Lane-Changing Model with Explicit Target Lane Choice

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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 no change) on the basis of the utilities of these lanes only. The lane choice set is therefore dictated by the current position of the vehicle and in multilane 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 that explicitly incorporates the choice of target lane is presented. The target lane is the lane that the driver perceives to be the best when a wide range of factors and goals are taken into account. The immediate direction in which a driver changes 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 with the use of a microscopic traffic simulator. The results indicate that the proposed model performs significantly better than the previous model.

The lane-changing model is an important component of microscopic traffic simulation tools that 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 classify lane changes as either mandatory or discretionary (*1–8*). Drivers consider mandatory lane changes when they must move away from their current lanes to follow their paths, 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, even though a lane change is not required. The evaluation of the current and adjacent lanes is based on variables such as the 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 who 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 by the use of 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 those of 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. proposed a model that integrates mandatory and discretionary lane changes in a single utility model and so captures trade-offs between conflicting goals (*9*). The driver chooses the direction of a lane change to an adjacent lane or decides 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 no change) on the basis of the utilities of these lanes only. The lane choice set is therefore dictated by the current position of the vehicle and in multilane 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 lane to get to the target lane. Instead, these myopic models can explain only one lane change at a time.

This deficiency of existing models is most evident in situations in which there are large differences in the attributes and utilities of the available lanes. An example of this are facilities with high-occupancy vehicle (HOV) lanes or other types of exclusive lanes, which may be significantly more attractive than other lanes. Eligible vehicles may make several lane changes to get to the exclusive lane. However, in the existing models, because 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 a significantly higher level of service than the other lanes. The lane utilities may be affected by various variables. For simplicity, it is assumed here that the lane utilities are fully captured by the average speed. Furthermore, it is assumed that the subject vehicle, Vehicle A, is eligible to enter the HOV lane. With the existing models, the driver compares only the current lane (Lane 2) with the left lane (Lane 3) and the right lane (Lane 1). On the basis of the lane speeds, Lane 1 is the most desirable of the three and the driver will change to that lane. However, a more plausible model would be that, on the basis of 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 farther away (Lane 4).

This paper presents a generalized lane-changing model that explicitly incorporates the choice of a target lane. All parameters of the model were jointly estimated with detailed vehicle trajectory data and were validated by using a microscopic traffic simulator. The rest

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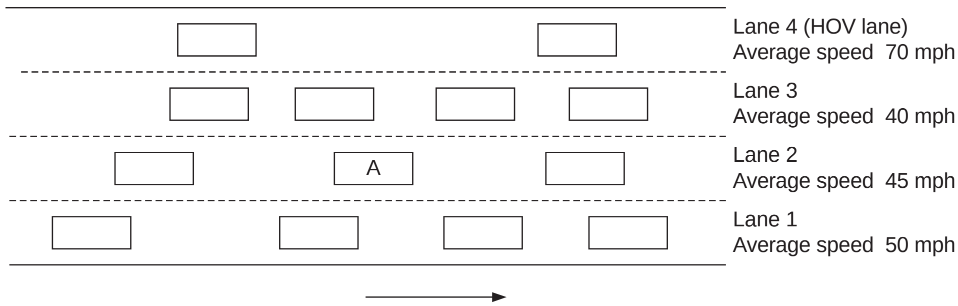

FIGURE 1 Illustration of myopic behavior in existing lane-changing models.

of this paper is organized as follows. First, the structure and detailed specifications of the proposed model are presented. Next, the data used to estimate the model parameters and formulate the likelihood function that explains these data are described. Estimation results and the validation within a microscopic traffic simulator are then presented. The paper concludes with a summary of the findings.

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 that the driver perceives to be the best lane when a wide range of factors and goals are taken into account. These factors may include the attributes of specific lanes as well as variables that relate to the spatial relations between the subject vehicle and the other vehicles around it, the driver's path plan, and driver-specific characteristics. The choice of the immediate direction in which a driver changes 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 in Figure 2*a* is for a vehicle that is currently in the second lane to the right (Lane 2) on 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 to existing models, the choice set constitutes 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 in Figure 2*a*). Otherwise, the direction of change is to the right if the target lane is Lane 1 (right in Figure 2*a*) and to the left if the target lane is either Lane 3 or Lane 4 (left in Figure 2*a*). 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 in Figure 2*a*) or rejects the available gap and stays in the current lane (no change in Figure 2*a*). The decision structure in Figure 2*b* 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 Figure 2 latent choices are shown as ovals and observed choices are represented as rectangles.

