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Latent class model for car following behavior

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Car-following behavior, which describes the behavior of a vehicle while following the vehicle in front of it, has a significant impact on traffic performance, safety, and air pollution. In addition, car-following is an essential component of micro-simulation models. Over the last decade the use of microscopic simulation models as a tool for investigating traffic systems, ITS applications, and emission impacts, is becoming increasingly popular. The paper presents a flexible framework for modeling car-following behavior that relaxes some limitations and assumptions of the most commonly used car following models. The proposed approach recognizes different regimes in driving such as car-following, free-flow, emergency stopping, and incorporates different decisions in each regime, such as acceleration, deceleration, and do-nothing depending on the situation. A case study using NGSIM vehicle trajectory data is used to illustrate the proposed model structure. Statistical tests suggest that the model performs better than previous models.

1. Introduction

Car-following behavior significantly impacts traffic performance, safety, and air pollution. Rear-end collisions, for example, are one of the most frequently occurring type of collisions (Wang et al., 1999; Oh et al., 2006; Adell et al., 2010). Twenty-five percentage of all police-reported collisions in the US (Martin and Burgett, 2001) and more than 13% of all casualties from road accidents in Europe (Várhelyi, 1996) are related to rear-end collisions. Studying drivers' car-following behavior and their decision-making is important for understanding how to avoid rear-end collisions. In addition, car-following models are essential in microscopic traffic simulation models and impact their fidelity.

Initial studies on car-following behavior developed models which capture situations where the subject vehicle reacts to the leader's actions (Reuschel, 1950; Pipes, 1953). Later on, several researchers developed general acceleration models which also capture the behavior of drivers in other situations, such as car-following, free-flowing, and emergency (Yang and Koutsopoulos, 1996; Ahmed, 1999; Toledo, 2003). Free-flowing regime is assumed when drivers are not close to their leaders and therefore may apply a free-flowing acceleration to attain their desired speed. Emergency regime is assumed when drivers get too close to their leaders and therefore they may apply an emergency deceleration.

Over the past decade, several car-following models have been proposed and described in the literature. Brackstone and McDonald (1999) categorized car-following models into five groups, namely: Gazis–Herman–Rothery (Gazis et al., 1961) models, safety distance/collision avoidance models (Kometani and Sasaki, 1959; Gipps, 1981), linear models (Helly, 1959), psycho-physical or action point models (Wiedemann, 1974), and fuzzy logic based models (Kikuchi and Chakroborty, 1992). Olstam and Tapani (2004) classify car-following models into classes depending on the underlying logic: (1) General car-following models, which state that "the following vehicle's acceleration is proportional to own speed, the speed difference between the follower and the leader and the space headway"; (2) Safety-distance models, "these models are based on

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the assumption that the follower always keeps a safe distance to the vehicle in front"; and (3) Psycho-physical car-following models or action point models, "use thresholds based on the speed and distance difference between the subject and the lead vehicle. Drivers are able to react to changes in spacing or relative velocity only when these thresholds are reached".

The objective of this paper is to present a general framework for modeling car following behavior that also facilitates the systematic estimation of the model. A case study is used to estimate the proposed model and compare its performance to previous models. The rest of the paper is organized as follows: Section 2 presents previous work in the area. Section 3 presents the formulation of the proposed model. Section 4 illustrates the model structure for the car-following regime. Section 5 describes the data collected and used for the calibration process followed by presentation of the estimation results. Finally, Section 6 summarizes the conclusions and suggests future research directions.

2. Background

The concept of car-following was proposed for the first time by Reuschel (1950) and Pipes (1953). A car-following situation is defined when the subject vehicle follows the vehicle in front of it (leader) and reacts to its actions. The California Vehicle Code recommends drivers to keep a distance of 15 ft from the lead vehicle for every 10 mph of speed. Following this recommendation, Pipes (1953) assumes that the following vehicle desires to keep safe time headway of 1.02 s from the lead vehicle. He developed theoretical expressions for the acceleration that a following vehicle applies for a given behavior of a lead vehicle using Laplace transformations (Toledo, 2003).

Sensitivity-stimulus framework, which was presented by researchers at the General Motors Research Laboratories, is the basis for most car-following models up till today (Toledo, 2003). These models, based on the sensitivity-stimulus framework, assume that a following driver reacts to a stimulus from the environment, which is proposed to be the leader relative speed (i.e. the speed of the leader minus the speed of the subject vehicle). The response, which is translated to positive or negative acceleration, is lagged to account for the follower reaction time. This framework became the basis of several other models that were developed later on. These models differed in the specification of the sensitivity term. The simplest model is the linear car-following model, developed by Chandler et al. (1958) and Herman et al. (1959) with a constant sensitivity term:

$$a_n(t) = \alpha \cdot \Delta V_n^{front}(t - \tau_n) \tag{1}$$

where $a_n(t)$ is the acceleration applied by driver n at time t. $\Delta V_n^{front}(t - \tau_n)$ is the leader relative speed measured at time $(t - \tau_n)$. τ_n is the reaction time. α is a parameter.

In spite of the advantage of its simplicity, the assumption of the linear GM model that the spacing between the follower and the leader has no effect on the response to the stimulus is unrealistic.

Gazis et al. (1961) developed the most general form of the GM model where they considered a non-linearity in the sensitivity of the response to the spacing and the subject vehicle speed:

$$a_n(t) = \alpha \cdot \frac{V_n(t)^{\beta}}{\Delta X_n^{front}(t - \tau_n)^{\gamma}} \cdot \Delta_n^{front}(t - \tau_n) \tag{2}$$

where $V_n(t)$ is the speed of subject vehicle n measured at time t. $\Delta V_n^{front}(t - \tau_n)$ and $\Delta X_n^{front}(t - \tau_1 n)$ are the leader relative speed and the relative distance respectively measured at time $(t - \tau_n)$. τ_n is the reaction time of the follower and α, β, and γ are parameters to be estimated.

Studies that followed this line of research over the years tried to overcome some of the limitations by suggesting several extensions to the GM model. For example, Herman and Rothery (1965) accounted for differences in drivers' alertness to an increase in the relative leader speed, as opposed to a decrease, by suggesting different sets of parameters for acceleration and deceleration decisions. Subramanian (1996) determined that drivers react faster under deceleration than acceleration response, which is intuitive.

Ahmed (1999) proposed a general acceleration model that captures both car-following and free-flow behaviors. He assumed that the state is determined by comparing the headway with the lead vehicle to a critical value, which is assumed to have a distribution among the drivers. Ahmed improved Subramanian's car-following model by adding traffic density in the sensitivity term and assumed nonlinearity in the stimulus term and different reaction times for the sensitivity and the stimulus:

$$a_n(t) = \begin{cases} \alpha_i \cdot \frac{V_n(t-\xi\tau_n)^{\beta^i}}{\Delta X_n^{front}(t-\xi\tau_n)^{\gamma^i}} \cdot k_n(t)^{\delta^i} \Delta V_n^{front}(t-\tau_n)^{\rho^i} = \varepsilon_n^{cf,i}(t) & \text{if } h_n(t-\tau_n) \le h_n^* \\ \lambda^{ff} \cdot [V_n^*(t-\tau_n) - V_n(t-\tau_n)] + \varepsilon_n^{ff}(t) & \text{otherwise} \end{cases} \tag{3}$$

where $i \in \{acc, dec\}$, $k_n(t)$ is the density of the traffic ahead of the subject within its view at time t. A visibility distance of 100 m ahead of the driver was used. $\xi \in [0,1]$ is a sensitivity lag parameter. λ^{ff} is the constant sensitivity. $V_n^*(t - \tau_n)$ is the desired speed of the driver. $h_n(t - \tau_n)$ is the time headway at time.$(t - \tau_n)h_n^*$ is the unobserved headway threshold for driver n $\varepsilon_n^{cf,i}$and $\varepsilon_n^{ff}(t)$ are normally distributed error terms for the car-following and free-flowing, respectively.

