Technion - Israel Institute of Technology
Transportation Research Institute

הטכניון - מכון טכנולוגי לישראל
המכון לחקר התחבורה

State Dependence in Lane Changing Models

By
Romina Katz
Tomer Toledo

Haifa, August 2008 **Research report 326/2010**

Technion City, Haifa 32000, Israel
Tel. (04) 829 2901 .טל
Fax 972-4-822 5716 פקס
קרית הטכניון, חיפה 32000

Contents

Contents (cont.)

Technion – Israel Institute of Technology Transportation Research Institute	Name of Publication: State Dependence in Lane Changing Models
Publication No. /Resarch Report No. 326/2010	Project No./Research Code No.
Type of Publication:	Authors: Romina Katz, Tomer Toledo
Publication Classification:	Performing Department:

Abstract

The purpose of this research is to enhance existing lane changing models to incorporate and capture the persistence of the driver's behavior, through modeling of the underlying lane selection process. Persistent behavior is assumed and accepted for strategic travel choices (e.g. destination, path and schedule). Based on this, we can also assume that drivers may persist in trying to complete driving goals such as lane changing. Thus, the decisions drivers make over time are not independent, but are related by a logical and stable relation.

Hidden Markov Models (HMMs) are appropriate for taking into account the transitions between phases and find their use in categorizing sequences of data. HMMs are based on two hypotheses: there exists a latent selection process which evolves from state to state (in our case, the selection of the target lane) and that the study of an observable output (i.e. the observed lane changing action) could provide information on this process. The observable state depends on the previous choices, which are the underlying hidden states. For example, we observe that a driver stays in his current lane, but we can not observe the real reason that caused him to stay there. The driver may have chosen not to pursue a lane change and to stay in his current lane or he may have chosen to move to another lane but could not complete the lane change. In summary, we can assume that the lane changing decision process is latent and only the driver's actions (lane changes) are observed.

A framework for modeling the lane changing behavior taking into account the state dependence between observations of a given driver over time, which utilizes the above mentioned concepts, is developed. Statistical tests show that the State Dependence Model does better fit the data compared to previous models and therefore should be selected for prediction.

Keywords	Distribution	
Comments:	Pages: 85	Date: August2008

List of Tables

List of Figures

Abstract

The purpose of this research is to enhance existing lane changing models to incorporate and capture the persistence of the driver's behavior, through modeling of the underlying lane selection process. Persistent behavior is assumed and accepted for strategic travel choices (e.g. destination, path and schedule). Based on this, we can also assume that drivers may persist in trying to complete driving goals such as lane changing. Thus, the decisions drivers make over time are not independent, but are related by a logical and stable relation.

Hidden Markov Models (HMMs) are appropriate for taking into account the transitions between phases and find their use in categorizing sequences of data. HMMs are based on two hypotheses: there exists a latent selection process which evolves from state to state (in our case, the selection of the target lane) and that the study of an observable output (i.e. the observed lane changing action) could provide information on this process. The observable state depends on the previous choices, which are the underlying hidden states. For example, we observe that a driver stays in his current lane, but we can not observe the real reason that caused him to stay there. The driver may have chosen not to pursue a lane change and to stay in his current lane or he may have chosen to move to another lane but could not complete the lane change. In summary, we can assume that the lane changing decision process is latent and only the driver's actions (lane changes) are observed.

A framework for modeling the lane changing behavior taking into account the state dependence between observations of a given driver over time, which utilizes the above mentioned concepts, is developed. Statistical tests show that the State Dependence Model does better fit the data compared to previous models and therefore should be selected for prediction.

Chapter 1

Introduction

1.1 Motivation

Overloaded freeways and congested main roads all over the world reflect the fact that the existing road networks are not able to cope with the increasing demand for mobility. Traffic Congestion has been one of the major challenges facing road authorities around the world and it continues to grow not only in urban areas, but also in suburban and rural areas. Israel is no exception. Traffic Congestion has a significant adverse economic impact through deterioration of mobility, safety and air quality. Development of the road network has in many cases, almost exhausted the available land. Moreover, in many areas, environmental constraints limit construction of new roads or expansion of existing ones. Thus, on the one hand, it is socially untenable to expand the existing infrastructure further in order to relax the situation; and on the other hand, mobility is vital for the economic development.

As a result, the importance of better management of the road network to efficiently utilize existing capacity is increasing. In recent years, a large array of traffic management schemes have been proposed and implemented. The main idea of traffic management is to efficiently utilize roads and traffic systems that are already built to minimize congestion and maximize safety. Methods and algorithms proposed for traffic management need to be calibrated and tested. In most cases, only limited, if any, field tests are feasible because of prohibitively high costs and lack of public acceptance. Furthermore, the usefulness of such field studies is deterred by the inability to fully control the conditions under which they are conducted. Hence, tools to perform such evaluations in a laboratory environment are needed.

Intelligent Transportation Systems (ITS) applications, such as dynamic traffic control and route guidance, have emerged as efficient tools for traffic management. These applications involve information dissemination from a traffic management center to drivers and deployment of management and control strategies. The impact of information and control strategies on traffic flow can be realistically modeled only through the response of individual drivers to the information.

