A Lane-changing Model with Explicit Target Lane Choice

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ABSTRACT

The lane-changing model is an important component of microscopic traffic simulation tools. With the increasing popularity of these tools, a number of lane-changing models have been proposed and implemented in various simulators in recent years. Most of these models are based on the assumption that drivers evaluate the current and adjacent lanes and choose a direction of change (or not to change) based on the utilities of these lanes only. The lane choice set is therefore dictated by the current position of the vehicle, and in multi-lane facilities would be restricted to a subset of the available lanes. Thus, existing models lack an explicit tactical choice of a target lane and therefore cannot explain a sequence of lane changes from the current lane to this lane.

In this paper, a generalized lane-changing model, which explicitly incorporates the choice of target lane, is presented. The target lane is the lane the driver perceives as the best to be in taking a wide range of factors and goals into account. The immediate direction for changing lanes is determined by the target lane choice. All parameters of the model were jointly estimated with detailed vehicle trajectory data. The model was validated and compared with an existing lane-changing model using a microscopic traffic simulator. The results indicate that the proposed model performs significantly better than the previous model.

INTRODUCTION

The lane-changing model is an important component of microscopic traffic simulation tools, which has a significant impact on the characteristics of traffic flow. With the increasing popularity of these tools, a number of lane-changing models have been proposed and implemented in various simulators in recent years.

Most lane-changing models (e.g., Gipps 1986, Yang and Koutsopoulos 1996, Ahmed et al. 1996, Halati et al. 1997, Zhang et al. 1998, Ahmed 1999, Hidas and Behbahanizadeh 1999, Hidas 2002) classify lane changes as either mandatory or discretionary. Drivers consider mandatory lane changes when they must move away from their current lanes in order to follow their path, avoid a lane blockage or comply with lane use regulations. In any of these cases, drivers will change to the nearest acceptable lane. Drivers pursue discretionary lane changes when they perceive that driving conditions in an adjacent lane are better although a lane change is not required. The evaluation of the current and adjacent lanes is based on variables such as traffic speeds and densities in these lanes, the positions and speeds of vehicles that surround the subject vehicle and the presence of heavy vehicles. Drivers that decide to change to an adjacent lane evaluate whether the available gap in traffic in this lane can be used to complete the lane change or not. This choice is often modeled using gap acceptance models, in which drivers compare the available gaps to the smallest acceptable gap, the critical gap. Critical gaps depend on the relative speed of the subject vehicle with respect to the lead and lag vehicles in the adjacent lane and on the type of lane change.

In all these models the need for mandatory lane changes preempts discretionary ones. Toledo et al. (2003) proposed a model that integrates mandatory and discretionary lane changes in a single utility model, and so captures trade-offs between conflicting goals. The driver chooses the direction of a lane change to an adjacent lane or to stay in the current lane. A gap acceptance model determines whether the change in the chosen direction is completed. The model proposed in this paper adopts this approach.

The models listed above are all based on the assumption that drivers evaluate the current and adjacent lanes and choose a direction of change (or not to change) based on the utilities of these lanes only. The lane choice set is therefore dictated by the current position of the vehicle, and in multi-lane facilities would be restricted to a subset of the available lanes. Thus, existing models lack an explicit tactical choice of a target lane, which may require a sequence of lane changes from the current to get to. Instead these myopic models can only explain one lane change at a time.

This deficiency of existing models is most evident in situations where there are large differences in the attributes and utilities of the available lanes. An example of that are facilities with high occupancy vehicle (HOV) lanes or other types of exclusive lanes, which may be significantly more attractive compared to other lanes. Eligible vehicles may make several lane changes in order to get to the exclusive lane. However, in existing models since only the adjacent lane is considered for each lane change, the presence of the exclusive lane may not be captured. To illustrate this, consider the situation presented in FIGURE 1. Suppose that lane 4 is an HOV lane with significantly higher level of service compared to the other lanes. The lane utilities may be affected by various variables. For simplicity we assume here that the lane utilities are fully captured by the average speed. We further assume that the subject vehicle, vehicle A, is eligible to enter the HOV lane. With existing models, the driver only compares the current lane (lane 2) to the left lane (lane 3) and the right lane (lane 1). Based on the lane speeds, lane 1 is the most desirable of the three and the driver will change to this lane. However, a more plausible model would be that based on the lane speeds, the driver chooses lane 4 as the most desirable lane. Thus, vehicle A will change to lane 3 to eventually reach lane 4. In other words, the driver may move to a ‘worse’ adjacent lane (lane 3) as the means of getting to a ‘lot better’ target lane further away (lane 4).

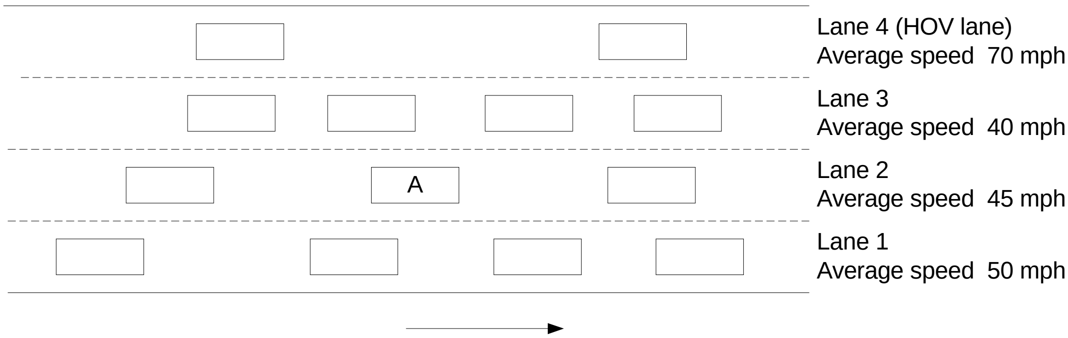

FIGURE 1 Illustration of myopic behavior in existing lane-changing models

In this paper, a generalized lane-changing model, which explicitly incorporates the choice of a target lane, is presented. All parameters of the model were jointly estimated with detailed vehicle trajectory data and validated using a microscopic traffic simulator. The rest of this paper is organized as follows: We first present the structure and detailed specification of the proposed model. Next, we describe the data used to estimate the model parameters and formulate the likelihood function that explains this data. The following sections present the estimation results and the validation within a microscopic traffic simulator. We conclude with a summary of our findings.