According to Siuhi and Kaseko (2010) existing stimulus–response models have three main limitations: (a) identical reaction time distribution is assumed for all drivers and vehicle types; (b) drivers are able to perceive even small stimulus; and (c) a single value is estimated for each of the model parameters, and hence these models do not capture individual differences between drivers and also between different types of lead and following vehicles. To relax these limitations the authors developed separate car-following models for acceleration and deceleration situations on a freeway during a peak period which consider different response time lag and stimulus response thresholds for acceleration and deceleration and also takes into account heterogeneity in driving behavior. The authors found that driver reaction time is lower for deceleration (0.7 s) than for acceleration (0.8 s). The stimulus threshold for a deceleration response was found to be lower than for an acceleration response. The authors associate this result with drivers' higher sensitivity when faced with the need to decelerate for maintaining safe separation.

Treiber et al. (2000) proposed the Intelligent Driver Model (IDM) which describes the acceleration of a driver as a function of the gap $s_\alpha(t)$, the speed $v_\alpha(t)$ and the speed difference $\Delta v_\alpha(t)$ between vehicle α and the vehicle in front using the following expression:

$$\frac{d}{dt}v_\alpha = a \cdot \left(1 - \left(\frac{v_\alpha}{v_0}\right)^\delta - \left(\frac{s^* v_\alpha, \cdot \Delta v_\alpha)}{s_\alpha}\right)^2\right) \tag{4}$$

where the desired gap s^* is given by:

$$s^*(v_\alpha, \Delta v_\alpha) = s_0 + s_1 \cdot \sqrt{\frac{v_\alpha}{v_0}} + T \cdot v_\alpha + \frac{v_\alpha \cdot \Delta v_\alpha}{2\sqrt{a \cdot b}} \tag{5}$$

Assuming that the vehicles are identical, the five parameters to be estimated are: the maximum acceleration 'a', the maximum deceleration 'b', the free flow speed 'v_o', the minimum time headway 'T', the stopping distance 's_0', the jam distance 's_1' and the acceleration exponent δ. Hoogendoorn and Hoogendoorn (2010) used maximum likelihood to estimate the parameters of the Intelligent Driver Model.

Treiber et al. (2006) were interested to examine whether the destabilizing effects, such as finite reaction times and estimation errors, are compensated for by temporal and spatial anticipation (looking several vehicles ahead) of drivers, named as the stabilizing effects. To test that, the authors extended the Intelligent Driver Model (Treiber et al., 2000) by assuming: (a) finite reaction times, (b) estimation errors, (c) spatial anticipation, and (d) temporal anticipation. The new model was named by the authors as the human driver (meta-) model (HDM). The results confirmed their hypothesis that the spatial and temporal anticipation compensate for the destabilizing effects of reaction times and estimation errors, resulting in the same qualitative macroscopic dynamics as that of the simple car-following model.

The GM family of models has been estimated using trajectory data (Ahmed, 1999; Toledo, 2003). The estimation of the model assumes that a driver accelerates when the relative speed ΔV_n^{front} is positive, and decelerates when V_n^{front} is negative. This decision is deterministic.

Wiedemann (1974) and Leutzbach (1988) address two limitations of many GM-type models from a behavioral standpoint: that drivers remain affected by the actions of their leader even when the spacing between them is large, and that drivers are able to perceive and react to even small changes in the stimulus. To overcome these limitations they introduced the psycho-physical model which uses "perceptual thresholds". Perceptual thresholds are a function of space headway and relative speed between the following and followed vehicles. It is assumed that drivers do not react unless these thresholds are reached and therefore it captures the increased awareness of drivers for small headways and lack of following behavior at large headways. It was found that the perceptual thresholds for acceleration differ from those of deceleration decisions.

Wiedemann and Reiter (1992) applied the "perceptual thresholds" approach in the microscopic simulation system MISSION. Human perception and reaction are captured by a set of thresholds and desired distances. These thresholds set the boundaries between three different areas which describe different interaction situations between the subject vehicle and the lead vehicle: (a) free-flowing: the behavior of the subject vehicle is not influenced by the vehicles in front of him; (b) approaching mode: the behavior of the subject vehicle is consciously influenced since the driver perceived a slower lead vehicle; (c) car-following: the subject vehicle is unconsciously following the lead vehicle (d) emergency situation: the headway between the subject vehicle and the lead vehicle is below a desired safety gap.

Brackstone and McDonald (1999) state that the basis upon which the psychophysical model is built is reasonable and best able to describe the features of driving behavior. However, more research is needed to validate these principals.

Other models have also been proposed in the literature. Gipps (1981) was the first to develop a general acceleration model which captures car-following and free-flow conditions. According to Gipps there are two constrains that determine the maximum applicable acceleration, upon which the model was based, these are: the desired speed may not be exceeded and a minimum safe headway must be maintained. The safe headway is defined as the minimum headway that provides a driver with an opportunity to avoid a crash with a lead vehicle that applies an emergency braking. Different types of vehicles are accounted for by adopting different values of maximum acceleration and deceleration (Toledo, 2003). This collision avoidance car-following model is incorporated in several microscopic simulation softwares, including AIMSUN (Barceló, 2006), SISTM (Hardman, 1996), and DRACULA (Liu et al., 1995). Rakha and Wang (2009) developed a procedure for calibrating the Gipps' car-following model which included the following two steps: (1) using macroscopic loop detector data to calibrate the steady-state car following model in order to estimate four traffic stream parameters: the free-flow speed, speed-at-capacity, capacity, and jam density; (2) using vehicle performance data attained from automobile manufacturers to calibrate the Gipps vehicle acceleration component. The authors validated the calibration procedures by using field data of sample light-duty and heavy-duty vehicles.

Zhang and Kim (2005) proposed a car-following model for multiphase flow which is a function of a gap-time that a driver desires to achieve. This gap-time is a function of the gap-distance between the back of the lead vehicle and the front of the subject vehicle, and the traffic phase. By specifying different forms of this function it is possible to obtain several specific models. Among these are models that can reproduce the capacity drop and/or traffic hysteresis. The authors indicate that both the capacity drop and traffic hysteresis are important because capacity drop has significant implications for traffic control, and traffic hysteresis is fundamentally linked to instability (stop-and-go) in traffic.

Hamdar and Mahmassani (2008) calibrated, and tested several existing car-following models using the NGSIM (Next Generation SIMulation) data. The authors tested these models in terms of vehicle trajectories, flow-density relationships and ability to model driver behavior during incident conditions. They found two advantages of the Gipps (1981) model when compared to the other models tested in the study (which motivated them to further modify the Gipps model): (1) the driving behavior is based on some cognitive logic that drivers might implement while driving; (2) the model is more stable when relaxing its safety constraints which is reflected by the relatively low number of accidents. The modified Gipps model is able to capture instability during congestion, traffic hysteresis, traffic breakdown, and does not require having an-accident-free environment. The authors considered also a lane-changing model to provide a more comprehensive modeling framework.

Tordeux et al. (2010) developed a car-following model based on time gap and estimated it using maximum likelihood method. The results revealed significant differences between vehicle types and between acceleration and deceleration situations. Regarding vehicle types, it was found that motorcyclists tend to accelerate more sharply than cars and trucks whereas trucks were found to decelerate more intensely.