The lane-changing model explains the choices that drivers make in two dimensions: the target lane choice and the gap acceptance. Furthermore, the estimation data include 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 that these correlations be captured in the utility functions. However, the data available for model estimation do not include information about these characteristics. Therefore, an individual-specific latent variable is introduced 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

$$U_{int}^{c} = \beta_i^{c^T} X_{int}^{c} + \alpha_i^{c} \upsilon_n + \epsilon_{int}^{c} \tag{1}$$

where

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

The resulting error structure [a detailed discussion is given elsewhere (*10, 11*)] is given by

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

where $\sigma_i^{c^2}$ is the variance of ϵ_{int}^{c}.

The specification of the models is now described in further detail to explain the two choices that drivers make within the lane-changing model: the target lane choice and the gap acceptance.

Target Lane Model

At the highest level of the lane-changing model the driver chooses a target lane. The target lane choice set constitutes all available lanes

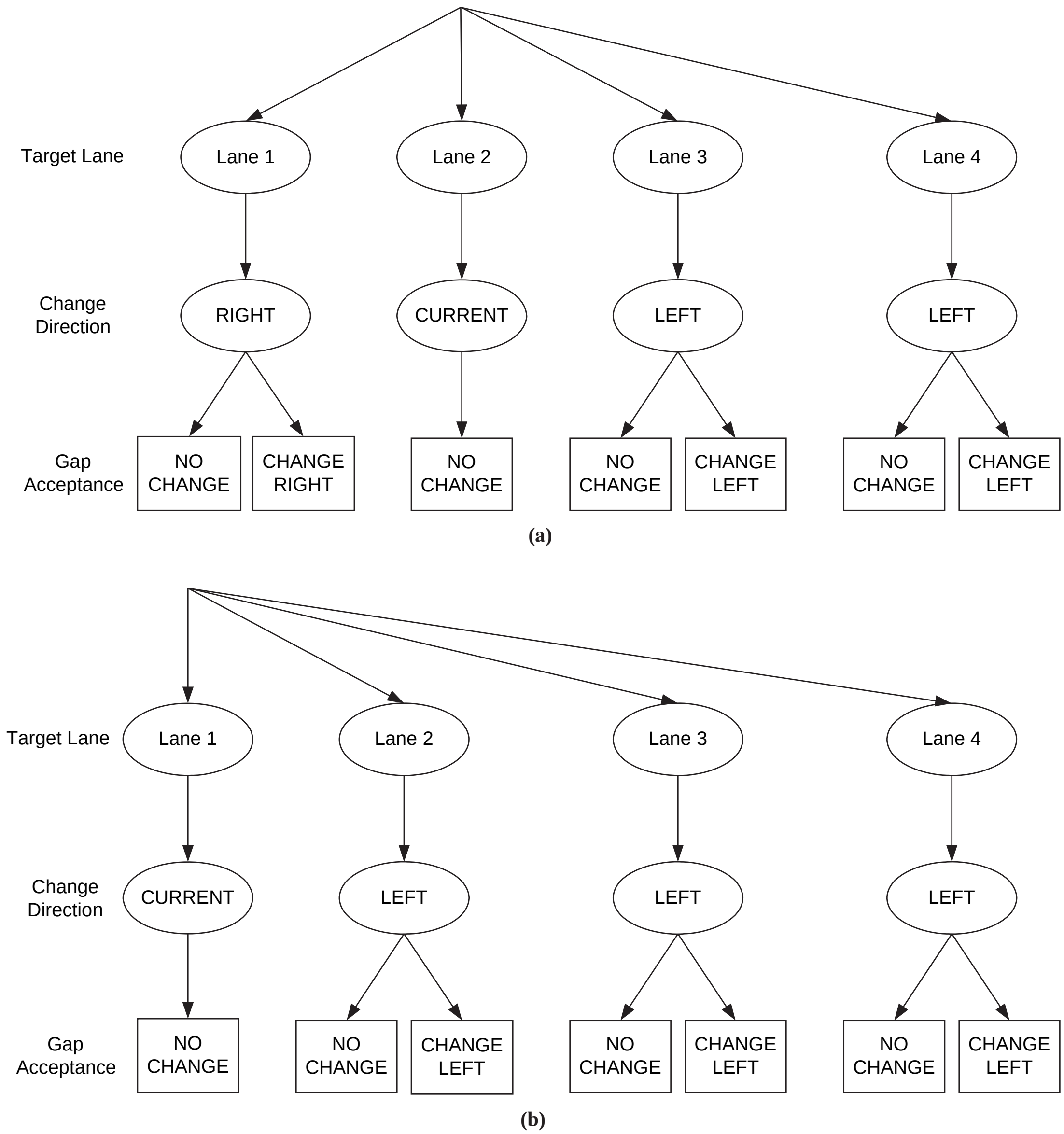

FIGURE 2 Examples of structure of proposed lane-changing model.

to which the driver is eligible to move. In the 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 is not the same for all drivers. The utilities of the various lanes are given by

$$U_{int}^{TL} = \beta_i^{TL} X_{int}^{TL} + \alpha_i^{TL} \upsilon_n + e_{int}^{TL} \qquad \forall i \in \{\text{lane 1, lane 2, lane 3, lane 4}\} \qquad (3)$$

where

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

The target lane utilities are affected by the lane attributes, such as the density and the speed of traffic in the lane and the 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 a specific lane and the number of lane changes required to go from the target lane to the correct lane. In addition, the vehicle's current lane and position may affect the target lane choice through variables that capture the number of lane changes from the current lane to the target lane