CAR-DRIVER MODELS FOR MANUAL AND AUTOMATED TRAVEL

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Abstract: This paper presents a model for manual and automated traffic flow. The model is based on the abstraction of vehicle activities by the space and time taken up by the vehicle engaged in the activity. The manual driver model includes the activities of vehicle following and lane change and allows for different levels of aggressiveness of drivers. The parameters of the activities are calibrated with real highway data. The expectation is that this model will provide more realistic estimates of highway capacity while retaining the efficiency of macro-scale simulators.

Keywords: traffic flow models, capacity, automated highways

1. INTRODUCTION

In this paper we present a model for manual traffic based on ideas of automated traffic flow modeling. The model resembles traditional vehicle-follower models in that it uses vehicle follower behavior to determine the maximum density of traffic flows. It departs from traditional approaches by allowing differentiation among types of drivers and types of activities that drivers perform. The model is an outgrowth of work on automated traffic flow on an AHS (Broucke and Varaiya, 1996).

The paper is structured as follows. We begin by presenting the activity model, including the conservation of vehicles law and velocity dynamics and show how vehicle activities are abstracted in the model by the space-time they use up. Next we describe the activities performed by manual drivers and how these are incorporated in the model. A tool called SmartCap is used to calibrate and perform simulations with the model. An example of the model is presented for the Bay Bridge in San Francisco. In this example, variations in the driver's behaviour are modelled by the activity descriptions which include the desired headway distribution and tunable parameters for the lane-changing logic.

2. ACTIVITY MODEL

In automated traffic vehicles perform a sequence of maneuvers or activities that are implemented through vehicle control laws. The control law defines a desired velocity and/or safe spacing from the vehicle ahead (as well as desired steering angle). These characteristics of the control law are abstracted in the activity model by the space-time of vehicle activities. The space-time abstraction is used to set an upper limit on the density of traffic flow. In simplest terms, it means if all vehicles perform an activity α and the space-time for this activity is $\lambda(\alpha) = s \cdot \tau$, with s in meters and τ in seconds then the maximum density is $k = \frac{1}{s}$. The situation becomes more interesting when s, τ, and the choice of activity α are all variable.

* This research is supported by the California Department of Transportation through the California PATH program and the Federal Highway Administration through the National Automated Highway System Consortium.

Thus, the model can predict more realistic estimates of capacity when vehicles are performing maneuvers on the AHS, such as doing entry or exit. This idea is carried over to manual traffic, where manual drivers perform the activities entry, exit, lane change, and vehicle following.

The highway is divided into segments indexed $i = 1, ...I$, which are one lane wide and of length $L(i)$. Time is discretized $t = 1, 2, ...$ with a time period of T seconds. Flow types, indexed by θ, are distinguished in the model by the destination and vehicle body type. The states of the model are $n(i, t, \theta)$, the number of vehicles in each highway section at each time and of each flow type and $v(i, t)$, the average velocity in each highway section at each time.

Because the model is intended for automated flow it allows several parameters of the flow to be controlled. These include $v_d(i, t)$, the desired average speed in each section, $f(i, t)$, the volume of entry flow, and $\pi(\alpha, i, t, \theta)$, the proportion of vehicles of type θ in section i at time t that will perform activity α. By including these control parameters in a manual driver setting we are able to examine the effect of partial control of manual traffic such as advised speeds, metering at entrances, and advised lane changes. The model also allows mixed manual/automated traffic to be investigated. Values for the controlled variables are issued by a Traffic Management Center (TMC). In a manual driver setting the TMC will model the will of the collective of drivers.

The activity model uses a conservation of vehicles law and velocity dynamics equation to update the states. The conservation law can be thought of as consisting of two steps: first, move vehicles doing a lane change activity laterally, and second, move vehicles longitudinally. We let α_r (α_l) denote the set of activities that turn right (left) and π_r (π_l) be the proportion of vehicles that turn right (left). π_s is the proportion of vehicles that go straight. (Note that $\pi_r(i, t, \theta) + \pi_l(i, t, \theta) + \pi_s(i, t, \theta) = 1$.) We assume that π_r and π_l represent successful lane changes. Considering vehicles that go straight, we define $\rho(i, t)$ to be the fraction of vehicles in section i at time t that remain in the section at time $t + 1$. Using the assumption of uniform spatial distribution of vehicles of the same flow type within a section, we have:

$$\rho(i, t) := 1 - \frac{v(i, t) \times T}{L(i)} . \qquad (1)$$

Let $n_{long}(i, t, \theta)$ be the number of vehicles in section i at time t of type θ after lane changes are done, given by:

$$n_{long}(i, t, \theta) = n(i, t, \theta)\pi_s(i, t, \theta) + n(j, t, \theta)\pi_r(j, t, \theta) + n(k, t, \theta)\pi_l(k, t, \theta). \qquad (2)$$

