be calculated, and the best plan can be selected. The scoring of candidate plans should be performed to represent the driver's evaluation of the relative advantage of each plan. For example, a scoring system which is to be used in the example to be explained below includes two scoring criteria: (a) longitudinal displacement from the current location at the time horizon (how far ahead the driver will go using this plan), and (b) location in the shoulder lane at the time horizon. The system of scoring should be based on knowledge of driver's assessment of the relative advantage of alternative situations, and the score on each criteria should reflect its relative importance to the driver's assessment. Various other criteria are also possible, such as minimizing the number of lane changes, avoiding following behind large vehicles or minimizing speed fluctuations, but are not included in this example. In the example below, the scoring system chosen was to give points to criterion (a) in proportion to the linear displacement, and (b) as either *2* if the subject vehicle is in the shoulder lane at the time horizon, or *0* otherwise. The choice of *2* points for being in the shoulder lane here reflects the judgment of the relative importance of this criterion compared to the longitudinal displacement advantage.

Consider the example shown in Figure 2, a two-lane freeway where the left lane is the shoulder lane and the right lane is the overtaking lane. The subject vehicle (marked with a star) is overtaking two slower vehicles spaced slightly apart. According to the limitations on subject and non-subject vehicle actions described above, the subject vehicle driver has two possible action sequences: (1) Return to the shoulder lane after passing the first slow car, or (2) stay in overtaking lane and overtake both slow cars. In plan (1), he can see that there is a faster vehicle behind him which will delay him when he later tries to return to the overtaking lane. The difference in the performance of the two plans is shown in the scoring tally in Figure 3. From the earliest (leftmost) scene, he can consider plans (1) and (2) and determine which plan will best serve his goals, such as moving forward as far as possible (i.e. minimizing travel time).

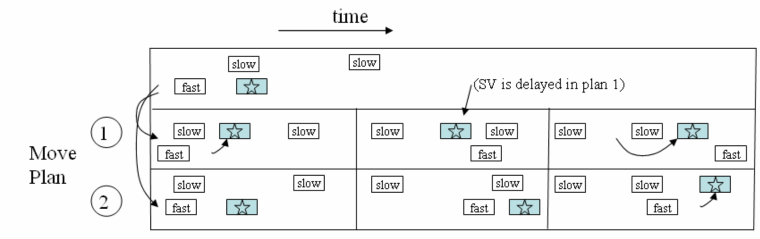

Figure 2. Example of tactical path planning.

In the example, the numeric scoring values were assigned to both plans (1) and (2) based on these criteria, and a total score was computed for each plan. Plan (2) is seen to have a higher score, therefore in the model, the driver would choose plan (2).

Performance		Getting ahead	Finally in travel lane	Total score
	1	8	2	10
	2	10	2	12

Figure 3. Evaluation of alternative plans.

To account for a human driver's imperfect perception, reasoning, and control, a random utility discrete choice model could be used. A random error term could be added to the utility of each plan *i* (eq. 1), and the probability of the driver choosing the plan can be proportional to a function such as *Log* of its utility (eq. 2).

$$U(i) = Score(i) + random\ error\ term \qquad (1)$$

$$P(i) = \frac{Log(U(i))}{Log(\sum_{\forall j} U(j))} \qquad (2)$$

In the above example, the proposed forward search tactical driver lane change heuristic may be able to explain the widely-observed macroscopic phenomenon of overuse of the overtaking lane on long intercity two-lane sections. In the proposed tactical heuristic, each driver makes a rational choice to stay in the overtaking lane to avoid delay. The large scale (macroscopic) effect is to have a platoon of vehicles in the overtaking lane, and slower vehicles using the shoulder lane, widely spaced apart.

The proposed tactical decision framework considers possible lane changing action sequences, and selects the action which gives the best performance in meeting the final goal, not merely intermediate goals. This paper presents only the conceptual framework. In further research, a quantitative model of the vehicle motion will be developed and calibrated with real traffic data, and validated based on its ability to replicate real traffic situations.

Acknowledgment

The author receives financial support for this research through the Japanese Ministry of Education, Culture, Sports, Science and Technology.

References

1. SMARTEST. Simulation Modelling Applied to Road Transport European Scheme Tests. University of Leeds. Final Project Report. www.its.leeds.ac.uk/projects/smartest/ 1999.

2. 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.

3. Toledo, T. Integrated Driving Behavior Modeling. PhD Dissertaion. MIT. 2003.

4. Gipps, P.G. A Model for the Structure of Lane-Changing Decisions. Transport. Res. 20B, 107–120. 1986

5. Delorme, D., and Song, B. Human Driver Model for SmartAHS. California PATH Research Report UCB-ITS-PRR-2001-12. 2001.

6. Hidas, P. Modelling lane changing and merging in microscopic traffic simulation. Transportation Research Part C. 10, 351 – 371. 2002.

7. Hidas, P. Modelling vehicle interactions in microscopic simulation of merging and weaving. Transportation Research Part C 13, 37–62. 2005.

8. Russell, S. J. and Norvig, P. Artificial Intelligence: A Modern Approach, 2nd ed., Prentice Hall, 2002.