Microscopic traffic simulators are becoming increasingly popular as evaluation and planning tools for transportation improvement initiatives and particularly valuable in the context of dynamic traffic management systems. They are used to test and evaluate infrastructure design and operation and control policies in a virtual environment. These tools can evaluate complex traffic systems which incorporate various components (i.e., traffic signals, ramp metering, incidents and traveler information) operating simultaneously. They offer cost savings and flexibility compared to testing or implementation in the real world. The advantages of microscopic traffic simulation tools have motivated researchers to study driving behaviors for accurate modeling.

Modern traffic simulation tools are a synthesis of a number of interacting models. These models belong to two categories: models that capture traffic dynamics and models that capture travel behavior (i.e., route choice and response to travelers' information). Traffic dynamics are captured by detailed driving behavior models.

Driving behavior models describe drivers’ decisions with respect to their vehicle movement under different traffic conditions. These models include speed/acceleration models, which describe the movement of the vehicle in the longitudinal direction, and lane changing models, which describe drivers' lane selection and gap acceptance behaviors. Thus, the lane changing model is in particular an important component of microscopic traffic simulation tools.

Lane changing models consist of lane selection models, which concern drivers' desire in changing lanes, and gap acceptance models, which concern the decision to execute the lane-change. Modeling the lane changing decision process is very complex due to its latent nature and the potentially large number of factors a driver considers before making a decision. The only observable part of this process is a successful lane change action. The exact time at which a driver decides to change lanes cannot be observed. Most current models assume that drivers make repeated instantaneous decisions. At each point in time the driver assesses the situation and selects the immediate action independent of previous decisions. However, in reality, the decisions drivers make over time are not independent. This work will develop a framework and estimate models for lane changing behavior taking into account dependencies in the lane changing decisions drivers make over time.

1.2 Problem Description

Driving is a hierarchical task with three interacting levels. Any action the driver completes, such as a lane change, requires the driver to undertake the following tasks:

- Navigation or planning (Strategic): Route choice and trip schedule decisions drivers make pre-trip and en-route.
- Guidance (Tactical): Determination of the two dimensional movement of the vehicle in traffic.
- Control (Operational): Continuous activities the driver performs to control and direct the vehicle (e.g. steering, throttle and braking).

The driver makes strategic decisions: chooses a path and determines a schedule for the trip (e.g. in terms of desired arrival time). Tactical decisions are affected by the vehicle's driving neighborhood and by the strategic considerations: the driver has to be in the correct lanes in order to follow the path plan; the trip schedule affects desired speeds. If the trip schedule is not kept or in the presence of traffic information the driver may decide to re-evaluate the path plan and switch paths. The choices of speed and lane are translated to mechanical actions to control the vehicle.

Existing driving behavior models have several important limitations. Among them is that in many cases they do not adequately capture the sophistication of drivers: they do not capture the interdependencies among the decisions made by the same drivers over time; and represent instantaneous decision-making, which fails to capture drivers' planning and anticipation capabilities.

Persistent behavior is assumed and accepted for strategic travel choices (e.g. destination, path and schedule). Based on this, it is also realistic to assume that drivers may persist in trying to complete tactical goals such as lane changing, as well. Thus, the decisions drivers make over time are not independent, but are related by a logical and stable relation.

Hidden Markov Models – HMMs – (Rabiner, 1986) are appropriate for taking into account the transitions between phases and find their use in modeling sequences of data. HMMs are based on two hypotheses: there exists a latent selection process which evolves from state to state and that the study of an observable output that is affected by this process could provide information on this process. The observable state is the consequence of the previous decisions, which are the underlying hidden states.

This thesis explores the integration of HMM structures within lane changing models in order to introduce persistent behavior into these models. A model that captures drivers' lane changing behavior under the assumption of stability and persistence is developed in this thesis.

1.3 Thesis Outline

This thesis consists of six chapters. In Chapter 2, a literature review of existing lane changing models and Hidden Markov Models is presented. Chapter 3 presents the framework and structure of the proposed lane changing model. In chapter 4, the available data for estimation of this model is described. Estimation results are presented in Chapter 5. Finally, conclusions and directions for further research are summarized in Chapter 6.

Chapter 2

Literature Review

This chapter reviews literature on two subjects: Lane Changing Models and Hidden Markov Models. The next section summarizes some of the relevant literature on lane changing models and their limitations.

2.1 Lane Changing Models

Lane changing is usually modeled in two steps: the decision to consider a lane change – lane selection process, and the decision to execute the lane change – gap acceptance model. Lane changing behavior has received considerable attention, particularly as part of the development of microscopic traffic simulation models in recent years.

2.1.1 Background

Lane changing behavior has a significant effect on traffic flow. A great deal of research has been conducted in the last two decades to develop mathematical models to simulate the lateral movements of a vehicle in multi-lane road facilities.

In most lane changing models it is assumed that drivers' behavior is governed by two basic considerations: achieving a desired speed and being in the correct lane to undertake an intended turning maneuver. Thus, lane changes can be broadly classified as either mandatory or discretionary. Drivers undertake mandatory lane changes (MLC) when they must leave their current lane due to lane blockages or some other traffic restrictions. They perform discretionary lane changes (DLC) when they perceive that they can improve their driving conditions by moving to another lane, although it is not necessary to do so. Drivers may have different levels of acceptable risks under these two conditions. The execution of lane changes is modeled using gap acceptance models.