This study aims to develop a general, flexible framework for modeling car following behavior that also facilitates the systematic estimation of the model. One of the fundamental issues that motivated the development of the proposed model is the desire to relax the assumption in the estimation procedure of the GM model which assumes that if ΔV is positive, i.e. the lead vehicle is driving faster than the subject vehicle, the driver will accelerate and if ΔV is negative, i.e. the subject vehicle is driving faster than the lead vehicle, the driver will decelerate. However, examination of existing databases, such as the Next Generation Simulation–NGSIM (Alexiadis et al., 2004) and Federal Highway Administration –FHWA (1985), show that in many cases the opposite is true. Therefore, it is important to relax this assumption and develop a model which presents more accurately the actual behavior. For this purpose this study utilizes the concepts of latent class models and car-following models. Latent class models have been previously used in discrete choice modeling and also driving behavior. Toledo (2003), for example, developed a latent integrated driving behavior model which captures both lane changing and acceleration behaviors. Greene and Hensher (2003) applied this approach to study drivers' choice of road type in long distance travel in New Zealand in order to understand their preferences for road environments. Ben-Akiva et al. (2006) model drivers' lane-changing behavior on freeways using latent states. Choudhury (2007) introduced latent plans in the decisions of drivers with respect to lane-changing. The author states that "these latent plans are ignored in the state-of-the-art driving behavior models and this could lead to unrealistic traffic flow characteristics and incorrect representation of congestion". She conducted a case study using NGSIM data, where the latent models were compared to standard models. The results indicate that the latent models outperformed previous approaches.

3. Formulation

The objective of the paper is to develop a modeling framework for acceleration behavior that is flexible from a behavioral point of view and lends itself to rigorous calibration methods. The proposed framework is based on the recognition that there are different regimes in driving with respect to the acceleration behavior of drivers. These regimes include for example car-

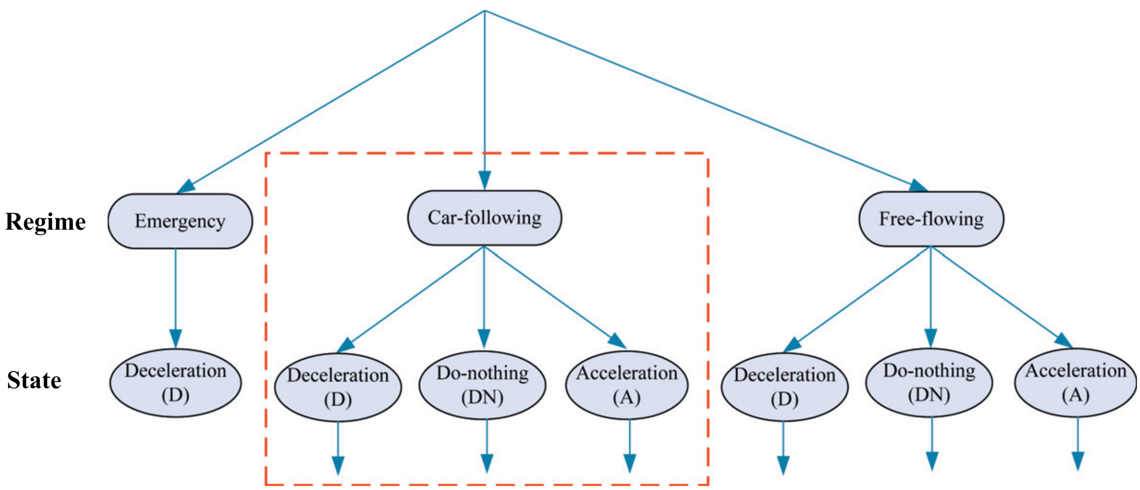

Fig. 1. Model framework.

following, free-flowing, emergency, etc. Previous studies use time headway to decide on the appropriate regime (Yang and Koutsopoulos, 1996; Ahmed, 1999; Katja, 2002; Toledo, 2003). The regimes are not observed and they are a function of explanatory variables, such as speed difference, time and space gaps and speed.

In each regime, the driver makes decisions based on influencing factors from the surrounding environment. For example in the car-following regime the driver might decide to accelerate (A), decelerate (D), or do-nothing (DN) in response to stimuli from other vehicles (in particular the lead vehicle). Again, these decisions (unlike previous models) are probabilistic and the result of a number of explanatory variables such as time headways and speeds. In the free-flowing regime the driver has three possible states (acceleration, deceleration or do-nothing) but the stimulus in this case may be the driver's own desired speed (Ahmed, 1999). In the emergency regime, a single state can be assumed which includes deceleration of the vehicle to maintain safe gaps. The decisions related to the regime and state can be represented in a discrete choice framework (and/or a combination of thresholds). The structure of the proposed modeling framework is illustrated in Fig. 1.

In the remaining sections the paper focuses on the car-following regime to illustrate the proposed model structure. However, the same methodology can be used to model the other regimes.

4. Car-following behavior

4.1. Model structure

According to the structure presented in Fig. 2 a driver has three possible states: acceleration (A), deceleration (D), or do nothing (DN). Drivers' choices are unobserved or latent and what is observed is the driver's final action: acceleration (+) or deceleration (−). Latent states are shown as ovals and observed actions as rectangles.

Usually accelerations/decelerations are a result of drivers' intentions to accelerate/decelerate. However, small accelerations/decelerations could also be triggered even if the driver is in the DN state and result from the difficulty that a driver faces to keep a constant speed. Fig. 3, illustrates the nature of the underlying distribution in each state. The parameters of each distribution are assumed to be a function of traffic conditions.

From an estimation point of view the underlying states are latent and only the magnitude of the acceleration (deceleration) is observed. As a result, if a driver accelerates (decelerates) then she/he may be in the acceleration (deceleration) state or the do-nothing state. Hence, each observation (acceleration or deceleration) maybe triggered by the direct action (conscious intention to accelerate or decelerate) or may be due to the noise in behavior in the do-nothing state (which results from the difficulty to keep a constant speed).

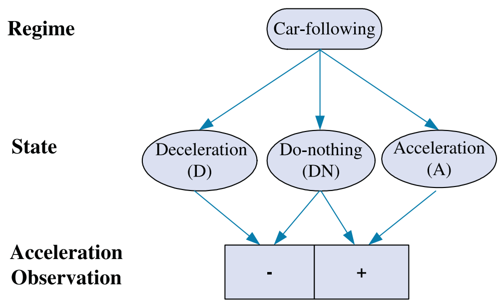

Fig. 2. Car-following model structure.

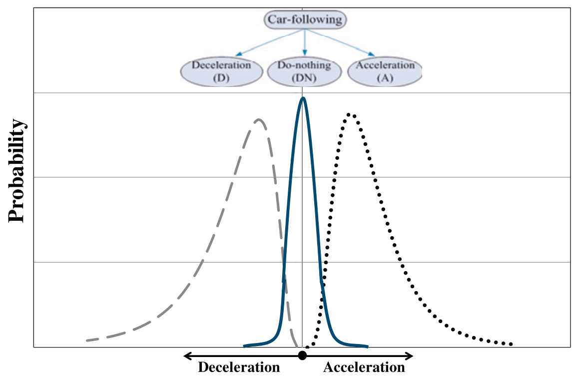

Fig. 3. Latent class model structure of the car-following behavior.

The proposed structure allows for estimation of more general models and relaxes some assumptions used in earlier estimation results. For example, the GM-type models have been estimated assuming a deterministic rule, that the expected value of the response to the stimuli is positive (acceleration) for positive leader relative speeds, i.e., when the leader is faster than the subject vehicle and negative (deceleration) for negative leader relative speeds.