THE LANE-CHANGING MODEL

The discussion in the previous section demonstrates the need to introduce an explicit choice of a target lane in the lane-changing model framework. The target lane is the lane the driver perceives as the best lane to be in taking a wide range of factors and goals into account. These factors may include attributes of specific lanes as well as variables that relate to the spatial relations between the subject vehicle and other vehicles around it, the driver's path plan and driver specific characteristics. The choice of the immediate direction for changing lanes is determined in the direction from the current lane to the target lane.

Examples of the structure of this lane-changing model are shown in FIGURE 2. The decision structure shown on the top is for a vehicle that is currently in the second lane to the right (lane 2) in a four-lane road. Lanes 3 and 4 are on its left, and lane 1 is on its right. At the highest level, the driver chooses the target lane. In contrast with existing models the choice set constitutes of all four lanes in the road (lanes 1, 2, 3 and 4). The driver chooses the lane with the highest utility as the target lane. If the target lane is the same as the current lane (lane 2 in this case), no lane change is required (NO CHANGE). Otherwise, the direction of change is to the right if the target lane is lane 1 (RIGHT), and to the left if the target lane is either lane 3 or lane 4 (LEFT). If the target lane choice dictates a lane change, the driver evaluates the gaps in the adjacent lane corresponding to the direction of change and either accepts the available gap and moves to the adjacent lane (CHANGE RIGHT or CHANGE LEFT) or rejects the available gap and stays in the current lane (NO CHANGE). The bottom decision structure in FIGURE 2 is for a vehicle in lane 1 in a similar situation. The model hypothesizes two levels of decision-making: the target lane choice and the gap acceptance. The target lane choice and the direction of immediate lane change that is implied by the selected target lane are latent. Only completed lane changes (or no changes) are observed. In the figure latent choices are shown as ovals and observed choices are represented as rectangles.