that are required and the spatial relations of the subject vehicle to the 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 term ϵ_{int}^{TL}. If it is assumed that they are independently and identically Gumbel distributed, target lane choice probabilities (P), conditional on the individual specific error term, are given by a multinomial logit model:

$$P(\text{TL}_{\text{int}} = i * \upsilon_n) = \frac{\exp(V_{\text{int}}^{\text{TL}} * \upsilon_n)}{\sum_{j \in \text{TL}} \exp(V_{\text{int}}^{\text{TL}} * \upsilon_n)}$$

$$\forall i \in \text{TL}\{\text{lane 1, lane 2, lane 3, lane 4}\} \qquad (4)$$

where $V_{\text{int}}^{\text{TL}}|\upsilon_n$ 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.

Gap Acceptance Model

The gap acceptance model captures a driver's 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 that they define are shown in Figure 3.

The driver compares the available space lead and lag gaps with 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 nonnegative:

$$\ln(G_{nt}^{gd,cr}) = \beta^{g^T} X_{nt}^{gd} + \alpha^g \upsilon_n + \epsilon_{nt}^{gd}$$

$$g \in \{\text{lead, lag}\}, d \in \{\text{right, left}\} \qquad (5)$$

where

$G_{nt}^{gd,cr}$ = critical gap g in the direction of change d (m),
X_{nt}^{gd} = vector of explanatory variables,
β^g = corresponding vector of parameters,
ϵ_{nt}^{gd} = random term, where $\epsilon_{nt}^{gd} \sim N(0, \sigma_g^2)$, and
α^g = parameter of the driver specific random term υ_n.

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

$$P(\text{change in direction } d \,|\, d_{nt}, \upsilon_n) = P(l_{nt} = d \,|\, d_{nt}, \upsilon_n)$$
$$= P(\text{accept lead gap} \,|\, d_{nt}, \upsilon_n) P(\text{accept lag gap} \,|\, d_{nt}, \upsilon_n)$$
$$= P(G_{nt}^{\text{lead } d} > G_{nt}^{\text{lead } d,cr} \,|\, d_{nt}, \upsilon_n) P(G_{nt}^{\text{lag } d} > G_{nt}^{\text{lag } d,cr} \; d_{nt}, \upsilon_n) \qquad (6)$$

where

$d_{nt} \in$ {right, current, left} and the chosen direction of change for driver n at time t, which is determined by the target lane choice;
$G_{nt}^{\text{lead } d}$ and $G_{nt}^{\text{lag } d}$ = available lead and lag gaps in direction d, respectively; and
l_{nt} = lane-changing action.