Gipps (1986) introduced the first lane changing model intended for micro-simulation tools. The necessity, desirability and safety of lane changes were considered in the model. The model is essentially a structure connecting the decisions drivers make before changing lanes. Their behavior falls into one of three patterns, depending on the distance to the intended turn. While the turn is remote it has no effect on lane changing decisions and the driver concentrates on maintaining the desired speed. When the intended turn is in the middle distance zone, the driver ignores opportunities to improve speed that involve changing lanes in the wrong direction. The driver also tends to move to and remain in the lanes most appropriate for his turn. Finally, in the zone close to the turn, the driver is interested solely in reaching the correct lane and speed is unimportant. When more than one lane is acceptable the conflict is resolved deterministically by a priority system considering, in order of importance, locations of obstructions, presence of heavy vehicles and potential speed gain.

This framework was implemented in different microscopic traffic simulation models. One example is CORSIM (Halati et al. 1997, FHWA 1998). In Corsim, the motivation to perform DLC is quantified in terms of the subject vehicle's speed and headway with respect to the vehicle in front. A risk factor is computed for each potential lane change. The risk is calculated for the subject with respect to its intended leader and for the intended follower with respect to the subject. The risk factor is calculated in terms of the deceleration a driver must apply if its leader is to break to a stop, and subsequently compared to a threshold value, which is determined by the type of lane change and its urgency.

This framework was also implemented in MITSIM (Yang and Koutsopoulos, 1996), which uses a probabilistic approach to model conflicting goals in selecting lanes. Lane changes are again classified as MLC or DLC. MLC are modeled with an assumption that the driver has four goals in performing MLC: to move to the next destination on his travel path, to bypass a lane blockage, to avoid a restricted-use lane and to comply with signs. If there are conflicting goals, they are resolved probabilistically based on utility theory. DLC, are modeled with the assumption that the primary goal of the driver in changing lanes is to achieve desired speed. A driver performs lane changing only when both the lead and lag gaps in the target lane are acceptable.

Hidas and Behbahanizadeh (1998) implemented a similar model in the micro-simulator SITRAS. The two distinct features that make their model unique are a new definition of goals for DLC and the introduction of cooperative lane changing in MLC. In addition to the speed advantage in DLC, similar to Yang and Koutsopoulus' model, a queue advantage was added as a motivation for DLC. In other words, if the adjacent lane provides a faster speed or a shorter queue, a driver has a motivation to change lanes. The second additional feature of this model is that the model accounts for cooperativeness when determining mandatory lane changes. In heavily congested traffic conditions, MLC may occur through cooperation with the intended follower. The willingness of the follower to allow the subject vehicle to change lanes is a function of his aggressiveness. A cooperative follower will start following the subject vehicle and the subject will start following the intended leader in the target lane. As a result of this cooperation, the subject vehicle is now able to change lanes into the gap opened up in the target lane.

The distinction between MLC and DLC in the above models is artificial and prohibits capturing trade-offs between mandatory and discretionary considerations. The parameter values used with these models are usually based on the modelers' judgment. Frameworks for rigor estimation of the model parameters were not proposed. Inconsistencies in the behavior of a driver over time and variability between drivers are ignored. The different zones are defined deterministically. Moreover, normally it is assumed that the decision process is repeated at every time step and the decisions drivers make over time are independent.

Ahmed et al. (1996) and Ahmed (1999) developed a lane-changing model that captures both MLC and DLC situations. Ahmed (1999) proposed a framework to jointly estimate parameters of the lane selection and gap acceptance components of lane changing models. The structure of the model is shown in Figure 2.1. The lane changing process is modeled with three steps: a decision to consider a lane change, choice of a target lane and acceptance of gaps in the target lane. A discrete choice framework is used to model these decisions. Logit models are used to capture the various choices. When a MLC situation applies, the decision whether or not to respond to it depends on the time delay since the MLC situation arose. DLC is considered when MLC conditions do not apply or the driver chooses not to respond to them. A two-step decision process is assumed: First, drivers examine their satisfaction with driving conditions in the current lane, which is affected by the difference between the subject speed and its desired speed. The model also captures differences in the behavior of heavy vehicles and the effect of the presence of a tailgating vehicle. If the driver is not satisfied with driving conditions in the current lane, he compares conditions in neighboring lanes to those in the current lane in order to choose the target lane. Lane utilities are affected by the speeds of the lead and lag vehicles in these lanes relative to the current and desired speed of the subject vehicle. A gap acceptance model is also included within the lane changing framework.