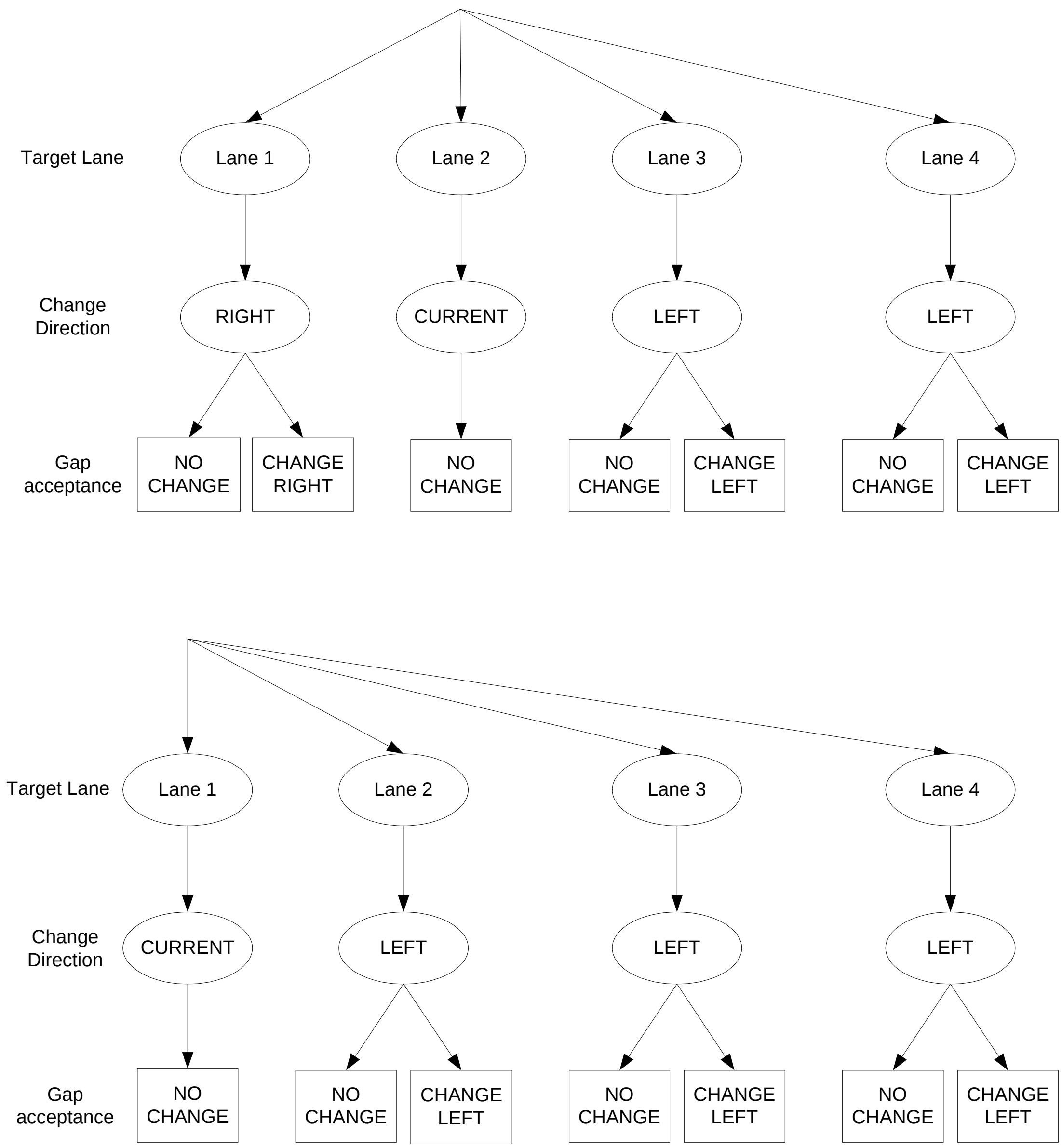

FIGURE 2 Examples of the structure of the proposed lane-changing model

The lane-changing model explains choices drivers make in two dimensions: the target lane choice and the gap acceptance. Furthermore, the estimation data includes repeated observations of drivers' lane changing choices over a period of time. The time-invariant characteristics of the drivers and their vehicles, such as aggressiveness, level of driving skill and the vehicle's speed and acceleration capabilities create correlations among the choices made by a given driver over time and choice dimensions. It is important to capture these correlations in the utility functions. However, the data available for model estimation does not include information about these characteristics. Therefore, we introduce individual-specific latent variable in the various utilities to capture these correlations. The model assumes that conditional on the value of this latent variable, the error terms of different utilities are independent. This specification is given by:

$$U_{int}^{c} = \beta_i^{c^T} X_{int}^{c} + \alpha_i^{c} \upsilon_n + \varepsilon_{int}^{c} \qquad (1)$$

U_{int}^{c} is the utility of alternative *i* of choice dimension *c* to individual *n* at time *t*. X_{int}^{c} is a vector of explanatory variable. β_{i}^{c} is a vector of parameters. υ_n is an individual-specific latent variable assumed to follow some distribution in the population. α_{i}^{c} is the parameter of υ_n. ε_{int}^{c} is a generic random term with i.i.d. distribution across alternatives, individuals and time. ε_{int}^{c} and υ_n are independent of each other.

The resulting error structure (see Heckman 1981, Walker 2001 for a detailed discussion) is given by:

$$cov\left(U_{int}^{c}, U_{i'n't'}^{c'}\right) = \begin{cases} \left(\alpha_i^c\right)^2 + \sigma_i^{c2} & if\ \ n = n',\ c = c',\ i = i'\ and\ t = t' \\ \alpha_i^c \alpha_{i'}^{c'} & if\ \ n = n',\ c \neq c'\ and/or\ i \neq i'\ and/or\ t \neq t' \\ 0 & if\ \ n \neq n' \end{cases} \tag{2}$$

σ_i^{c2} is the variance of ε_{int}^{c}.

We now describe in further detail the specification of the models to explain the two choices drivers make within the lane changing model: the target lane choice and the gap acceptance.

The Target Lane Model

At the highest level of lane changing model the driver chooses a target lane. The target lane choice set constitutes of all the available lanes the driver is eligible to move to. In presence of exclusive lanes, the choice set would depend on the eligibility of the vehicle to enter the exclusive lanes and thus the choice set will not be the same for all drivers. The utilities of the various lanes are given by:

$$U_{int}^{TL} = \beta_i^{TL^T} X_{int}^{TL} + \alpha_i^{TL} \upsilon_n + \varepsilon_{int}^{TL} \qquad \forall i \in \{lane1, lane2, lane3, lane4\} \tag{3}$$

U_{int}^{TL} is the utility of lane *i* as a target lane to driver *n* at time *t*. X_{int}^{TL} is the vector of explanatory variables that affect the utility of lane *i*. β_i^{TL} is the corresponding vector of parameters. ε_{int}^{TL} is the random term associated with the target lane utilities. α_i^{TL} is the parameter of υ_n.

The target lane utilities are affected by the lane attributes, such as the density and speed of traffic in the lane and presence of heavy vehicles, and variables that relate to the path plan, such as the distance to a point where the driver needs to be in specific lanes and the number of lane changes required from the target lane to the correct lanes. In addition, the vehicle’s current lane and position may affect the target lane choice through variables that capture the number of lane changes that are required from the current lane to the target lane and the spatial relations of the subject vehicle with vehicles around it.

The driver chooses as the target lane the lane with the highest utility. Different choice models are obtained depending on the assumption made about the distributions of the random terms ε_{int}^{TL}. Assuming that they are independently and identically Gumbel distributed, target lane choice probabilities, conditional on the individual specific error term, are given by a multinomial logit model:

$$P(TL_{nt} = i | \upsilon_n) = \frac{exp(V_{int}^{TL} | \upsilon_n)}{\sum_{j \in TL} exp(V_{jnt}^{TL} | \upsilon_n)} \qquad \forall i \in TL = \{lane1, lane2, lane3, lane4\} \tag{4}$$

$V_{int}^{TL} | \upsilon_n$ are the conditional systematic utilities of the alternative target lanes.

The choice of the target lane dictates the change direction d_{nt}. If the current lane is also the target lane, no change is needed. Otherwise, the change will be in the direction from the current lane to the target lane.