If it is assumed that critical gaps follow lognormal distributions, the conditional probabilities that gap $g \in$ {lead, lag} is acceptable are given by

$$P(G_{nt}^{gd} > G_{nt}^{gd,cr} \,|\, d_{nt}, \upsilon_n) = P[\ln(G_{nt}^{gd}) > \ln(G_{nt}^{gd,cr}) \,|\, d_{nt}, \upsilon_n]$$
$$= \Phi\left[\frac{\ln(G_{nt}^{gd}) - (\beta^{g^T} X_{nt}^{gd} + \alpha^g \upsilon_n)}{\sigma_g}\right] \qquad (7)$$

where $\Phi[\cdot]$ 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's relative speed and position with respect to the lead and lag vehicles.

DATA FOR MODEL ESTIMATION

A set of detailed vehicle trajectory data that were collected by FHWA (*12*) in a section of I-395 southbound in Arlington, Virginia, was used to estimate the parameters of the lane-changing model. This data set 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 m long with two off-ramps and an on-ramp and therefore has the length necessary to capture the impact of the path plan and other variables on lane-changing behavior.

The data set contains observations of the position, lane, and dimensions of every vehicle within the section every 1 s. The vehicle tra-

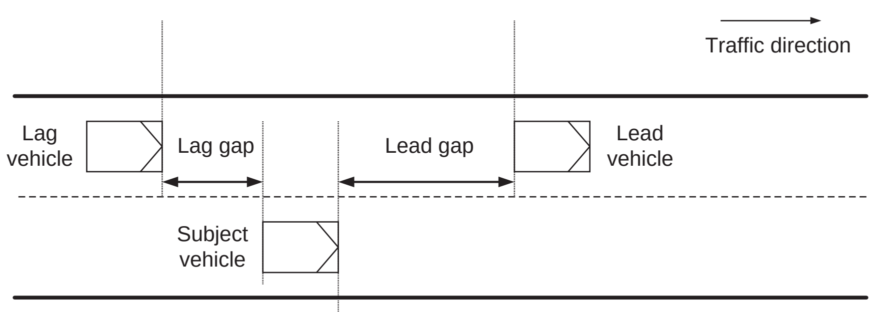

FIGURE 3 Definitions of lead and lag vehicles and gaps that they define.

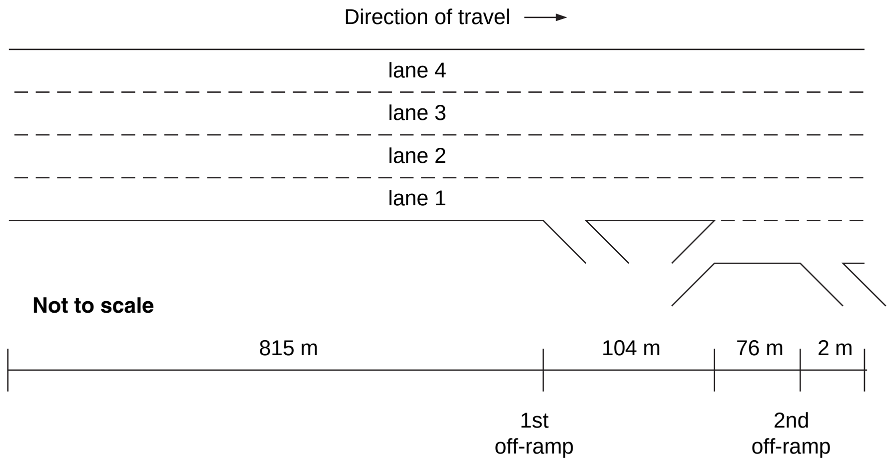

FIGURE 4 I-395 data collection site, Arlington, Virginia.

jectory data were used to generate the required explanatory variables, including the speeds and the relations between the subject vehicle and other vehicles. The estimation data set includes the trajectories of 442 vehicles, with a total of 15,632 observations. On average, a vehicle was observed for 35.4 s (observations). All vehicles were first observed at the upstream end of the freeway section. At the downstream end, 76% stayed on the freeway, and 8% and 16% used the first and second off-ramps, respectively. The observed speeds range from 0.4 to 25.0 m/s, with a mean of 15.6 m/s. Densities range from 14.2 to 55.0 vehicles per kilometer per lane (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 that explains lane-changing behavior. The impact of the path plan is captured by variables such as the distance to an off-ramp that 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. To capture the effects 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. A discrete distribution of the distances that exploits information on the locations of off-ramps downstream of the section was used. The alternatives considered were the first, second, and subsequent off-ramps. The probability mass function of distances to the off-ramps [$\omega(s_n)$] beyond the downstream end of the segment is given by

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

where π_1 and π_2 are the parameters to be estimated; and 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, respectively) were extracted from map information. For the subsequent exits, an infinite distance was used ($s^3 = \infty$). This corresponds to an assumption that while they are on the section being studied, drivers that use these exits are not constrained by their path plans.