Then, the conservation of vehicles law is:

$$n(i, t + 1, \theta) = n_{long}(i, t, \theta)\rho(i, t) + n_{long}(i - 1, t, \theta)[1 - \rho(i - 1, t)] + f(i, t, \theta). \qquad (3)$$

The velocity in a section i is limited by the space available in the downstream section. Let $v_s(i, t)$ be the maximum speed in section i so as not to exceed the space available in section $i + 1$. Then the speed achieved in a section can be no larger than $v_d(i, t)$ and $v_s(i, t)$ and the velocity law gives the average speed over period t as

$$v(i, t) = \min\{v_d(i, t), v_s(i, t)\} . \qquad (4)$$

Finally, the flows and activities are constrained by the maximum available space-time in a section over one period. First, the space-time for an activity can be computed using a specification of the space as a function of time, given by $s(t)$, and the duration of the activity, given by τ. The space-time is

$$\lambda(\alpha) = \int_0^\tau s(t)dt.$$

The space-time constraint is

$$\begin{aligned} L(i) \cdot T \geq & \qquad (5) \\ & \sum_\alpha \sum_\theta n(i, t, \theta)\pi(\alpha, i, t, \theta)\lambda(\alpha) + \\ & \sum_{\alpha_r} \sum_\theta n(j, t, \theta)\pi(\alpha, j, t, \theta)\lambda_r(\alpha) + \\ & \sum_{\alpha_l} \sum_\theta n(k, t, \theta)\pi(\alpha, k, t, \theta)\lambda_l(\alpha) \end{aligned}$$

where j is the lane to the left and k is the lane to the right.

3. SMARTCAP - A MESOSCALE SIMULATOR

SmartCap is a tool that simulates automated and manual traffic based on the activity model just discussed. It is part of a toolset for evaluating AHS designs for the National Automated Highway System Consortium. SmartCap takes as input a description of the highway in the form of a set of sections consisting of contiguous lanes which are typically 500 meters long, and a connectivity map linking the sections into a graph. The relevant parameters of the highway configuration are section length, number of lanes, and exit capacity.

The simulator evolves vehicle flows according to the conservation and velocity dynamics laws. It keeps track of flow types, which are distinguished by vehicle class and by the exit taken by the vehicle. The rates of entry for each flow type are defined as functions of time. A simulation is initialized by specifying the number of vehicles, average velocity, and proportion of each activity in each section. The capacity of exits is fixed in order to model the capacity limits of urban arterials.

The AHS "design" is encoded in the activity specification and in the TMC plan. The activity specification for manual traffic is described below. The TMC plan models the commands sent to vehicles from the TMC: proportion of vehicles of a given flow type in each section performing an activity α, the desired speed, and the entry metering policy. Thus, the TMC plan consists of a velocity plan, entry plan, and activity plan. Each of these modules will be described for the manual driver scenario.

One iteration of the algorithm over period t executes the following steps:
1. Update TMC commands $\pi(\alpha, i, t, \theta)$, $v_d(i,t)$, and $f(i,t)$.
2. Check that space-time is not exceeded in any section, Equation (6).
3. Given the current TMC commands, compute $v_s(i,t)$.
4. Calculate $n(i, t+1, \theta)$, $v(i, t+1)$ using Equations (1), (2), (3), and (4).

The output produced is $n(i,t,\theta)$ and $v(i,t)$. Capacity, travel time, total time delay, queues at entrances and other performance figures can be derived from these values.

4. MANUAL DRIVER MODEL

In traditional macro-level traffic flow models the characteristics of drivers are described by statistically generated distributions and the parameters of the model are calibrated with field data. Alternatively, micro-level models capture the dynamics of vehicle-following and lane keeping in detail. We take a somewhat different approach in that we do not directly incorporate a statistical representation of the driver's vehicle follower behavior in the model nor do we use vehicle dynamics models. An abstracted model of driver behavior is used which includes the activities of vehicle following and lane change and allows for different levels of aggressiveness of drivers. (Entry and exit as separate activities from lane change have not been studied.) The parameters of these activities are calibrated with real highway data. The expectation is that this model will provide more realistic estimates of highway capacity while retaining the efficiency of macro-scale simulators.

The driver types are distinguished by their relative aggressiveness. The driver types are indexed by T_d, a driver type code (in the range of $1-5$) which is assigned according to a normal distribution with its peak at the average. Very cautious drivers have index 1 and dangerous drivers have index 5. T_d will be used determining the distance needed before taking an exit and in determining the likelihood to do lane changes in order to increase speed.