The Gap Acceptance Model

The gap acceptance model captures drivers' choice whether the available gap in the adjacent lane in the change direction can be used to complete the lane change or not. The driver evaluates the available lead and lag gaps, which are defined by the clear spacing between the rear of the lead vehicle and the front of the subject vehicle, and between the rear of the subject vehicle and the front of the lag vehicle, respectively. The lead and lag vehicles, and the gaps they define are shown in FIGURE 3.

The driver compares the available space lead and lag gaps to the corresponding critical gaps, which are the minimum acceptable space gaps. An available gap is acceptable if it is greater than the critical gap. Critical gaps are modeled as random variables. Their means are functions of explanatory variables. The individual specific error term captures correlations between the critical gaps of the same driver over time. Critical gaps are assumed to follow lognormal distributions to ensure that they are always non-negative:

$$ln\left(G_{nt}^{gd,cr}\right) = \beta^{g^T} X_{nt}^{gd} + \alpha^g \upsilon_n + \varepsilon_{nt}^{gd} \qquad g \in \{lead, lag\}, d \in \{right, left\} \tag{5}$$

$G_{nt}^{gd,cr}$ is the critical gap *g* in the direction of change *d*, measured in meters. X_{nt}^{gd} is a vector of explanatory variables. β^g is the corresponding vector of parameters. ε_{nt}^{gd} is a random term: $\varepsilon_{nt}^{gd} \sim N\left(0, \sigma_g^2\right)$. α^g is the parameter of the driver specific random term υ_n.

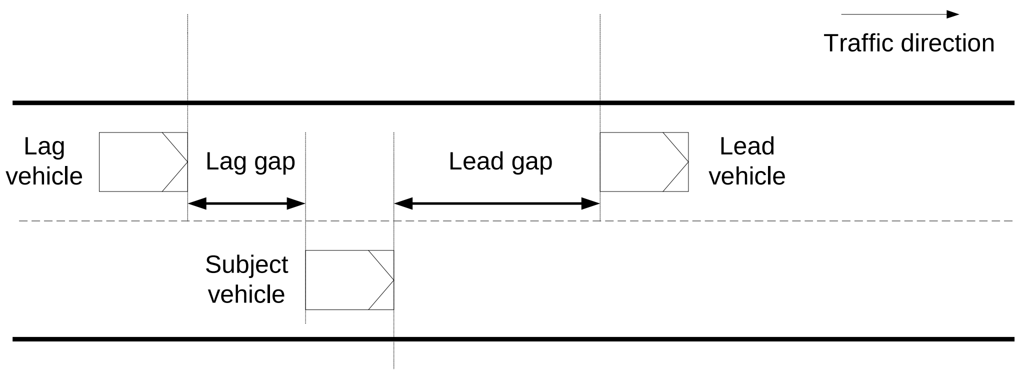

FIGURE 3 Definitions of the lead and lag vehicles and the gaps they define

The gap acceptance model assumes that the driver must accept both the lead gap and the lag gap to change lanes. The probability of changing lanes, conditional on the individual specific term and the choice of direction of change is therefore given by:

$$\begin{aligned} & P\left(change\ in\ direction\ d \middle| d_{nt}, \upsilon_n\right) = P\left(l_{nt} = d \middle| d_{nt}, \upsilon_n\right) = \\ & P\left(accept\ lead\ gap \middle| d_{nt}, \upsilon_n\right) P\left(accept\ lag\ gap \middle| d_{nt}, \upsilon_n\right) = \\ & P\left(G_{nt}^{lead\ d} > G_{nt}^{lead\ d,cr} \middle| d_{nt}, \upsilon_n\right) P\left(G_{nt}^{lag\ d} > G_{nt}^{lag\ d,cr} \middle| d_{nt}, \upsilon_n\right) \end{aligned} \tag{6}$$

$d_{nt} \in \{Right, Current, Left\}$ is the chosen direction of change for driver *n* at time *t*, which is determined by the target lane choice. $G_{nt}^{lead\ d}$ and $G_{nt}^{lag\ d}$ are the available lead and lag gaps in this direction, respectively. l_{nt} is the lane-changing action.

Assuming that critical gaps follow lognormal distributions, the conditional probabilities that gap $g \in \{lead, lag\}$ is acceptable is given by:

$$P\left(G_{nt}^{gd} > G_{nt}^{gd,cr} \middle| d_{nt}, \upsilon_n\right) = P\left(ln\left(G_{nt}^{gd}\right) > ln\left(G_{nt}^{gd,cr}\right) \middle| d_{nt}, \upsilon_n\right) =$$

$$\Phi\left[\frac{ln\left(G_{nt}^{gd}\right) - \left(\beta^{g^T} X_{nt}^{gd} + \alpha^g \upsilon_n\right)}{\sigma_g}\right] \tag{7}$$

$\Phi[\cdot]$ denotes the cumulative standard normal distribution.

Gap acceptance is affected by the spatial relations between the subject vehicle and the lead and lag vehicles in the adjacent lane, which is captured by variables such as the subject relative speed and position with respect to the lead and lag vehicles.

DATA FOR MODEL ESTIMATION

A dataset of detailed vehicle trajectory data, which was collected by the FHWA (1985) in a section of I-395 Southbound in Arlington VA, was used to estimate the parameters of the lane-changing model. This dataset is particularly useful for estimation of the lane-changing model because of the geometric characteristics of the site, which is schematically shown in FIGURE 4. It is 997 meters long with two off-ramps and an on-ramp and therefore has the necessary length to capture the impact of the path plan and other variables on lane-changing behavior.