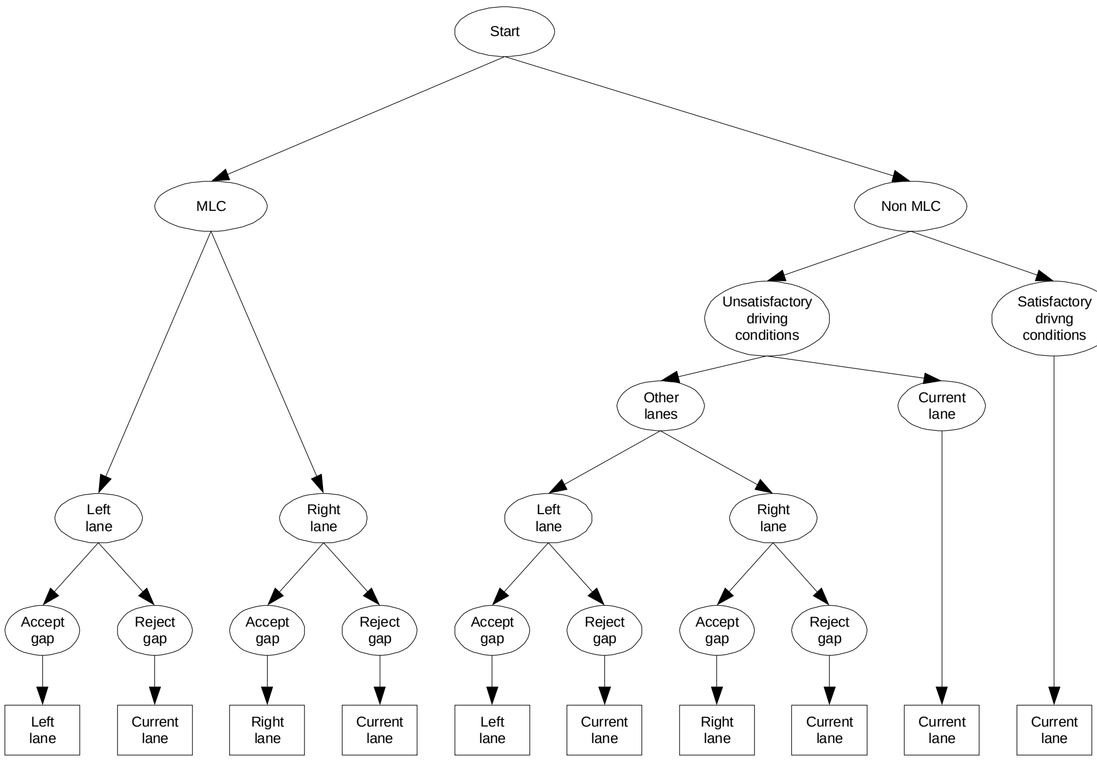


Figure 2.1 - Structure of the lane changing model proposed by Ahmed (1999)

It is difficult to estimate models for the choice to react to an MLC situation (the upper level decision in Figure 2.1) which is unobserved. Therefore the discretionary and mandatory lane change models were estimated separately, for special cases, where the nature of the lane changes is obvious. The data used for estimation was collected on

200 meters section of Interstate 93 at the Central Artery, located in downtown Boston. Ahmed (1999) estimated the MLC model using data for the special case of drivers that merge to the freeway from an on-ramp, under the assumption that all vehicles are in MLC state.

Wei et al. (2000) developed a set of deterministic lane selection rules for drivers that turn into two-lane urban arterials and their subsequent lane changing behavior based on observations made in Kansas City, Missouri. The model captured the effect of the driver's path plan on the lane choice. Lane selection is determined by the location and direction of intended downstream turns. Drivers that intend to turn at the next intersection choose the correct lane. Drivers that intend to turn further downstream choose the correct lane if it is the closest to the side they are entering the arterial from. If the correct lane is the farthest, the lane choice is based on the aggressiveness of the driver. Driver's lane change behavior in the arterial is influenced by a similar set of rules. It was observed that passing is an important behavior that needs to be modeled. Vehicles already in the correct lane may undertake a passing maneuver in order to gain speed. The model requires that both the adjacent gap in the other lane and the gap in the current lane between the subject and its leader be acceptable for passing to take place.

Toledo et al. (2003) developed an integrated lane-shift model that allows joint evaluation of mandatory and discretionary considerations and captures trade-offs between these considerations. He proposed a lane changing model based on the tactical choice of the target lane, stating that a driver may need to perform a sequence of actions in order to complete a desired lane change. The awareness to the MLC situation is more realistically represented as a continuously increasing function rather than a step function. The model consists of two levels: choice of a lane shift and gap acceptance decisions. The structure of the model is shown in Figure 2.2.

The first step in the decision process, lane shift, is latent since the target lane choice is unobservable and only the driver's lane-changing actions are observed. Latent choices are shown as ovals and observed ones are represented as rectangles. The driver has, at any particular instance, the option of selecting to stay in the current lane or opting to move to an adjacent lane. The Current branch corresponds to a situation in which the driver decides not to pursue a lane change. In the Right and Left branches, the driver perceives that moving to these lanes, respectively, would improve his condition in terms of speed and path plan. In these cases, the driver evaluates the adjacent gap in the target lane and decides whether the lane-change can be executed or not. The lane change is executed (change Right or change Left) only if the driver perceives that the gap is acceptable, otherwise the driver does not execute the lane-change (no change). This decision process is repeated at every time step.

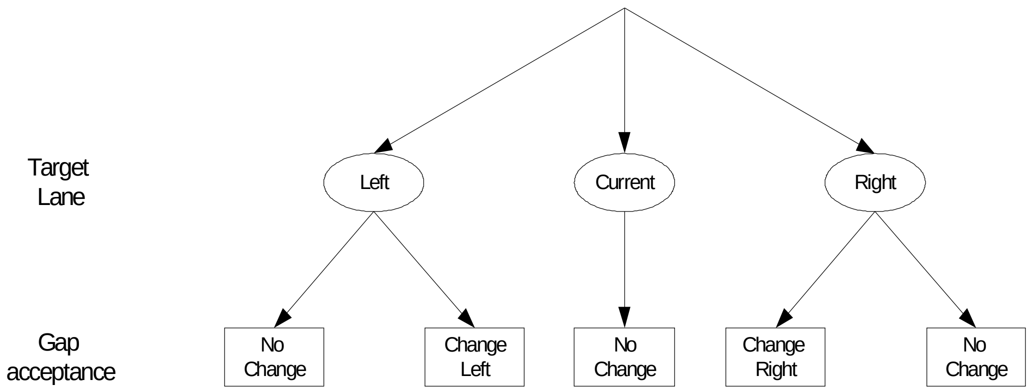


Figure 2.2 - Structure of the lane changing model proposed by Toledo et al. (2003)