4.2. State choice model

The decision of driver n to accelerate, decelerate or do nothing is formulated as a discrete choice problem based on the utilities U_n^i of the different states ($i = A, D$ and DN):

$$U_n^{DN}(t) = \varepsilon_n^{DN}(t) \tag{6}$$

$$U_n^A(t) = V_n^A(t) + \varepsilon_n^A(t) = X_n^A(t) \cdot \beta_A + \varepsilon_n^A(t) \tag{7}$$

$$U_n^D(t) = V_n^D(t) + \varepsilon_n^D(t) = X_n^D(t) \cdot \beta_D + \varepsilon_n^D(t) \tag{8}$$

where $V_n^i(t)$ is the systematic utility for driver n at time t for state i ($i = A, D, DN$). β_i is the vector of parameters for the different explanatory variables $X_n^i(t)$. Relevant explanatory variables can include for example, the relative speed and distance between the subject vehicle and its lead vehicle, traffic density, subject vehicle speed, etc. $\varepsilon_n^i(t)$ is the random error term of driver n choosing state i. The error term structure can be more general to incorporate explicitly heterogeneity in driver behavior. (Toledo, 2003) for example uses $a_n\vartheta_n + \varepsilon_n(t)$ to represent heterogeneity (α_n is a parameter of ϑ_n, an individual specific error term). Assuming that error terms follow an i.i.d Gumbel distribution the decision problem can be formulated as a multinomial logit choice model:

$$P_n(i) = \frac{e^{V_n^i}}{\sum_i e^{V_n^i}} \tag{9}$$

The independence assumptions, following the i.i.d Gumbel distribution, are not as restrictive. Part of the correlations between various decisions is accounted for by including reaction times of drivers which are assumed to be randomly distributed in the population. Moreover, since the situation is dynamic and uncertain, drivers reconsider and re-evaluate their decisions as conditions change. The modeling framework used is consistent with the "partial short-term plan" approach (Sukthankar, 1997; Toledo, 2003) which assumes that state dependencies are captured through the explanatory variables (which in many cases are a function of the previous actions of the vehicle).

4.3. Acceleration model

The acceleration model depends on the state the driver is in. Assuming that the driver is in the acceleration or deceleration state, the corresponding mean value of the acceleration (deceleration) can be expressed as a function of explanatory variables. This approach increases the flexibility of the developed model in which different explanatory variables and different car-following models can be applied. For example, assuming a car-following model that is based on the sensitivity – stimulus framework:

$$a_n^i(t) = s[X_n^i(t)] \cdot g[\Delta V_n^{front}(t - \tau_n)] \cdot \varepsilon_n^i(t) \tag{10}$$

where $i \in \{A, D\}$ τ_n: reaction time of driver n, a random variable; $s[X_n^i(t)]$: sensitivity, a function of explanatory variables, $X_n^i(t)$; $X_n^i(t)$: vector of explanatory variables affecting the car-following acceleration sensitivity observed at time t; $g[\Delta V_n^{front}(t-\tau_n)]$: stimulus, a function of the relative speed, $[\Delta V_n^{front}(t-\tau_n)] = (v_n^{lead}(t-\tau_n) - v_n(t-\tau_n))$ and $\varepsilon_n^i(t)$: error term.

In the proposed framework, this model explicitly captures acceleration and deceleration decisions. As such, if for example, a driver accelerates the result will be always positive. Therefore, the error term should be a positive random variable (the same applies under deceleration decisions). In this case study the error term was assumed to follow the log-normal distribution. In the literature critical gaps have been modeled in a similar way (Farah and Toledo, 2010). Furthermore, this is common in the estimation of multiplicative models (Dhrymes, 1962; Leech, 1975; Evans and Shaban, 1976).

The corresponding distribution of the acceleration (deceleration) is:

$$f_{CF}^i(a_n^i(t)) = \frac{1}{|a_n(t)|\sigma^i}\,\phi\left(\frac{\ln\{|a_n(t)|\} - \ln\{s[X_n^i(t)] \cdot g[\Delta V_n^{front}(t-\tau_n)]\}}{\sigma^i}\right) \tag{11}$$

where $i = \{A, D\}$. $f_{CF}^i(a_n^i(t))$ is the probability density function for acceleration/deceleration. $|a_n(t)|$ is the absolute value of the acceleration/deceleration applied by driver n at time t. $\phi(\cdot)$ is the probability density function of a standard normal random variable. $s[X_n^i(t)]$ is the sensitivity term for acceleration/deceleration. σ^i is the standard deviation of the lognormal acceleration/deceleration probability density function.

In the above formulation it is assumed that when a driver is in state A (D) this always results in an acceleration (deceleration) action with no ambiguity.

For the do-nothing state it is assumed that the acceleration/deceleration has a normal distribution with mean value μ^{DN} and standard deviation σ^{DN}:

$$f_{CF}^{DN}(a_n^{DN}(t)) = \frac{1}{\sigma^{DN}}\phi\left(\frac{a_n(t) - \mu^{DN}}{\sigma^{DN}}\right) \tag{12}$$

where $a_n(t)$ is the acceleration/deceleration applied by driver n at time t. $\phi(\cdot)$ is the standard normal distribution. It is expected that μ^{DN} will have a value very close to 0.

4.4. Reaction time distribution

The reaction time is the time delay from the appearance of the stimulus to the application of the response. It includes the perception time, foot movement time, vehicle response time and decision time. The reaction time is affected by characteristics of the driver (e.g. age, gender, alertness, physical condition) and the vehicle, as well as by environmental conditions (e.g. weather conditions, visibility, road geometry) and traffic conditions (Toledo, 2003). Following Ahmed (1999) and Toledo (2003) a truncated lognormal distribution is used to account for the finiteness of the value of the reaction time.

$$f^{RT}(\tau_n) = \begin{cases} \dfrac{\frac{1}{\sigma_\tau \tau_n}\phi\left(\frac{\ln(\tau_n)-\mu_\tau}{\sigma_\tau}\right)}{\Phi\left(\frac{\ln(\tau_{\max})-\mu_\tau}{\sigma_\tau}\right)} & \text{if } 0 < \tau \leqslant \tau_{\max} \\ 0 & \text{otherwise} \end{cases} \tag{13}$$

where τ_n is the reaction time of driver n. μ_τ and σ_τ are the mean and standard deviation of the distribution of $\ln(\tau)$, respectively. $\tau_{\max}$ is the maximum value of the reaction time. $\phi(\cdot)$ and $\Phi(\cdot)$ are the probability density function and cumulative probability of the standard normal distribution, respectively.

It is assumed that the reaction time distribution is common to the various regimes, although this assumption can be relaxed.

4.5. Likelihood function formulation

Typical data used for estimating such models includes observations about the acceleration (deceleration) of a vehicle in discrete times (e.g. every 1 s or even more frequently).

According to the proposed model formulation, as mentioned in Section 4.1, drivers' acceleration/deceleration might result from either their conscious decision to accelerate/decelerate (i.e. the driver is in state *A*/*D*) or from the noise that results from control difficulties while trying to drive with constant speed (i.e. *DN* state). Fig. 4 presents the relationship between these considerations and the resulting observation.

The overall distribution of acceleration, $f^+(a_n^+(t))$, is a mixture of the distribution of acceleration while in the "*A*" state and the distribution of acceleration while in the "*DN*" state. Hence it is the sum of the probability density functions of acceleration in each state (*A* or *DN*), weighted by the corresponding probabilities that a driver is in "*A*" or "*DN*" (conditional on the fact that the driver accelerates). Similarly for the overall distribution of deceleration, $f^-(a_n^-(t))$.

Let, +($-$): An acceleration (deceleration) observation; $P_n(D/-)$: Probability that driver n is in "*D*" given that she/he decelerates; $P_n(DN/-)$: Probability that driver n is in "*DN*" given that she/he decelerates; $P_n(A/+)$: Probability that driver n is in "*A*" given that she/he accelerates; $P_n(DN/+)$: Probability that driver n is in "*DN*" given that she/he accelerates; $f_{CF}^A(a_n^A(t)/+)$: Probability density function of "*A*" for an acceleration observation; $f_{CF}^{DN}(a_n^{DN}(t)/+)$: Probability density function of "*DN*" for an acceleration observation; $f_{CF}^D(a_n^D(t)/-)$: Probability density function of "*D*" for a deceleration observation and $f_{CF}^{DN}(a_n^{DN}(t)/-)$: Probability density function of "*DN*" for a deceleration observation (note that $P_n(D/-) + P_n(DN/-) = 1$ and $P_n(A/+) + P_n(DN/+) = 1$).