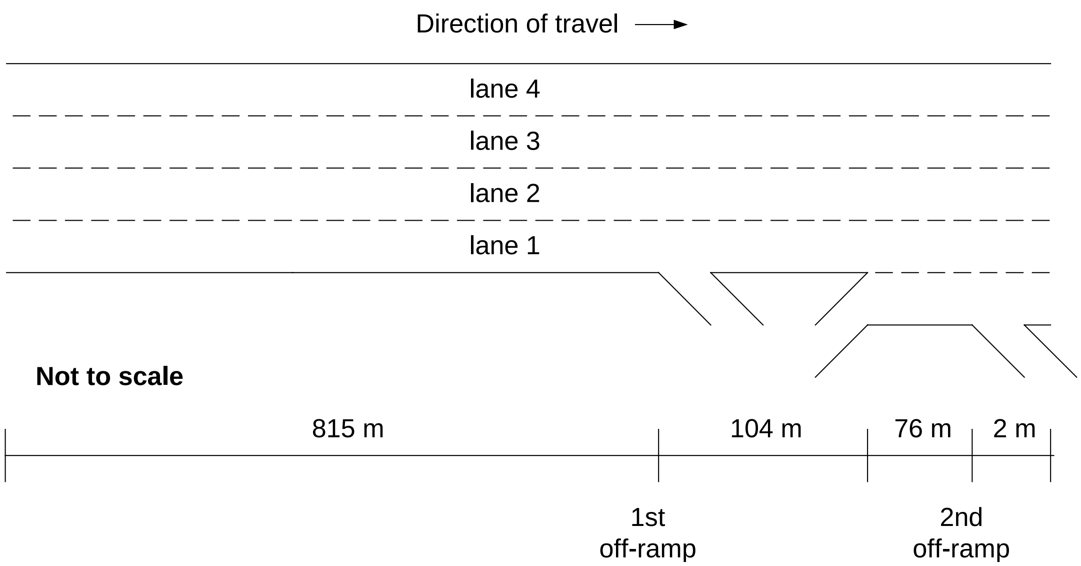

FIGURE 4 The I-395 data collection site in Arlington VA

The dataset contains observations of the position, lane and dimensions of every vehicle within the section every 1 second. The vehicle trajectory data was used to generate the required explanatory variables including speeds and relations between the subject vehicle and other vehicles. The estimation data set includes the trajectories of 442 vehicles, with a total of 15632 observations. On average, a vehicle was observed for 35.4 seconds (observations). All vehicles were first observed at the upstream end of the freeway section. At the downstream end, 76% stay on the freeway, 8% and 16% use the first and second off-ramps, respectively. Observed speeds range from 0.4 to 25.0 m/sec., with a mean of 15.6 m/sec. Densities range from 14.2 to 55.0 veh/km/lane, with a mean of 31.4 veh/km/lane. The level of service on the section ranges from D to E.

LIKELIHOOD FUNCTION

The path plan is an important factor, which explains lane-changing behavior. The impact of the path plan is captured by variables such as the distance to an off-ramp the driver needs to use. However, the path plans of drivers who remain on the freeway at the downstream end of the section are unknown. In order to capture the effect of these variables, a distribution of the distance from the downstream end of the section being studied to the exit points was used. The parameters of this distribution were estimated jointly with the other parameters of the model. We used a discrete distribution of the distances, which exploits information on the locations of off-ramps downstream of the section. The alternatives considered were the first, second and subsequent off-ramps. The probability mass function of distances to the off-ramps, beyond the downstream end of the segment:

$$\omega(s_n) = \begin{cases} \pi_1 & \textit{first downstream exit } (s^1) \\ \pi_2 & \textit{second downstream exit } (s^2) \\ 1-\pi_1-\pi_2 & \textit{otherwise } (s^3) \end{cases} \tag{8}$$

π_1 and π_2 are parameters to be estimated. s^1, s^2 and s^3 are the distances beyond the downstream end of the section to the first, second and subsequent exits, respectively.

The first and second exit distances (s^1 and s^2) were extracted from map information. For the subsequent exits an infinite distance was used ($s^3 = \infty$). This corresponds to an assumption that while on the section being studied, drivers that use these exits are not constrained by their path plan.

The joint probability density of a combination of target lane (*TL*) and lane action (*l*) observed for driver *n* at time *t*, conditional on the distance to the exit point, s_n, and the individual-specific characteristic, υ_n is given by:

$$P\left(TL_{nt} = i, l_{nt} \middle| s_n, \upsilon_n\right) = P\left(TL_{nt} = i \middle| s_n, \upsilon_n\right) P\left(l_{nt} \middle| TL_{nt} = i, \upsilon_n\right) \tag{9}$$

$P\left(TL_{nt} = i \mid \cdot\right)$ and $P\left(l_{nt} \mid \cdot\right)$ are given by Equations (4) and (6), respectively.

Only the lane-changing action is observed over a sequence of T_n consecutive time intervals. Assuming that conditional on s_n and υ_n these observations are independent, the joint probability of the sequence of observations, $\boldsymbol{l_n}$, is given by:

$$P\left(\boldsymbol{l_n} \middle| s_n, \upsilon_n\right) = \prod_{t=1}^{T_n} \sum_{j \in TL} P\left(TL_{nt} = i, l_{nt} \middle| s_n, \upsilon_n\right) \tag{10}$$

The unconditional individual likelihood function (L_n) is obtained by integrating (summing for the discrete variable s_n) over the distributions of the unobserved individual-specific variables:

$$L_n = \int_{\upsilon} \sum_{s} P\left(\boldsymbol{l_n} \middle| s, \upsilon\right) \omega(s) f(\upsilon) \tag{11}$$

Assuming that the observations from different drivers are independent, the log-likelihood function for all *N* individuals observed is given by:

$$L = \sum_{n=1}^{N} ln\left(L_n\right) \tag{12}$$

Maximum likelihood estimators of the model parameters can be found by maximizing this function.