Explanatory variables in this model include neighborhood variables, path plan variables, network knowledge and experience, and driving style and capabilities. Since information about the driver's style and characteristics is not available, individual specific error terms are introduced to capture unknown information. The parameters of the model were estimated jointly using second by second trajectory collected in a section of I-395 Southbound in Arlington, VA.

Choudhury (2005) developed a lane changing model that captures the lane-changing behavior in presence of exclusive lanes. That is, the drivers' preference to specific lanes, such as in the case when travel lanes and passing lanes are defined, can be captured in the model. The direction for an immediate lane change is based on an explicit choice of a target lane rather than myopic evaluation of adjacent lanes as in previous models. The model was estimated using a maximum likelihood estimator.

The model consists of two levels of decision making: the target lane choice and the gap acceptance. The structure of the model is shown in Figure 2.3.

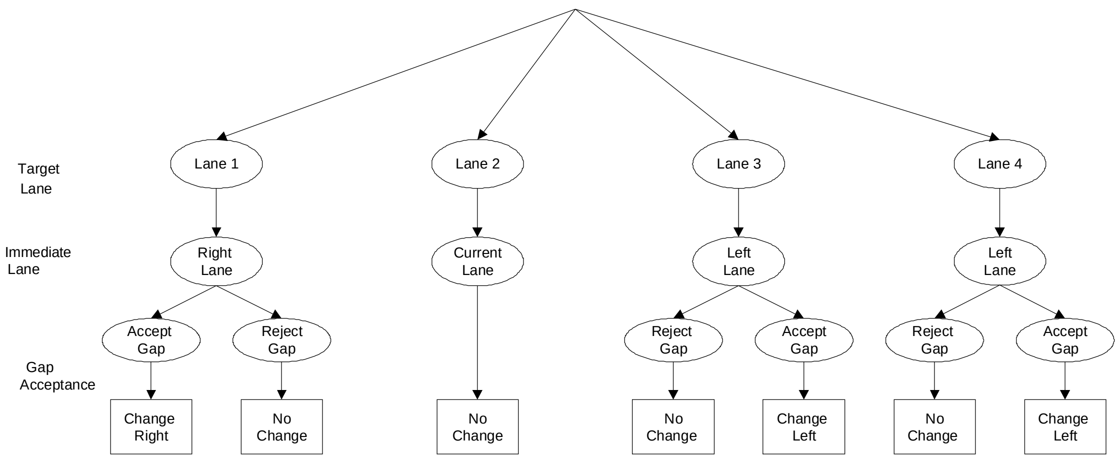


Figure 2.3 - Structure of the lane-changing model for a four-lane road with the subject vehicle in Lane 2 proposed by Choudhury (2005)

The decision structure shown on the top is for a vehicle that is currently in the second lane to the right (Lane 2) in a four-lane road. Therefore, Lane 3 and Lane 4 are on its left, and Lane 1 is on its right. At the highest level, the driver chooses the target lane. In contrast with existing models the choice set constitutes of all available lanes in the road (Lane 1, Lane 2, Lane 3 and Lane 4 in this example). The driver chooses the lane with the highest utility as the target lane. If the target lane is the same as the current lane (Lane 2 in this case), no lane change is required (No Change). Otherwise, the direction of change is to the right (Right Lane) if the target lane is Lane 1, and to the left (Left Lane) if the target lane is either Lane 3 or Lane 4. If the target lane choice dictates a lane change, the driver evaluates the gaps in the adjacent lane corresponding to the direction of change and either accepts the available gap and moves to the adjacent lane (Change Right or Change Left) or rejects the available gap and stays in the current lane (No Change).

Explanatory variables affecting the target lane utilities of a driver are lane attributes, surrounding vehicle attributes and path plan. Information about the driver's style and characteristics is however not available and is captured by introducing individual specific error terms.

Table 2.1 - Estimation results of the target lane model proposed by Choudhury, 2005.

Variable	Parameter value	t-statistic
Target Lane Model		
Lane 1 constant	-1.696	-3.03
Lane 2 constant	-0.571	-1.68
Lane 3 constant	0.059	1.16
Lane density, vehicle/km	-0.013	-1.21
Average speed in lane. m/sec	0.176	1.59
Front vehicle spacing, m	0.024	3.86
Relative front vehicle speed, m/sec	0.115	1.46
Tailgate dummy	-4.935	-1.96
CL dummy	2.686	1.55
1 lane change from the CL	-0.845	-1.15
Each additional lane change from the CL	-3.338	-1.91
Path plan impact, 1 lane change required	-2.549	-4.57
Path plan impact, 2 lane changes required	-4.953	-2.19
Path plan impact, 3 lane changes required	-6.955	-1.65
Next exit dummy, lane change(s) required	-0.872	-1.35
θ_{MLC}	-0.417	-2.48
π_1	0.001	0.68
π_2	0.086	1.38
α^{lane1}	-1.412	-2.29
α^{lane2}	-1.072	-0.50
α^{lane3}	-0.071	-3.61
α^{lane4}	-0.089	-1.56
Lead critical gap		
Constant	1.541	5.59
Max (ΔS_{nt}^{lead},0) , m/sec	-6.210	-3.6
Min (ΔS_{nt}^{lead},0) , m/sec	-0.130	-2.09
α^{lead}	-0.008	-3.17
σ^{lead}	0.854	1.29