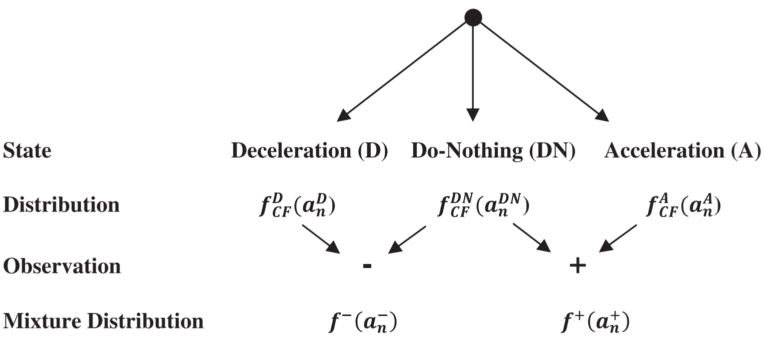

Fig. 4. Possible regimes in car-following.

The probability density function of observed accelerations (decelerations) conditional on the reaction times is defined below (the conditional term τ_n has been ignored to simplify the presentation):

$$f^{+}\left(a_n^{+}(t)\right) = f_{CF}^{A}(a_n^{A}(t)/+)\cdot P_n(A/+) + f_{CF}^{DN}((a_n^{DN}(t)/+)\cdot P_n(DN/+) \tag{14}$$

$$f^{-}\left(a_n^{-}(t)\right) = f_{CF}^{D}(a_n^{D}(t)/-)\cdot P_n(D/-) + f_{CF}^{DN}((a_n^{DN}(T)/-)\cdot P_n(DN/-) \tag{15}$$

The individual terms in Eqs. (14) and (15) can be determined as follows:

$f_{CF}^{A}(a_n^{A}(t)/+) = f_{CF}^{A}(a_n^{A}(t))$ and $f_{CF}^{D}(a_n^{D}(t)/-) = f_{CF}^{D}(a_n^{D}(t))$ (see Eq. (11)).

$f_{CF}^{DN}(a_n^{DN}(t)/+)$ and $f_{CF}^{DN}(a_n^{DN}(t)/-)$ are the probability density functions of acceleration/deceleration in the do-nothing state given that driver n is accelerating/decelerating respectively. These conditional density functions are therefore truncated normal distributions (assuming that the unconditional probability density function of the DN state is normal).

$$f_{CF}^{DN}\left(a_n^{DN}(t)/+\right) = \frac{\frac{1}{\sigma^{DN}}\phi\left(\frac{a_n(t)-\mu^{DN}}{\sigma^{DN}}\right)}{1-\Phi\left(\frac{-\mu^{DN}}{\sigma^{DN}}\right)}, \quad a_n^{DN}(t) \geqslant 0 \tag{16}$$

$$f_{CF}^{DN}\left(a_n^{DN}(t)/-\right) = \frac{\frac{1}{\sigma^{DN}}\phi\left(\frac{a_n(t)-\mu^{DN}}{\sigma^{DN}}\right)}{\Phi\left(\frac{-\mu^{DN}}{\sigma^{DN}}\right)}, \quad a_n^{DN}(t) < 0 \tag{17}$$

where μ^{DN} and σ^{DN} are the mean and standard deviation of the do-nothing normal distribution. $a_n(t)$ is the acceleration/deceleration applied by driver n at time t. $\phi(.)$ and $\Phi(.)$ are the standard normal probability density and cumulative density function, respectively.

The probability $P_n(A, +)$ to be in the acceleration state conditional on observing acceleration (the driver accelerates) is defined as:

$$P_n(A/+) = \frac{P_n(A,+)}{P_n(+)} = \frac{P_n(A)}{P(+/A)\cdot P_n(A) + P(+/DN)\cdot P_n(DN)} \tag{18}$$

where $P_n(A, +)$ is the joint probability of driver n to be in the acceleration state and accelerates: $P_n(A, +) = P_n(A)$. $P_n(+)$ is the probability to observe an acceleration for driver n, $P_n(DN)$ is the probability of driver n to be in the do-nothing state and $P_n(A)$ is the probability of driver n to be in the acceleration state (see Eq. (9)). $P(+/A)$ is the probability to observe an acceleration given that the driver is in the acceleration state $P(+/A)$.$P(+/DN)$ is the probability to observe an acceleration given that the driver is in the do-nothing state:

$$P(+/DN) = \left[1-\Phi\left(\frac{-\mu^{DN}}{\sigma^{DN}}\right)\right] \tag{19}$$

μ^{DN} and σ^{DN} are the mean and standard deviation of the do-nothing normal distribution, respectively.

The probability to be in the do-nothing regime, conditional on observing acceleration for driver n, is given by:

$$P_n(DN/+) = \frac{P_n(DN,+)}{P_n(+)} = \frac{P(+/DN)\cdot P_n(DN)}{P(+/A)\cdot P_n(A) + P(+/DN)\cdot P_n(DN)} \tag{20}$$

where $P_n(DN, +)$ is the joint probability of driver n to be in the do-nothing regime and accelerates. $P_n(+)$, $P_n(A)$, $P(+/A)$ and $P(+/DN)$ are as defined previously.

Substituting Eqs. (18) and (20) in Eq. (14), leads to the acceleration probability density function conditional on the reaction time distribution:

$$f^{+}\left(a_n^{+}(t)/\tau_n\right) = f_{CF}^{A}(a_n^{A}(t))\cdot\frac{P_n(A)}{P_n(A)+P(+/DN)\cdot P_n(DN)} + f_{CF}^{DN}\left(a_n^{DN}(t)/+\right)\cdot\frac{P(+/DN)\cdot P_n(DN)}{P_n(A)+P(+/DN)\cdot P_n(DN)} \tag{21}$$

Similarly, the overall distribution of deceleration is given by:

$$f^{-}(a_n^{-}(t)/\tau_n) = f_{CF}^{D}(a_n^{D}(t))\cdot\frac{P_n(D)}{P_n(D)+P(-/DN)\cdot P_n(DN)} + f_{CF}^{DN}\left(a_n^{DN}(t)/-\right)\cdot\frac{P(-/DN)\cdot P_n(DN)}{P_n(A)+P(-/DN)\cdot P_n(DN)} \tag{22}$$

where $P_n(DN)$ is the probability of driver n to be in the do-nothing state and is the probability of driver n to be in the deceleration state (see Eq. (9)). $P(-/DN)$ is the probability to observe a deceleration given that the driver is in the do-nothing state, $P(-/DN) = \Phi\left(\frac{-\mu^{DN}}{\sigma^{DN}}\right)$.

The joint distribution of a sequence of T observations for driver n is given by:

$$f(a_n(1), a_n(2), \ldots, a_n(T)/\tau_n) = \Pi_{t=1}^{T} f(a_n(t)/\tau_n) \tag{23}$$

where $f(an(t)/\tau_n)$ is the probability density function of acceleration/deceleration conditional on the reaction time τ_n:

$$f(a_n(t)/\tau_n) = f^+(a_n^+(t)/\tau_n)^{\delta(a_n(t))} \cdot f^-(a_n^-(t)/\tau_n)^{1-\delta(a_n(t))} \quad (24)$$

where $f^+(a_n^+(t)/\tau_n)$ and $f^-(a_n^-(t)/\tau_n)$ are defined in (21) and (22) and $\delta(a_n(t))$ is an indicator that receives a value of 0 or 1 depending on the value of $a_n(t)$:

$$\delta(a_n(t)) = \begin{cases} 1 & \text{if } a_n \geq 0 \\ 0 & \text{if } a_n < 0 \end{cases} \quad (25)$$

where $a_n(t)$ is the observed acceleration/deceleration.