ESTIMATION RESULTS

Estimation results of the proposed lane-changing model are presented in Table 1.

The Target Lane Model

Target lane choices are affected by the attributes of the alternative lanes, such as average speed and density as well as variables related to the path plan and the spatial relations between the subject vehicle and vehicles around it.

The estimated values of the lane specific constants imply that, everything else being equal, the right-most lane is the most undesirable. This may be the result of drivers' preference to avoid the merging and weaving activities that take place in that lane. In general, lanes to the left are more desirable. However, lanes 3 and 4 have similar constants, which may indicate that the advantage of being away from the slower right lanes is balanced by the disadvantage associated with being in lanes that are further away from the off-ramp, and by the increased interaction with vehicles traveling at higher speeds. As expected, the results also indicate that drivers are more likely to choose lanes with higher average speeds and lower densities. The relations between the subject vehicle and the vehicles in front of it in the current and adjacent lanes in terms of spacing and relative speeds also affect the target lane choice. Results show that lane utilities increase with the relative front speed and the spacing between the vehicles. The tailgating dummy variable, which captures the presence of a tailgating vehicle behind the subject in its current lane was important both in the magnitude of its contribution to the utility and in its statistical significance. This variable thus captures drivers' strong preference to avoid being tailgated.

The values of the coefficients of the current lane dummy and the number of lane changes required from the current lane to the target lane capture the preference to stay in the current lane and the disutility associated the need to make lane changing maneuvers to get to other lanes. The path plan impact variables indicate that the utility of a lane decreases with the number of lane-changes the driver needs to perform from that lane in order to maintain its path. This effect is magnified as the distance to the off-ramp decreases. This has been captured by the negative power of the distance to the off-ramp (θ^{MLC} =-0.371). The disutility associated with being in a wrong lane is larger when the driver needs to take the next exit.

The heterogeneity coefficients, α^{lane1}, α^{lane2} and α^{lane3} capture the effects of the individual-specific error term υ_n on the target lane choice. All three estimated parameters are negative. Hence, υ_n can be interpreted as correlated with aggressiveness since aggressive drivers are less likely to choose the right lanes over the left ones compared to more timid drivers.

In summary, the target lane utilities are given by:

$$\begin{aligned} U_{int}^{TL} = {} & \beta_i - 0.011 D_{int} + 0.119 S_{int} + 0.022 \Delta X_{int}^{front} \delta_{int}^{adj} + 0.115 \Delta S_{int}^{front} \delta_{nt}^{adj} - 2.783 \delta_{nt}^{tailgate} \delta_{int}^{CL} \\ & + 1.000 \delta_{int}^{CL} - 2.633 \Delta CL_{int} + \beta_i^{path} \left[d_{nt}^{exit} \right]^{-0.371} - 0.980 \delta_{nt}^{next\ exit} \Delta Exit_i - \alpha_i v_n + \varepsilon_{int}^{TL} \end{aligned} \tag{13}$$

β_i is the lane *i* constant. D_{int} and S_{int} are the lane-specific densities and speeds, respectively. ΔX_{int}^{front} and ΔS_{int}^{front} are the spacing and relative speed of the front vehicle in lane *i*, respectively. δ_{int}^{adj} is an indicator with value 1 if *i* is the current or an adjacent lane, and 0 otherwise. Similarly, δ_{int}^{CL} has value 1 if *i* is the current lane, and 0 otherwise. $\delta_{nt}^{tailgate}$ is an indicator with value 1, if vehicle *n* is being tailgated at time *t* and 0 otherwise. ΔCL_{int} are the number of lane changes required to get from the current lane to lane *i*. β_i^{path} is the path plan impact coefficient for lane *i*. d_{nt}^{exit} is the distance to the exit driver *n* intends to use. $\delta_{nt}^{next\ exit}$ is an indicator with value 1 if the driver intends to take the next exit and 0 otherwise. $\Delta Exit_i$ are the number of lane changes required to get from lane *i* to the exit lane.

TABLE 1 Estimation Results of the Lane-changing Model

Variable	Parameter value	t-statistic
Target Lane Model		
Lane 1 constant	-1.570	-3.030
Lane 2 constant	-0.488	-1.552
Lane 3 constant	0.075	1.744
Lane density, vehicle/km	-0.011	-0.988
Average speed in lane, m/sec	0.119	1.560
Front vehicle spacing, m.	0.022	2.879
Relative front vehicle speed, m/sec.	0.115	1.463
Tailgate dummy	-2.783	-0.176
CL dummy	1.000	1.485
Number of lane-changes from CL	-2.633	-0.270
Path plan impact, 1 lane change required	-2.559	-3.265
Path plan impact, 2 lane changes required	-4.751	-3.584
Path plan impact, 3 lane changes required	-6.996	-0.097
Next exit dummy, lane change(s) required	-0.980	-0.377
θ^{MLC} θ^{MLC}	-0.371	-2.608
π_1	0.001	0.426
π_2	0.069	8.101
α_{lane1}	-1.371	-2.582
α_{lane2}	-0.985	-0.510
α_{lane3}	-0.691	-3.441
Lead Critical Gap		
Constant	1.553	3.311
$Max\left(\Delta S_{nt}^{lead},0\right)$, m/sec.	-6.389	-3.793
$Min\left(\Delta S_{nt}^{lead},0\right)$, m/sec.	-0.140	-2.191
α^{lead}	-0.008	-4.029
σ^{lead}	0.888	1.229
Lag Critical Gap		
Constant	1.429	6.611
$Max\left(\Delta S_{nt}^{lead},0\right)$, m/sec.	0.471	4.907
α^{lag}	-0.234	-0.469
σ^{lag}	0.742	4.802
Number of drivers = 442 Number of observations = 15632 Number of parameters = 29	$L(0) = -1434.76$ $L(\hat{\beta}) = -876.69$ $\bar{\rho}^2 = 0.368$	

The Gap Acceptance Model

The lead and lag critical gaps depend on the relative speed between the subject vehicle and the lead and lag vehicles. Surprisingly, both critical gaps were not significantly affected by the absolute speed of the subject. One possible reason may be that there is not enough variability in speeds in the estimation dataset to capture its effect.