Lag critical gap		
Variable	Parameter value	t-statistic
Constant	1.426	5.35
Max (ΔS_{nt}^{lag},0) , m/sec	0.640	3.36
α^{lag}	-0.205	-0.48
σ^{lag}	0.954	4.80
L(0) = -1434.76 L(β) = -875.81		

The parameters of the model were estimated jointly using second by second trajectory data collected in a section of I-395 Southbound in Arlington, VA, used also by Toledo et al. (2005). The estimation results of the target lane model are summarized in Table 2.1.

An important limitation of existing models is that drivers are still assumed to make decisions about lane changes at discrete point in time, independently of the decisions made earlier. In general, lane changes are modeled as discrete events occurring at specific points in time. Current models assume that the decision process is repeated at every time step. However, drivers may, for example, persist in trying to complete a lane change; it means; drivers may have the characteristics of persistence in trying to complete their lane changing. This behavior is not captured in the models described above. One of the ways to fill this gap in the existing models is applying the theory of the Markov chains.

The next section introduces the concept of Hidden Markov Models (HMM) and explains how they can be used to taking into account the transitions between phases.

2.2 Hidden Markov Models (HMMs)

In many areas it is often the case that we are interested in finding patterns in sequences of events that appear over time. There are processes that consist of a finite number of states. They start in one of these states and move successively from one state to another. Each move is called a step. At each point in time the system may have changed states from the state the system was in the moment before, or it may have stayed in the same state. If the chain is currently in state *i*, then it moves to state *j* at the next step with some known probabilities p_{ij}. The probabilities p_{ij}, called transition probabilities, do not depend upon which states the chain was in before the current state. Thus, every future state is conditionally independent of every prior state (except the current one). The above process is called Markov process.

However, in some cases the patterns that we wish to find are not described sufficiently by a Markov process. For example, the cases where the state is not directly visible, but variables influenced by the state are visible. In such cases the observed sequence of states is probabilistically related to the hidden process. We model such processes using a HMM where there is an underlying hidden Markov process changing over time, and a set of observable states which are related somehow to the hidden states. HMMs are based on two hypotheses: there exists a latent selection process which evolves from state to state and that the study of an observable output that is affected by this process could provide information on this process. The observable state is the consequence of the previous decisions, which are the underlying hidden states. It is important to note that the number of states in the hidden process and the number of observable states may be different. In a HMM, the history of states the model took cannot generally be determined from the data sequence. The relationship between the state of the latent process and the observable one is determined by a density function attached in each state of the process.

In the case of lane changing, we can say that the lane selection is a latent process which evolves from state to state and generates a sequence of hidden states. This evolution is based on two processes. The first process, evolving state by state, is invisible - unobservable state (for example, the driver wants to stay in his current lane, to exit, etc). The second is the observable state (for example the driver changes lane, stays in his current lane, etc). So, we are interested in finding a model for generating a data sequence. As it is explained in this section, HMMs are appropriate for taking into account the transitions between phases and find their use in modeling sequences of data.

A HMM is a triple (Π, A, B) , where:

$\Pi = (\pi_i)$; Vector of the initial state probabilities; contains the probability of the hidden model being in a particular hidden state at the beginning of the process.

$A = (a_{ij})$; State transition matrix; $\Pr(x_{i_t} \mid x_{j_{t-1}})$; holding the probability of a hidden state given the previous hidden state.

$B = (b_{ij})$; Confusion matrix; $\Pr(y_i \mid x_j)$; containing the probability of observing a particular observable state given that the hidden model is in a particular hidden state.

Each probability in the state transition matrix and in the confusion matrix is time independent - that is, the matrices do not change in time as the system evolves. In practice, this is one of the most unrealistic assumptions of Markov models about real processes.

For example, Figure 2.4 represents a 3-state HMM, where each hidden state (x_i) conducts to one of 4 observable states/actions (y_i) with some probability (b_{ij}). The state transition probabilities (a_{ij}) are the probabilities of moving from one hidden state to another one.

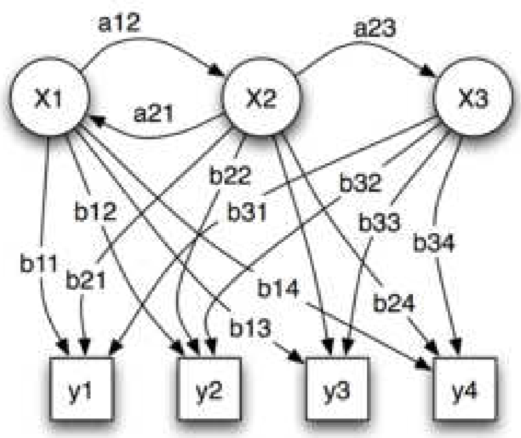


Figure 2.4 - A 3-state HMM, with 4 observable states/actions (Source: Wikipedia).