4.1 *Vehicle following*

To incorporate vehicle following in the activity model it was necessary to investigate headways from real freeway data. Field data was collected along the I-880 freeway in Oakland (Petty *et al.*, 1996) from loop detectors during peak hours. The loop detectors are placed 1/3 of a mile apart on the freeway and on all entry and exit ramps. The detectors are placed in pairs. The controller that monitors the loop detector records the time of every transition of the current across the predefined threshold. Taking the time difference between "down" transitions on a pair of loop detectors and knowing the distance between the detectors the speed is calculated:

$$v = \frac{D}{(t_2^k - t_1^k)}$$

where D is the distance between the loop detectors and t_i^k is the kth sample time of a "down" impulse on loop detector i. These values of speed are averaged over N cars, where N is a tunable parameter; its default value is 10. Taking the time interval between the "up" impulses on a single loop detector and using the average value of speed we obtain the headway:

$$S_k = (t_1^{k+1} - t_1^k)\tilde{v}$$

where $\tilde{v}$ is the average velocity found above. The analysis of this data, conducted in accordance with the guidelines found in (Petty *et al.*, 1996) revealed a discrepancy between the minimal headway to avoid collision and the desired (comfortable) headway distance. A significant proportion of cars (up to $15-25\%$) keeps a headway distance within $15-25$ meters regardless of speed, whereas the *average* headway distance is highly dependent on the velocity. The headway distribution depends somewhat on the lane. Rightmost lanes have larger average headways, as expected. The average headways are much longer – about $40-50$ meters at 25 m/s. Similar headway estimates could be found in (de Vos *et al.*, 76th Annual Meeting, 1997). This means that even the least aggressive driver is able to stay incident–free within the short headway; in order to get a more comfortable headway his only choice is to slow down or change lane. Thus in the SmartCap manual model the space-time for the activity "follow" is a constant $20T$ m-sec minimum spacing.

The headway that is selected is a minimum headway observed, but this headway is too short for all drivers, so an adaptive adjustment is performed. In the TMC plan, if the average headways, derived from the densities, in the current lane and its adjacent lanes are determined to be too short for the given speed, the speed is reduced to a value at which the headways are comfortable. In this manner, the model captures the behavior of drivers to reduce speed in congested conditions.

4.2 *Lane change*

Lane-changing behaviour in microscopic simulations is typically based on two assumptions: (1) impedance (slow down) caused by a preceding vehicle and availability of a gap in an adjacent lane, (2) proximity of a destination (freeway exit). These formulations may not go into particularities of the driver's behaviour and may lead to unrealistic oscillations of lane change between two lanes. Other factors that can be considered are:

- The vehicle is in a lane that does not accomodate its type.
- The downstream impedance in the lane is excessive.
- The current lane ends (or exit reached).
- The geometry downstream requires lane change soon.

Following (Skabardonis, 1996; Ahmed *et al.*, 1995) we classify the lane-change behaviour in two categories: discretionary and mandatory.

Before describing the types of lane changes, we first describe how the space–time for lane change is computed. We assume the duration of the maneuver is $\tau = 3$ seconds. The space requirement for the lane change is assumed to be a constant $30 + L_v$, where L_v is the length of the vehicle, provided the speed is the same in both lanes. The space requirement deviates from a constant value whenever the speed in the adjacent lane is different. In this case

$$s = (30 + L_v) + C_v(T_d) * |V_c - V_a|.$$

Here $C_v(T_d)$ is an adjustment function with respect to the driver type. Values for $C_v(T_d)$ are 2.6 for very cautious, 2.3 for cautious, 2 for average, 1.6 for aggressive, and 1.1 for dangerous. Thus, the total space–time needed for the lane–changing maneuver is the car–following headway in the current lane and $s\tau$ m-sec in the adjacent lane.

Mandatory lane changes are executed imminently, provided the space is available in the adjacent target lane. The distance remaining to the destination for a mandatory lane change may be different for different driver types. More aggressive drivers require less distance to the exit.

More difficult to model is the discretionary lane change, which is usually represented in macro-simulators by a probabilistic parameter. At the SmartCap level of abstraction we evaluate instead the proportion of cars of a certain type which exercise the discretionary lane change. The calculation of this proportion is based on an estimate of the benefit to the vehicle conducting the lane change. Higher speed in an adjacent lane is an obvious trigger for a discretionary lane change. However, whenever the volume of traffic is less than capacity, the speed, in steady-state, is maximum. A better indicator of the likelihood of discretionary lane change is density. We evaluate the differences in density or in the proportion of space remaining free in the adjacent lanes. Thus the standard way for describing the discretionary lane-changing logic at the micro-level (Skabardonis, 1996; Ahmed *et al.*, 1995) is substituted by a comparison of the densities in adjacent lanes and average velocity adjustments in the velocity calculation module of the TMC.