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

$$P(\mathrm{TL}_{nt} = i, l_{nt} \mid s_n, \upsilon_n) = P(\mathrm{TL}_{nt} = i \mid s_n, \upsilon_n) P(l_{nt} \mid \mathrm{TL}_{nt} = i, \upsilon_n) \qquad (9)$$

where $P(\mathrm{TL}_{nt} = i \mid \cdot)$ and $P(l_{nt} \mid \cdot)$ are given by Equations 4 and 6, respectively.

Only the lane-changing action is observed over a sequence of T_n consecutive time intervals. If it is assumed 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

$$P(\boldsymbol{l_n} * s_n, \upsilon_n) = \prod_{i=1}^{T_n} \sum_{j \in \mathrm{TL}} P(\mathrm{TL}_{nt} = i, l_{nt} * s_n, \upsilon_n) \qquad (10)$$

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:

$$L_n = \int_{\upsilon} \sum_{s} P(\boldsymbol{l_n} \mid s, \upsilon) \omega(s) f(\upsilon) \qquad (11)$$

If it is assumed that the observations from different drivers are independent, the log-likelihood function for all N individuals observed is given by

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

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

ESTIMATION RESULTS

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

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 the vehicles around it.

TABLE 1 Estimation Results of 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/s	0.119	1.560
Front vehicle spacing, m	0.022	2.879
Relative front vehicle speed, m/s	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}	−0.371	−2.608
θ^{MLC}		
π_1	0.001	−0.426
π_2	0.069	−8.101
$\alpha_{\text{lane 1}}$	−1.371	−2.582
$\alpha_{\text{lane 2}}$	−0.985	−0.510
$\alpha_{\text{lane 3}}$	−0.691	−3.441
Lead critical gap		
Constant	1.553	3.311
Max($\Delta S_{nt}^{\text{lead}}$, 0), m/s	−6.389	−3.793
Min($\Delta S_{nt}^{\text{lead}}$, 0), m/s	−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($\Delta S_{nt}^{\text{lead}}$, 0), m/s	0.471	4.907
α^{lag}	−0.234	0.469
σ^{lag}	0.742	4.802
Number of drivers = 442	$L(0) = -1434.76$	
Number of observations = 15,632	$L(\hat{\beta}) = -876.69$	
Number of parameters = 29	$\bar{\rho}^2 = 0.368$	

$\bar{\rho}^2$ = goodness of fit; $L(0)$ = likelihood function at a value of zero; $L(\hat{\beta})$ = likelihood function at the optimum.

The estimated values of the lane-specific constants imply that, with everything else being equal, the rightmost 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 farther 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. The 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 to go from the current lane to the target lane capture the preference to stay in the current lane and the disutility associated with 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 from that lane that the driver needs to perform to maintain his or her 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 ($\theta^{MLC} = -0.371$, where MLC is mandatory lane change). The disutility associated with being in a wrong lane is larger when the driver needs to take the next exit.

The heterogeneity coefficients, $\alpha_{\text{lane 1}}$, $\alpha_{\text{lane 2}}$, and $\alpha_{\text{lane 3}}$ 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 being correlated with aggressiveness because aggressive drivers are less likely than more timid drivers to choose the right lanes over the left ones.

In summary, the target lane utilities ($U_{\text{int}}^{\text{TL}}$) are given by

$$\begin{aligned} U_{\text{int}}^{\text{TL}} &= \beta_i - 0.011 D_{\text{int}} + 0.119 S_{\text{int}} + 0.022 \Delta X_{\text{int}}^{\text{front}} \delta_{\text{int}}^{\text{adj}} \\ &\quad + 0.115 \Delta S_{\text{int}}^{\text{front}} \delta_{\text{int}}^{\text{adj}} - 2.783 \delta_{nt}^{\text{tailgate}} \delta_{\text{int}}^{\text{CL}} + 1.000 \delta_{\text{int}}^{\text{CL}} \\ &\quad - 2.633 \Delta \text{CL}_{\text{int}} + \beta_i^{\text{path}} [d_{nt}^{\text{exit}}]^{-0.371} - 0.980 \delta_{nt}^{\text{next exit}} \Delta \text{Exit}_i \\ &\quad - \alpha_1 \upsilon_n + \epsilon_{\text{int}}^{\text{TL}} \end{aligned} \tag{13}$$