Once a system can be described as a HMM, the problem of generating a HMM given a sequence of observations can be solved. In other words, the model parameters most likely to have generated a sequence of observations can be determined.

2.2.1 Earlier Utilization of HMMs in the Transport Field

HMM are extensively used in the field of speech recognition. A few applications have also been proposed in transportation science, where most of them have been applied in the field of driving assistance systems and behavior recognition. Overall, the application of the HMM to lane changing models is at an early stage and rather incomplete and limited.

Pentland and Liu (1999) proposed a framework that captures the driver's intended action, for instance if the driver is about to brake or turn. They applied HMMs to identify drivers' current internal (intentional) state and to predict the most likely subsequent sequence of internal states. The modeled actions are events like stopping at the next intersection, turning left at the next intersection, turning right at the next intersection, changing lanes, passing the car in front, or doing nothing. Their model considers several hidden internal mental states that are the individual steps that make up the action, each with its own interstate transition probabilities. The observed variables are the changes in heading and acceleration of the car. The model assumes that the driving actions can be broken down into a long chain of simpler sub-actions. A lane change, for instance, may consist of the following steps, where each sequence was modeled by a HMM: (1) a preparatory centering the car in the current lane, (2) looking around to make sure the adjacent lane is clear, (3) steering to initiate the lane change, (4) the change itself, (5) steering to terminate the lane change, and (6) a final recentering of the car in the new lane. The model statistically characterizes the sequence of steps within each action and then using the first few preparatory steps to identify which action is being initiated. In order to recognize which action is occurring given the observed pattern of heading and acceleration, the observed pattern of driver behavior is compared to the HMM of each action. The data used in this work was collected with a driving simulator. The model achieved 95% recognition accuracy approximately 1.5 sec. after the initiation of the maneuver.

Another application of HMMs was carried out by Kuge et al. (2000). They proposed a method to predict drivers' lane change intentions by using steering behavior data. They characterized three different maneuvers that were considered the hidden states in the HMM: emergency lane change (LCE), normal lane change (LCN), and lane keeping (LKN). The steering angle, steering angle velocity, and steering force were the observable states, within each one they considered several sub-HMM. Recognition by the HMM involved calculating the probability that the given observation data sequence would be generated by one of the three models. The forward-backward algorithm was used in order to compute state probabilities and identify the most likely hidden state. The system simulates a set of possible driver intentions and their resulting behaviors using a lane changing model. The system compares the model's simulated behavior with a driver's actual observed behavior and thus continually infers the driver's unobservable intentions from the observable actions. The data used with this model was collected with a driving simulator. The system achieved 98% accuracy on detection of LCE within 0.5 sec. after the initiation of the maneuver, but did not report an analogous accuracy for LCN, citing problems with distinguishing between normal lane change and lane keeping data points.

Dapzol (2005) proposed a model that predicts driver behavior using an HMM. The model was used to identify the driver's aim and the driving situation he is in. The driving situation was divided into phases, which constitute the hidden states. A base driving situation model using HMM was built. This allowed defining for a given sequence of data to which situation it may belong. An experiment was conducted in real driving where 718 driving sequences were collected, but only 36 different driving situations were classified. For each sequence, the driver's actions, vehicle characteristics, and environment classification were recorded. In order to categorize the driver's current situation, the system compares a data temporal series with a library of driving situation models and selects the most adequate. The model allowed them to categorize driving sequences offline with 90% success rate (using all the data of each sequence), and online with 85% success rate (only using the data of the first second of each sequence).

Zou and Levinson (2006) implemented HMMs to model the unobservable driver attitudes and to achieve the classification of the driver actions in different situations at intersections. In this application, the hidden states are the attitudes of drivers towards traffic conditions; the observable states are defined by a combination of the acceleration rate of the vehicle and whether or not it is in a conflict with other vehicles. Thus, the observable vehicle state set includes 6 states which are generated by {Acceleration, Cruising, Deceleration} x {Conflict, Not Conflict}. An HMM might represent a set of states in real world, therefore a state is recognized by computing the probability that an HMM generates the observed states. The Baum-Welch estimation algorithm was applied to estimate these probabilities. They found that three clusters (states) are sufficient to represent distinct driving attitudes for the sample set. However, these states are behaviors without any "meaning" and in order to arrive to a real understanding of behavior, it is vital to obtain the meanings of the measured behaviors. The authors used observed vehicle movement data to estimate the model.

2.3 Discussion

The current emphasis in driving behavior modeling is in development of more realistic models to help improve the fidelity of microscopic traffic simulation. This could be achieved by increasing the level of detail in the specification of models to better capture the complexity and sophistication of human decision-making process.

The various lane changing models mentioned in the first part of this chapter are increasingly sophisticated and complex. However, they still assume that drivers make instantaneous decisions about lane changes. At each point in time, the driver assesses the situation and selects the immediate action, independently of the decisions made earlier. However, in reality drivers may be persistent in trying to complete a lane change. This behavior is not captured by these models.

It was also shown that driver behavior modeling and recognition of different types of lane changes is possible using HMMs. However, the application of the HMM to the lane changing models is at an early stage.