Therefore, the unconditional joint probability of the observations for a given driver is given by:

$$L_n = \int_\tau f(a_n(t)/\tau_n) f^{RT}(\tau_n) d\tau \quad (26)$$

Finally, the log-likelihood function for all drivers $1, \ldots, N$ (assuming independence) is given by:

$$LL = \sum_{n=1}^{N} \ln(L_n) \quad (27)$$

The Gauss econometric package was used for the estimation of the model parameters. The BFGS (Broyden, Fletcher, Goldfarb, and Shanno) algorithm was used for the maximization of the likelihood function (GAUSSTM, Version 5.0, Aptech Systems, Inc., 2001).

5. Case study

5.1. Data

NGSIM data is used to estimate the proposed model. The NGSIM data is often used for calibrating driving behavior models (Ranjitkar et al., 2005; Choudhury, 2007; Hamdar and Mahmassani, 2008; Thiemann et al., 2008).

The site considered for this study is part of I-80 in San Francisco Bay (see Fig. 5). It is approximately 900 m long, with 5 mainline lanes. An auxiliary lane exists between the on-ramp and the off-ramp.

The data includes vehicle ID, lane and position at 0.1 s. intervals. Locally weighted regression was applied to process the position data and develop vehicle trajectories and speed and acceleration profiles. Detailed description of this method and its application to vehicle trajectories can be found in Toledo et al. (2007a,b).

The data set was filtered to include only two successive vehicles driving in the same lane along the segment and driving on one of the main lanes (1–5 and not on the auxiliary lane 6 or ramps so that only car-following behavior was included). The final dataset included 132 vehicles for a total of 5196 observations. Eighty-five percentage of the vehicles were automobiles.

Vehicle speeds in the section ranged from almost 0 to 30.0 m/s with a mean of 18.0 m/s and standard deviation of 7.2 m/s. Densities ranged from 10.74 to 29.31 veh/km/lane, with a mean of 22.89 veh/km/lane and a standard deviation of 4.18 veh/km/lane. Acceleration observations varied from −6.0 to 6.0 m/s^2, while 90% of the observations were between −2.5 and 2.5 m/s^2. Fig. 6 presents the distribution of the acceleration 6(a) and deceleration 6(b) observations.

Note that the observed distribution is the mixture of the two distributions (acceleration (A)/deceleration (D) when drivers consciously accelerate/decelerate and acceleration/deceleration that stem from the do-nothing (DN) state).

Fig. 7 presents the scatter plot of the acceleration/deceleration observations versus the relative speed for a reaction time 0.35 s 7(a) and 0.95 s 7(b).

A good portion of the acceleration observations fall in the range of negative relative speeds (quadrant I), where the subject vehicle speed is higher than the speed of the leader. Similarly, a good portion of the deceleration observations fall in the range of positive relative speeds, with the subject vehicle speed being lower than the speed of the leader (quadrate II). These

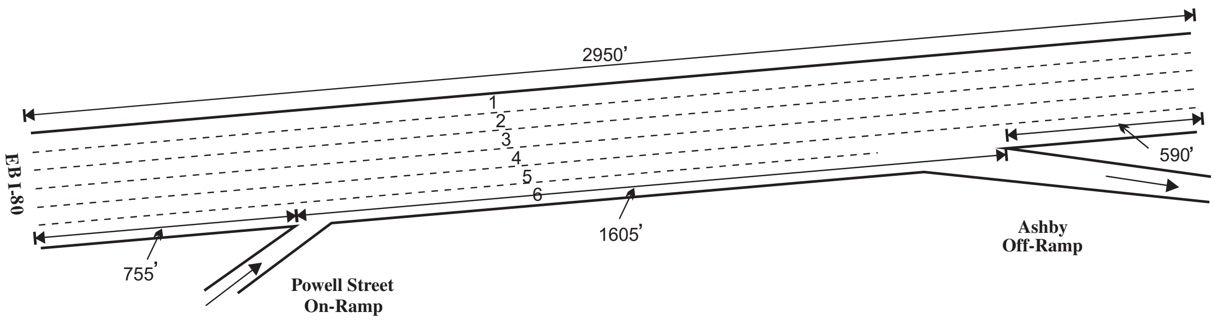

Fig. 5. Data collection site (*source*: Cambridge Systematics, 2004).

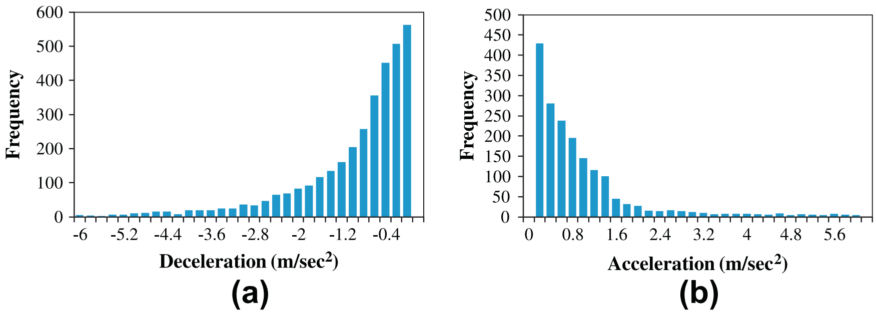

Fig. 6. Distribution of the deceleration (a) and acceleration (b) observations.

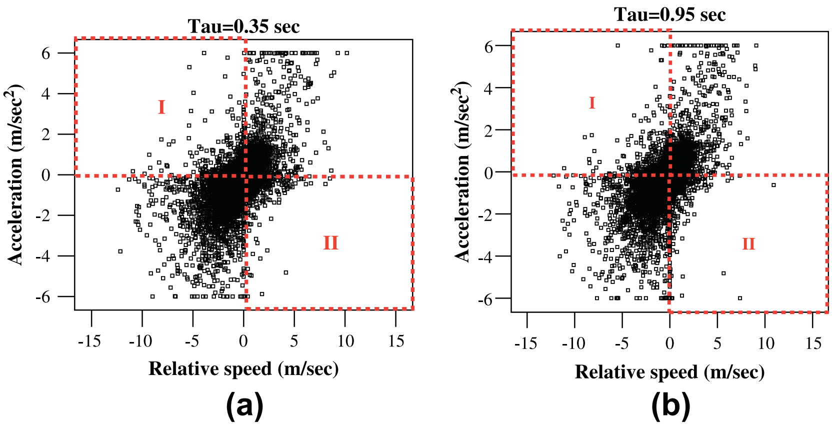

Fig. 7. Acceleration versus relative speed (leader speed minus subject vehicle speed).

results support the argument that previous modeling approaches which assume that a driver accelerates when the relative speed ΔV_n^{front} is positive, and decelerates when ΔV_n^{front} is negative are rather limited in capturing actual driving behavior.

5.2. Estimation results

The Gauss econometric package (Aptech Systems, 1994) was used for the estimation of the model parameters. The utilities for the different states, acceleration (*A*), deceleration (*D*), and do-nothing (*DN*), were specified as:

$$V_n^{DN}(t) = 0 \tag{28}$$

$$V_n^A(t) = \alpha^A + \beta^A \cdot \Delta X(t - \tau_n) + \gamma^A \cdot \Delta V(t - \tau_n)^+ \tag{29}$$

$$V_n^D(t) = \alpha^D + \beta^D \cdot \Delta X(t - \tau_n) + \gamma^D \cdot \Delta V(t - \tau_n)^- \tag{30}$$

where $V_n^{DN}(t)$ is the systematic utility for driver n associated with the do-nothing state, and $V_n^A(t)$ and $V_n^D(t)$ are the systematic utilities of acceleration and deceleration states, respectively. α^A, α^D are constants. β^A, γ^A and β^D, γ^D are the corresponding coefficients of the explanatory variables. $\Delta X(t - \tau_n)$ is the relative distance between the subject and lead vehicle. $\Delta V(t - \tau_n)^+$ and $\Delta V(t - \tau_n)^-$ are defined as follows:

$$\Delta V(t - \tau_n)^+ = \max(0, \Delta V(t - \tau_n)) \tag{31}$$

$$\Delta V(t - \tau_n)^- = \min(0, \Delta V(t - \tau_n)) \tag{32}$$

It is assumed that a positive speed difference (leader speed minus subject speed) increases the utility of the acceleration state but does not affect the utility of the deceleration state. Similarly, the negative speed difference increases the utility of the deceleration state but does not affect the utility of the acceleration state.