where

β_i = lane i constant;
D_{int} and S_{int} = lane-specific densities and speeds, respectively;
$\Delta X_{\text{int}}^{\text{front}}$ and $\Delta S_{\text{int}}^{\text{front}}$ = spacing and relative speed of the front vehicle in lane i, respectively;
$\delta_{\text{int}}^{\text{adj}}$ = indicator with a value of 1 if i is the current or an adjacent (adj) lane and 0 otherwise; similarly, $\delta_{\text{int}}^{\text{CL}}$ has a value of 1 if i is the current lane (CL) and 0 otherwise;
$\delta_{nt}^{\text{tailgate}}$ = indicator with a value of 1 if vehicle n is being tailgated at time t and 0 otherwise;
$\Delta \text{CL}_{\text{int}}$ = number of lane changes required to get from the current lane to lane i;

β_i^{path} = path plan impact coefficient for lane i;
d_{nt}^{exit} = distance to the exit that driver n intends to use;
$\delta_{nt}^{\text{next exit}}$ = indicator with a value of 1 if the driver intends to take the next exit and 0 otherwise; and
ΔExit_i = number of lane changes required to get from lane i to the exit lane.

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, neither critical gap was 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 data set 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 than 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 from 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 because their perception of the lag gap is not as reliable as their perception of the lead gap. Estimated coefficients of the unobserved driver characteristics variable, υ_n, are negative for both the lead and the lag critical gaps. Hence, it is consistent with the interpretation of υ_n as being correlated with aggressive drivers, who require smaller gaps for lane changing than timid drivers.

$$G_{nt}^{\text{lead}\,d,\,cr} \exp[1.553 - 6.389\max(0, \Delta S_{nt}^{\text{lead}\,d}) - 0.140\min(0, \Delta S_{nt}^{\text{lead}\,d}) - 0.008\upsilon_n + \epsilon_{nt}^{\text{lead}}] \quad (14)$$

$$G_{nt}^{\text{lag}\,d,\,cr} \exp[1.429 + 0.471\max(0, \Delta S_{nt}^{\text{lag}\,d}) - 0.234\upsilon_n + \epsilon_{nt}^{\text{lag}}] \quad (15)$$

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

TABLE 2 Statistics for Model with Explicit Target Lane and Change Direction Model

	Target Lane	Change Direction
Likelihood value	−888.78	−876.69
Number of parameters (k)	26	29
$\bar{\rho}^2$	0.368	0.362
AIC	−905.69	−914.78
BIC	−937.50	−943.30

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. (*9*). 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, three statistics that are often used for model selection [details are provided elsewhere (*13*)], $\bar{\rho}^2$, the Akaike information criterion (AIC), and the Bayesian information criterion (BIC), were calculated. These statistics account for the larger number of parameters in the model with the explicit target lane. The results are summarized in Table 2. With all these statistics, the model with explicit target lane choice has larger values, which indicates that it fits the data better and therefore should be selected for use for prediction.

MODEL VALIDATION

The new lane-changing model was implemented in the microscopic traffic simulation model MITSIMLab (*2*) and tested with data for a section of I-80 in Berkeley, California. This section, which is shown schematically in Figure 5, is about 6 km 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 a high degree of difference in the level of service among different lanes and is therefore useful for testing of the proposed lane-changing model. In addition to traffic count and speed observations that were collected in five sensor stations in the section, detailed trajectory data were available for the area between Powell Street and Ashby Street, which is shaded in Figure 5.