The lead critical gap decreases with the relative lead speed, i.e., it is larger when the subject vehicle is faster relative to the lead vehicle. The effect of the relative speed is strongest when the lead vehicle is faster than the subject. In this case, the lead critical gap quickly diminishes as a function of the speed difference. This result suggests that drivers perceive very little risk from the lead vehicle when it is getting away form them.

The lag critical gap increases with the relative lag speed: the faster the lag vehicle is relative to the subject, the larger the lag critical gap is. In contrast to the lead critical gap, the lag gap does not diminish when the subject is faster. A possible explanation is that drivers may maintain a minimum critical lag gap as a safety buffer since their perception of the lag gap is not as reliable as it is for the lead gap. Estimated coefficients of the unobserved driver characteristics variable, υ_n , are negative for both lead and lag critical gaps. Hence, consistent with the interpretation of υ_n as correlated with aggressive drivers, who require smaller gaps for lane changing compared to timid drivers. The estimated lead and lag gaps are given by:

$$G_{nt}^{lead\ d,cr} = exp\left(1.553 - 6.389 Max\left(0, \Delta S_{nt}^{lead\ d}\right) - 0.140 Min\left(0, \Delta S_{nt}^{lead\ d}\right) - 0.008\upsilon_n + \varepsilon_{nt}^{lead}\right) \tag{14}$$

$$G_{nt}^{lag\ d,cr} = exp\left(1.429 + 0.471 Max\left(0, \Delta S_{nt}^{lag\ d}\right) - 0.234\upsilon_n + \varepsilon_{nt}^{lag}\right) \tag{15}$$

$\Delta S_{nt}^{lead\ d}$ and $\Delta S_{nt}^{lag\ d}$ are the relative speeds of the lead and lag vehicles in the direction of change, respectively. $\varepsilon_{nt}^{lead} \sim N\left(0, 0.888^2\right)$ and $\varepsilon_{nt}^{lag} \sim N\left(0, 0.742^2\right)$.

Model selection

The lane-changing model with explicit target lane choice extends the model with a myopic direction change choice proposed by Toledo et al. (2003). However, the myopic model cannot be viewed as nested within the model with explicit target lane choice, and therefore classic statistical tests cannot be applied to select between the two. Instead, we calculated three statistics that are often used for model selection (see Gourieroux and Monfort 1995 for details): $\bar{\rho}^2$, the Akaike Information Criteria (AIC) and the Bayesian Information Criteria (BIC). These statistics account for the larger number of parameters in the model with explicit target lane. With all these statistics, the model with explicit target lane choice has larger values, which indicates that it better fits the data, and therefore should be selected for prediction.

TABLE 2 Statistics for the model with explicit target lane and the change direction model

	Target Lane (U)	Change Direction (R)
Likelihood Value	-876.69	-888.78
Number of Parameters (k)	29	26
$\bar{\rho}^2$	0.368	0.362
AIC	-905.69	-914.78
BIC	-937.50	-943.30

MODEL VALIDATION

The new lane-changing model was implemented in the microscopic traffic simulation model, MITSIMLab (Yang and Koutsopoulos 1996) and tested on a section of I-80, Berkeley CA. This section, which is shown schematically in FIGURE 5, is about six kilometers long, with four interchanges and six lanes throughout the section. The left-most lane is an HOV lane that can be accessed at any point in the section. The presence of this unlimited access HOV lane results in high difference in the level of service among different lanes and is therefore useful to test the proposed lane-changing model. In addition to traffic counts and speeds observations that were collected in five sensor stations in the section, detailed trajectory data was available for the area between Powell Street and Ashby Street, which is shaded in FIGURE 5.

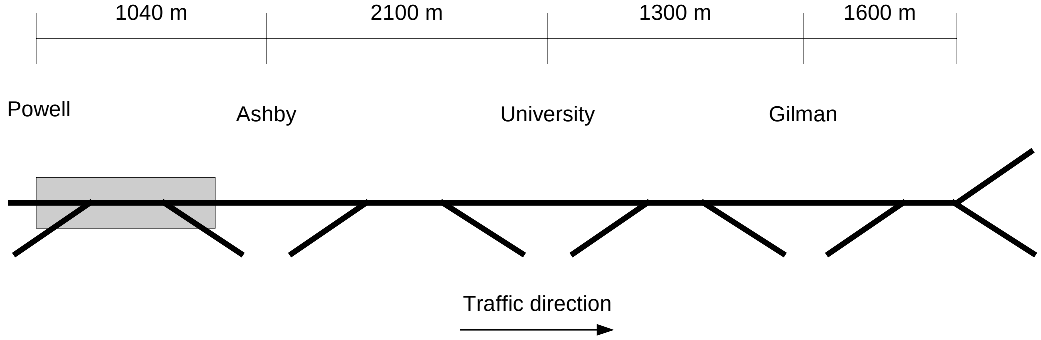

FIGURE 5 The I-80 validation site, Berkeley CA

The performance of the target lane model was compared with the performance of the model with myopic change direction proposed in Toledo et al. (2003). Both models were implemented in MITSIMLab. The two versions were calibrated using the available sensor data. The model validation was based on comparison of the simulated speeds and lane distribution at a key location using the two versions to the observations in the data.