We denote $f_c \in [0, 1]$ to be the proportion of free space in the current lane and $f_a \in [0, 1]$ to be the proportion of free space in the adjacent lane. If $f_c < f_a$ then some proportion of vehicles are modeled as changing lanes in order to balance the density. The proportion will depend on the values of f_c and f_a, and these in turn depend on the speeds in the lanes, because speed is used in the calculation of space–time for lane change, as we have seen. The proportion will also depend on the driver type T_d.

More specifically, the TMC implementation in SmartCap models a balancing of densities in adjacent lanes by selecting a proportion of discretionary lane changes as follows:

$$P = D_f(T_d)\left(\frac{f_c + f_a}{2} - f_c\right)$$

where D_f is a coefficient depending on driver type. It is current set to a constant .075, but can be adjusted to be lower for lower values of T_d. This parameter requires tuning to fit the real traffic data.

4.3 *Velocity plan*

The velocity plan for the manual driver model is designed to augment the velocity dynamics achieved by Equation (4). The velocity dynamics of Equation (4) causes shock waves which propogate too quickly compared to what is typical for manual traffic. In order to smooth the effect of shock waves a damping or averaging effect is included in the velocity dynamics. The velocity plan checks the average speed in the lane ahead and the adjacent lane and precribes a slowdown from V_c to $(V_c + V_a)/2$, where V_c is the current lane average velocity, and V_a is an adjacent lane average velocity. The adjustment is only done if the difference $|V_c - V_a| > R_c$, where R_c is a threshold value which is equal to 3 m/s if V_a corresponds to the lane ahead and is equal to 2 m/s if V_a corresponds to an adjacent lane.

5. BAY BRIDGE TRAFFIC

We have validated our model of manual driving using a SmartCap simulation of the San Francisco Bay Bridge during the morning rush hour. The San Francisco Bay Bridge is one of the busiest bridges in the world; estimating its capacity and comparing this estimate to real data comprises a good test for the model.

The model simulates the west-bound traffic flow over the 12 km span of the bridge which has 5 lanes and the maze of exits in San Francisco. The exit capacities estimated by Caltrans in vehicles per hour are: Embarcadero - 800; Fremont - two lanes, 1500 each; Fifth St. - two lanes 1500 each, Civic center - 1000; the continuation of the I-101 freeway is treated as an exit and its three lanes have a capacity of 1800 vehicles per hour each.

We used real OD data (*Bay Area Origin–Destination travel survey*, 1994) to model the flows entering the bridge and heading to their destination exits. This data reveals that the total number of vehicles passing the bridge in the morning rush hour is around 7000 vehicles per hour, or one vehicle every 2.25 seconds in each lane. Since the bridge has no stopping (curb) lane there may be no preference towards a particular lane with respect to safety. During peak hours there is a Caltrans dispatcher on duty who balances the load of the bridge, so the traffic density typically is uniform over all 5 lanes. Because of these two factors the driver type frequency is assumed to be uniform over the 5 lanes of the bridge (this is different for the regular freeway where the least aggressive drivers tend not to use left-most lanes). Here we assume

$$P = D_f * \left(\frac{f_c + f_a}{2} - f_c \right),$$

where $D_f = 0.75$ is a damping factor for the discretionary lane change.

As before, the driver/vehicle types were represented by an array of 5 types from the very cautious to very aggressive driver, their frequency of occurence given by the normal distribution with the peak of the distribution on the average type (50% of all vehicles). All vehicles are assumed to be passenger cars with a length of 5 meters.

The mandatory lane change maneuver is prescribed within the last 1200 meters of the bridge span, thus enabling the flows to proceed to their proper exit. All other sections of the bridge and the highway permit a discretionary lane change.

Observations show that a significant flow of traffic entering highway I-101 downstream which is beyond the scope of our model causes a slow-down and a shock wave propagated as far back as the last 4000 meters of the bridge span. In order to model this effect we explicitly programmed the velocity plan in the TMC module to slow down gradually from 25 m/s to 18 m/s by the end of the bridge.

In general the results of the simulation match the real life situation. The aggregated value of the space remaining free allows headways comparable or longer than given by the FSP data (Petty *et al.*, 1996).

The capacities of the exits exceed current demand. This implies that introduction of automated or semi-automated lanes may eliminate the slow-down on the bridge thus decreasing the overall travel time.

Acknowledgements The authors are grateful to Adib Kanafani for his informed advice.

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