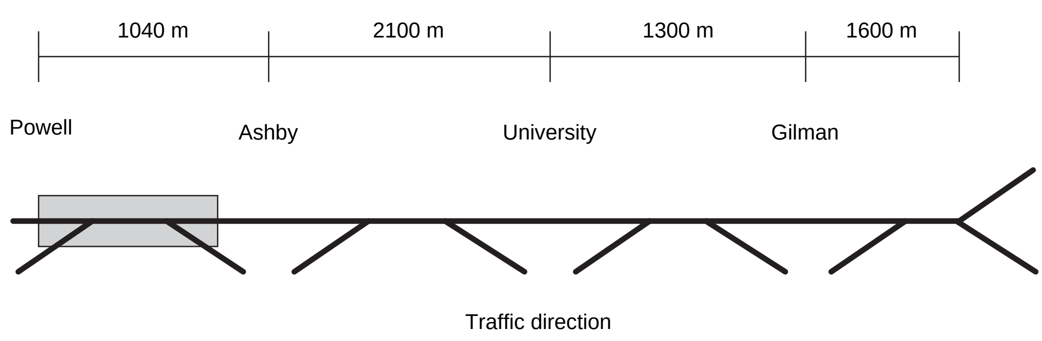

FIGURE 5 I-80 validation site, Berkeley, California.

TABLE 3 Goodness-of-Fit Statistics for Traffic Speed Comparison

	Target Lane Model	Shift Direction Model	% Improvement
Root mean square error, mph	3.30	4.70	29.79
Root mean square error (%)	12.67	14.63	13.41
Mean error (mph)	–0.90	1.59	42.96
Mean 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

The performance of the target lane model was compared with the performance of the model with myopic change direction proposed elsewhere (*9*). Both models were implemented in MITSIMLab. The two versions were calibrated by using the available sensor data. The model validation was based on a comparison of the simulated speeds and lane distribution at a key location by using the two versions with the observations in the data.

Traffic Speeds

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

Lane Distributions

The distribution of vehicles across lanes was extracted from the trajectory data and compared with the simulated lane distributions of both models. The validation results are shown in Figure 6. Overall, the model with explicit target lane choice matched the observations better, particularly with respect to the use 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 an explicit target lane and 2.3% and 13.4%, respectively, for the model with a choice of change direction.

CONCLUSION

This paper presents a new lane-changing model that incorporates an explicit choice of a target lane. This approach differs from those used in existing models that assume that drivers evaluate the current and adjacent lanes and choose a direction of change (or no change) on the basis of the utilities of these lanes only. While the proposed model is applicable to any freeway situation, it is most useful in cases in which there are large differences in the level of service among the lanes, such as in presence of exclusive lanes. The model structure can also capture drivers' preferences for specific lanes, such as in the case in which travel lanes and passing lanes are defined.

The model consists of two choices: the selection of a target lane and the selection of 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 accounted for.

The parameters of all components of the model were estimated jointly by 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 the 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 speed of the subject vehicle with respect to those of the lead and lag vehicles.

Statistical model selection criteria established by use of 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 versions of a microscopic traffic simulator that

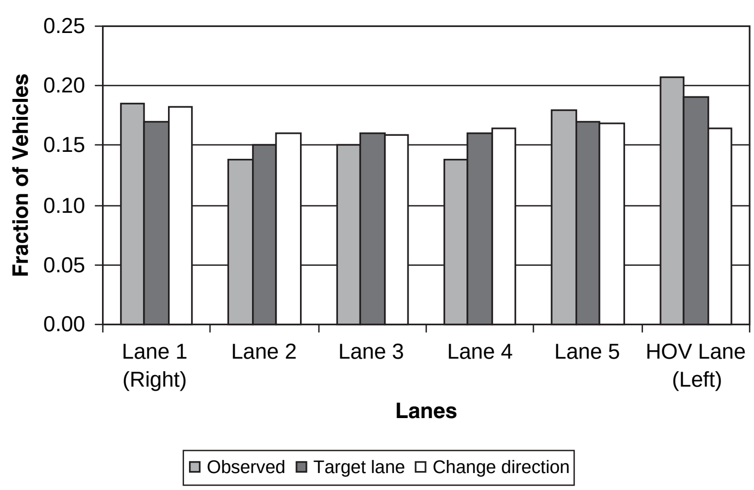

FIGURE 6 Observed and simulated distributions of vehicles between lanes.

implements the two models. The simulator was applied to a multilane freeway section that includes an HOV lane. The target lane model provided significantly better prediction in terms of both traffic speeds and the distributions of vehicles to lanes. While these results are promising, further research with detailed trajectory data from sites with various geometric and traffic characteristics is needed to develop more robust models that will be more generally applicable to urban freeway traffic. Unfortunately, only a few data sets that can support such research exist, and even fewer that are newer than the one used in this study exist but may not well represent current vehicle capabilities.

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