Traffic Speeds

A separate set of speed measurements from sensors (not used for calibration) was used for validation purpose. The comparisons of the goodness-of-fit measures are presented in TABLE 3. As with the estimation results, the target lane model consistently performs better.

TABLE 3 Goodness of fit statistics for the traffic speed comparison

	Target Lane Model	Shift direction Model	% Improvement
Root Mean Square Error, mph	3.30	4.70	29.79
Root Mean Square Percent Error (%)	12.67	14.63	13.41
Mean Error (mph)	-0.90	1.59	42.96
Mean Percent Error (%)	-2.74	5.17	47.01
U (Theil's inequality coefficient)	0.050	0.063	20.09
U_m (bias proportion)	0.151	0.165	8.63
U_s (variance proportion)	0.007	0.016	57.75

Lane Distributions

The distribution of vehicles across lanes was extracted from the trajectory data and compared with the simulated lane distributions of both the models. The validation results are shown in Figure 6. Overall, the model with explicit target lane choice matched the observations better, and particularly with respect to the usage of the HOV lane. The root mean square error and root mean square percent error were 1.5 % and 9.3% respectively for the model with explicit target lane and 2.3% and 13.4% respectively for the model with choice of change direction.

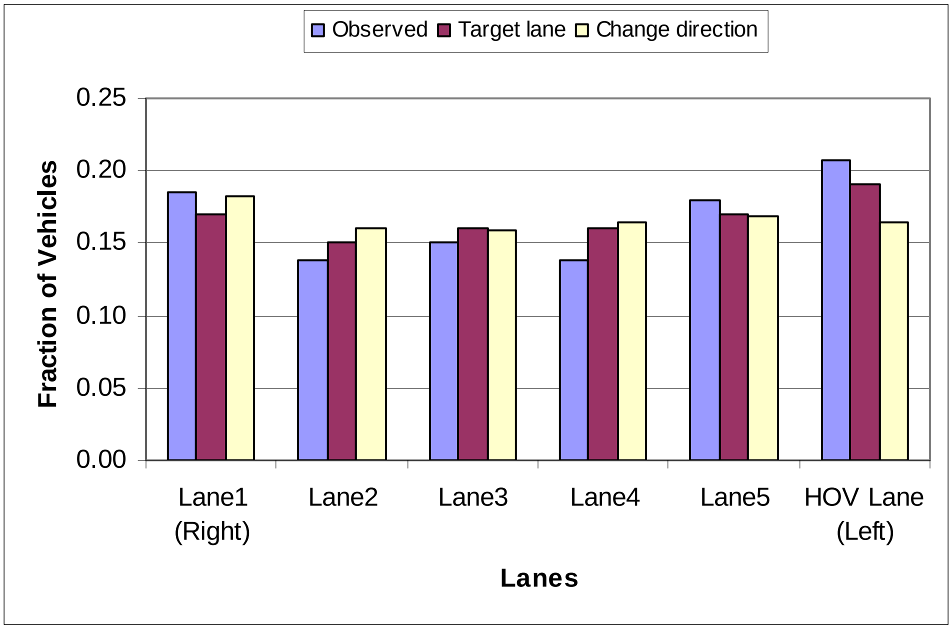

FIGURE 6 Observed and simulated distributions of vehicles among lanes.

CONCLUSION

This paper presents a new lane-changing model, which incorporates an explicit choice of a target lane. This approach differs from existing models that assume that drivers evaluate the current and adjacent lanes and choose a direction of change (or not to change) based on the utilities of these lanes only. While the proposed model is applicable to any freeway situation, it is most useful in cases where there are high differences in the level of service among the lanes, such as in presence of exclusive lanes. The model structure can also capture drivers' preference to specific lanes, such as in the case when travel lanes and passing lanes are defined.

The model consists of two choices: the selection of a target lane and gap acceptance. A random utility approach is adopted for both models. The model structure accounts for correlations among the choices made by the same driver over choice dimensions and time that are due to unobserved individual-specific characteristics by introducing a driver-specific random term, which is included in all model components. Missing data due to limitations of the data collection are also account for.

Parameters of all components of the model were estimated jointly using a maximum likelihood estimator and detailed vehicle trajectory data. Estimation results show that the target lane choice is affected by lane-specific attributes, such as average speed and density, variables that relate to the path plan and the vehicle's spatial relations with other vehicles surrounding it. Gap acceptance is modeled by comparing the available space lead and lag gaps to the corresponding critical gaps. Critical gaps depend on the relative subject speed with respect to the lead and lag vehicles.

Statistical model selection criteria using the estimation results showed that the proposed lane-changing model is superior to a previous myopic change direction model. This result was further strengthened by the validation case study, which compared the results obtained from two version of a microscopic traffic simulator that implement the two models. The simulator was applied to a multi-lane freeway section that includes an HOV lane. The target lane model provided significantly better prediction both in terms of traffic speeds and distributions of vehicles to lanes. While these results are promising, further research with detailed trajectory data from sites with varying geometric and traffic characteristics is needed in order to develop more robust models that will be more generally applicable to urban freeway traffic. Unfortunately, only few datasets that can support such research exist, and even fewer that are newer than the one used in this study, which may not well represent current vehicle capabilities.

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