The standard GM model with the modification proposed by Ahmed (1999) to the stimulus term was used to capture the acceleration (deceleration) in the *A*(*D*) state:

Table 1
Estimation results of the latent class car-following model.

Variable	Latent class car-following model	
	Parameter value	*t*-Statistic
Reaction time distribution		
μ_τ	−0.423	−9.734
$\ln(\sigma_\tau)$	−1.076	−9.448
Decision to accelerate		
Constant	−3.028	−12.325
Space headway (m)	0.012	3.577
Relative speed (m/s), $\max(0, \Delta V)$	1.021	11.145
Decision to decelerate		
Constant	−1.759	−13.335
Relative speed (m/s), $\min(0, \Delta V)$	−1.319	−11.987
Do-nothing acceleration		
μ^{DN}	0.095	3.456
$\ln(\sigma^{DN})$	−0.603	−22.122
Car-following acceleration		
Constant	−1.766	−8.691
Speed (m/s)	0.701	10.627
Relative speed (m/s)	0.453	10.277
$\ln(\sigma^A)$	−0.595	−12.174
Car-following deceleration		
Constant	−1.274	−7.617
Speed (m/s)	0.927	13.845
Space headway (m)	−0.468	−12.053
Relative speed (m/s)	0.324	11.123
$\ln(\sigma^D)$	−0.269	−11.186
No. of observations	5196	
Final log likelihood, *Lm*	−4479.55	

$$a_n^i(t) = \alpha \cdot \frac{V_n^\beta}{\Delta X_n^{front}(t)^\gamma} \cdot \Delta V_n^{front}(t-\tau_n)^\delta \cdot \varepsilon_n(t), \quad i \in \{A, D\} \tag{33}$$

$$\ln(\varepsilon_n(t)) \sim N(0, \sigma_n^2) \tag{34}$$

Other car-following models, beside the GM-type models, can also be used to describe drivers' acceleration (decelerations) in the $A(D)$ state.

Table 1 summarizes the estimation results. Most of the variables in the model are statistically significant at the 95% confidence level.

It should be noted that the mean of the distribution of the do-nothing acceleration is close to zero (=0.095), consistent with a priori expectations.

The standard car-following model (similar to Ahmed, 1999) was also estimated using the same data set. Table 2 summarizes the estimation results.

The Akaike's Information Criterion (AIC) (Akaike, 1974) was used to compare the two models. The AIC penalizes a model for the number of parameters involved and has been used to compare alternative driver behavior models (Toledo, 2003; Toledo et al., 2007a,b; Choudhury, 2007). It is defined as:

$$AIC = -2L_m + 2k \tag{35}$$

where k is the number of parameters in the model and Lm is the corresponding max log-likelihood value. The index takes into account both the statistical goodness of fit and the number of parameters that have to be estimated. Table 3 summarizes the AIC results.

Based on the AIC results the latent model has a better performance compared to the GM model. These results are consistent with the conclusions made by Choudhury (2007), who found that "latent plan models have a significantly better goodness-of-fit compared to the 'reduced form' models where the latent plans are ignored and only the choice of actions are modeled". Choudhury (2007) applied the latent plans methodology to four situations: freeway lane changing, freeway merging, urban intersection lane choice and urban arterial lane changing.

Table 2
Estimation results of the GM car-following model.

Variable	GM model	
	Parameter value	*t*-Statistic
Reaction time distribution		
μ_τ	−0.4114	−9.391
$\ln(\sigma_\tau)$	−0.8545	−10.191
Car following acceleration		
Constant	0.0185	1.756
Speed (m/s)	1.3582	7.999
Space headway (m)	−0.3286	−6.134
Relative speed (m/s)	1.241	24.527
$\ln(\sigma^A)$	0.1138	6.845
Car following deceleration		
Constant	−0.2556	−5.595
Speed (m/s)	0.958	13.82
Space headway (m)	−0.5653	−19.931
Relative speed (m/s)	0.6709	22.724
$\ln(\sigma^D)$	0.0725	5.198
No. of observations	5196	
Final log-likelihood, *Lm*	−7941.44	

Table 3
Model comparison according to the AIC.

Model	Final log-likelihood (*Lm*)	Number of parameters (k)	AIC
GM CF model	−7941.44	12	15,907
Latent class CF model	−4479.55	18	8995

The parameters for the individual specific error terms were also estimated accounting for the heterogeneity among drivers in the decision state, however, it was not found to be statistically significant. The inclusion of this term also made the model unstable.

Figs. 8 and 9 illustrate the impact of the relative speed and relative distance (spacing), respectively, on the probabilities to be in the acceleration, deceleration, and do-nothing states. The graphs were generated assuming a relative distance of 10 meters (Fig. 8) and relative speed of 3 m/s (Fig. 9).

The results in Fig. 8 are consistent with expectations. For example, as the positive leader relative speed increases, i.e. when the leader is faster than the subject vehicle, the driver's probability to be in the acceleration state increases. It is interesting to notice that the probability to be in the deceleration state is higher than the probability to be in the acceleration state for the same absolute relative speed difference (the slope of the probability to be in the deceleration state for negative relative speeds is steeper than the slope of the probability to be in the acceleration state for positive relative speeds). This is expected, since the main consideration in the reaction to a negative relative speed is safety; whereas the acceleration applied in a positive relative speed situation may be affected by speed advantage considerations and tendency to conform to the behavior of other vehicles. This also explains the fact that the probability to be in the do-nothing state for negative relative

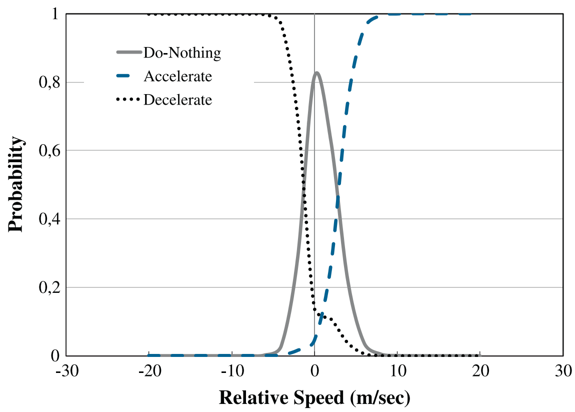

Fig. 8. Decision probability as a function of the relative speed.

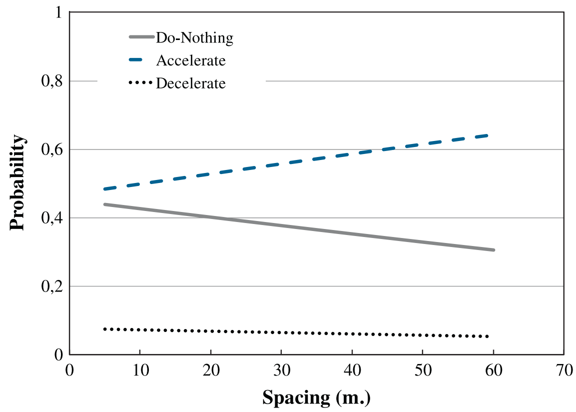

Fig. 9. Decision probability as a function of the spacing (relative distance).

speeds is smaller than the probability to be in the do-nothing state for positive relative speeds, when considering equal absolute relative speeds.

Fig. 9 illustrates the impact of the relative distance between the subject and lead vehicles on the probability of the subject vehicle to be in the acceleration, deceleration and do-nothing states. This impact is relatively small when compared to the impact of the relative speed illustrated in Fig. 8.

As expected, the probability to be in the acceleration state increases as the spacing between the subject and the lead vehicles increases. The probability to be in the deceleration state decreases as the space headway increases, however, the impact is very small and close to zero (0.012). The probability to be in the do nothing state decreases when the spacing increases as the subject vehicle is less constrained by the lead vehicle and the opportunity to accelerate abounds.

In order to analyze how different factors affect the car-following acceleration and deceleration mean values in both models, a sensitivity analysis for the different factors was conducted. The results in Figs. 10 and 11 are based on the assumption that the subject driver speed is 20 m/s, the relative speed between the subject vehicle and the lead vehicle is 3 m/s and the relative distance is 10 meters.

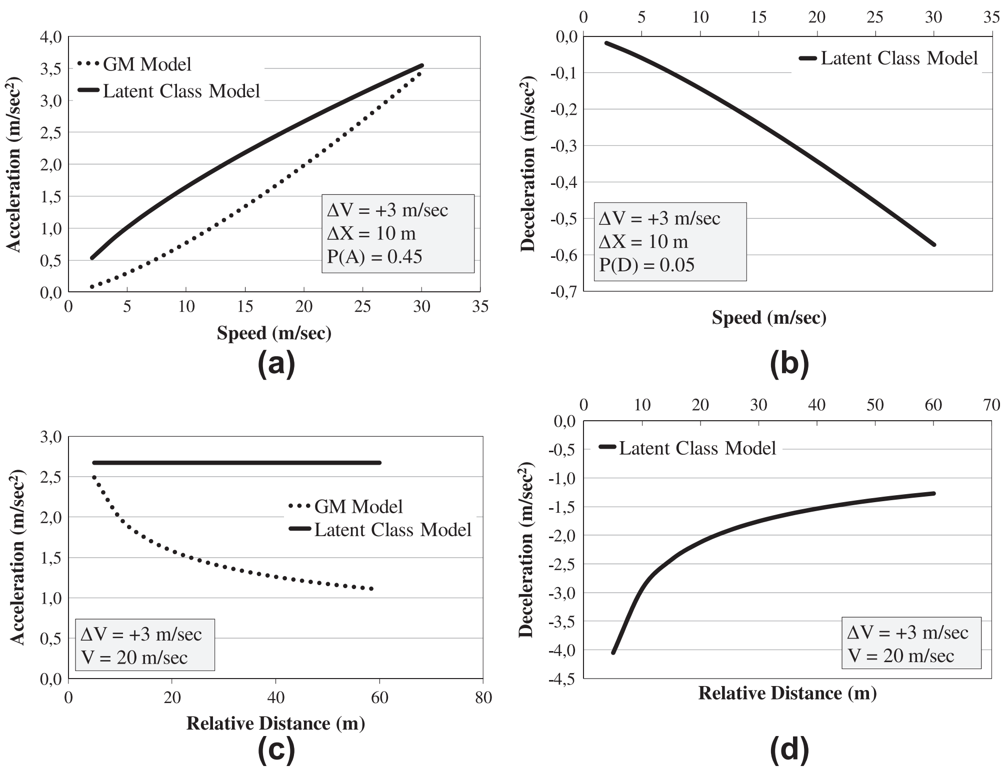

Fig. 10. Sensitivity of the car-following acceleration and deceleration mean value to the subject vehicle speed and relative distance.

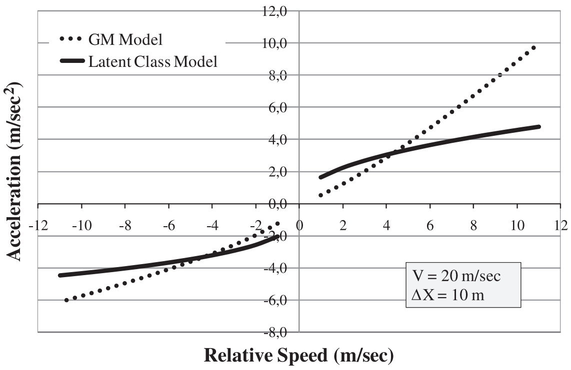

Fig. 11. Sensitivity of the car-following acceleration and deceleration mean value to the relative speed.

Table 4
Reaction time characteristics.

	GM model	Latent class model
Mean (s)	0.725	0.694
Median (s)	0.663	0.655
Variance (s)	0.133	0.074

It is found that when the speed of the subject vehicle increases, the mean acceleration increases as illustrated in Fig. 10a. In the general car following models calibrated by Ahmed (1999) and Toledo (2003) it was also found that the estimated coefficient of the subject's speed in the acceleration model was positive and highly significant. The authors explained this behavior by the fact that the acceleration capabilities of vehicles are higher at high speeds (and gear) relative to low speeds. However, for the deceleration model, the authors found that the speed of the subject vehicle was not statistically significant. Siuhi and Kaseko (2010) indicate that having a deceleration model that does not incorporate the subject speed is unrealistic. In this study the estimated coefficient of the subject vehicle's speed in the car-following deceleration model was significant and positive. This means that under deceleration drivers are likely to apply higher deceleration values at high speeds compared to low speeds as shown in Fig. 10b.

The estimated coefficient of the space headway is negative for both acceleration and deceleration models (Fig. 10c and d). This is consistent with expectation since as the space headway increases, drivers may tend to interact less with the lead vehicle. For deceleration car-following the sign is negative since the underlying safety concern increases when the spacing is reduced. Ahmed (1999) and Toledo (2003) found similar results. The magnitude of the coefficient for deceleration is larger than that for acceleration.

Fig. 11 illustrates the impact of the relative speed. The corresponding parameter is positive for acceleration, which implies that the acceleration increases with increasing relative speed (leader vehicle is driving faster than the subject vehicle). In the deceleration model, this parameter is also positive which implies that deceleration increases when the speed of the subject vehicle is greater than the speed of the lead vehicle. The slopes of the acceleration and deceleration curves with respect to the relative speed are decreasing. This captures the fact that the acceleration (deceleration) applied by drivers is limited by the acceleration (deceleration) capacity of the vehicle and acceleration (deceleration) gradually reaches the capacity as the relative speed increases.

Table 4 summarizes the results of the mean, median and variance of the reaction time distribution for the GM and latent class car-following models.

The results are consistent to some extent with values reported in earlier studies. Gipps (1981) used a value of 0.67 s for reaction time for all drivers, while in the microscopic simulation model DRACULA (Liu et al., 1995) the reaction time ranges between 0.8 and 2.0 s (Bonsall et al., 2005). Siuhi and Kaseko (2010) found that drivers' reaction time for deceleration is 0.7 s and for acceleration is 0.8 s. The estimated mean reaction time in the study by Ahmed (1999) is 1.34 s while in the study by Toledo (2003) 1.1 s. Ahmed (1999) used a truncated lognormal distribution for the reaction time with an upper bound of 3 s while Toledo (2003) used an upper bound of 6 s.

6. Conclusion

The paper presented a framework for modeling acceleration behavior of drivers. The structure is quite general and lends itself to systematic estimation of the corresponding parameters. A number of existing models can be viewed as special cases of the proposed model. The framework recognizes that there are different regimes in driving and that drivers may apply different actions in each regime.

The developed model was estimated based on the NGSIM trajectory data. According to Akaike's Information Criterion the latent model outperforms the GM model.

Despite of the promising results of the developed model, there are still some limitations that would be possible to relax in future research studies: estimation of a more complete model structure including other regimes such as free-flowing and emergency; examination of other formulations for drivers' decisions whether to accelerate, decelerate or do-nothing (for example, a nested logit model may also be considered), alternative and possibly simpler models for acceleration in the (A) and (D) states, different state-dependent reaction time distributions, mean reaction time as a function of explanatory variables such as the socio-demographic and socio-economic variables and geometric and traffic characteristics.

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