Most of the applications of the HMM structure for lane changing, focused in identifying the intention of the driver using observed behavior (i.e. acceleration, steering angle). These models could detect whether or not the driver is changing lanes at the time of the observation but did not explain why the lane changing is undertaking and so cannot predict lane changes ahead of time. Therefore, these models cannot be used in traffic simulation.

As it was also shown, most of the existing models that applied HMM, did not use real data to estimate them, but used data obtained from driving simulators. The results on dynamic simulator shows the capacity of this approach to cope with the variability of behavior, but caution must be taken in transferring them to real world driving. It is possible, for instance, that there are driving styles not seen in any of their subjects. The data used from a driving simulator is also purer than those obtained under real driving conditions. Most of the models also used a restricted number of situations. Introduction of new situations will decrease the recognition rate. There has been no effort to develop a model where a wide range of situations in a real event of lane changing are captured.

We can conclude that there are limited works where persistence and stability behavior is captured in the driver's behavior. These works also do not span the entire range of real driving situations. The purpose of this research is to enhance existing lane changing models to incorporate this behavior, using the HMMs formalism and in this way, be able to understand the conditions that conducted to the driver to execute a lane change.

Chapter 3

Model Structure

In this chapter the framework and structure of the proposed lane changing model are presented. The methodology presented in this study relies on the hypothesis that drivers are persistent in their behavior. A complete lane changing model that explicitly takes into account correlations and dependencies in the lane changing decisions drivers make over time is presented. The model is based on previous works of lane changing models. The contribution of the proposed model is the explicit addition of the state dependence concept and the treatment of the initial conditions problem it brings about. The presentation is organized as follows: first, the concepts of state dependence are introduced. Then, these concepts are utilized to develop the structure of the proposed lane changing model, which takes drivers' persistence into account. Finally, the likelihood function for the joint estimation of the lane-selection and gap-acceptance components of the model is formulated.

3.1 Theoretical Framework - Integration of the HMM

A lane change decision process is assumed to have two steps: the target lane choice and acceptance of a gap in the direction of the target lane. Modeling such a process is extremely complicated. The lane change decision process is latent in nature; the target lane is unobservable. All that is observed is the execution of the lane change (change left, change right or no change).

We can assume that lane changing is based on the evolution of two processes; the first one is the invisible underlying driving goal, for example the driver wants to stay in his current lane or change to another lane. This hidden process determines another visible process which explains the available observations - the lane a vehicle is in.

An important limitation of existing driving behavior models, discussed in Chapter 2, is that in most cases models assume that drivers make instantaneous decisions. At each point in time the driver assesses the situation and selects the immediate action. In reality, human drivers may conceive and perform action plans over a length of time and be consistent in trying to complete these plans.

In the next sections, possible general modeling structures that allow capturing state dependency will be discussed. Then their application for our particular case of study of lane changing will be presented. The observed actions are named o_t and the latent states are named s_t.

3.1.1 Static Model

An alternative approach, as was presented by Toledo et al. (2003) assumes that all state dependencies are captured by the explanatory variables. In other words, the state dependency is only indirectly considered. This approach is based on the concept of a partial short-term plan. The assumption is that the driver executes one step of the short-term plan, re-evaluates the situation and decides the next action to take.

Under the partial short-term planning assumption, the joint probability of a latent state and the observed actions, at time t, is given by:

$$p\left(o_t, s_t \mid X\right) = p\left(o_t \mid s_t, X\right) p\left(s_t \mid X\right) \tag{3.1}$$

Where, o_t are the observed actions (the alternatives), $o_t \in \{1, \ldots I\}$ and s_t are the latent states, $s_t \in \{0,1, \ldots t\}$. X are explanatory variables.

The marginal probability of an observation is given by:

$$p\left(o_t \mid X\right) = \sum_{s_t} p\left(o_t, s_t \mid X\right) \tag{3.2}$$

The joint probability of the entire sequence of observations is given by:

$$p\left(O \mid X\right)=\prod_{t=1}^{T} p\left(o_t \mid X\right) \tag{3.3}$$

Where, T is the number of observed time periods.

3.1.2 Full State Dependency

Another possible modeling approach, proposed by Toledo et al. (2003), would be to define latent states as combinations of a short-term goal and a short-term plan and capture the dynamics of the behavior by modeling state dependencies. The joint probability of a latent state (s_t) and observed action (o_t, i.e. lane changing) of a given vehicle at time t, conditional on the sequence of previous states is given by:

$$p\left(o_t, s_t \mid S_{t-1}, X\right)=p\left(o_t \mid s_t, S_{t-1}, X\right) p\left(s_t \mid S_{t-1}, X\right) \tag{3.4}$$

Where, S_t is the sequence of states up to time t, $S_t=\left\{s_i; i=0,1,\ldots t\right\}$. o_t are the observed actions (alternatives), $o_t \in \left\{1,\ldots I\right\}$. s_t are the latent states, $s_t \in \left\{0,1,\ldots t\right\}$. X are explanatory variables.

The probability of the entire sequence of states (S_t) and observations (O_t) is given by:

$$p\left(O_T, S_T \mid s_0, X\right)=\prod_{t=1}^{T} p\left(o_t, s_t \mid S_{t-1}, X\right) \tag{3.5}$$

Where, T is the number of observed time periods.

Finally, the joint marginal probability of observations is calculated by summation over all possible state sequences:

$$p\left(O_T \mid s_0, X\right)=\sum_{\substack{state\\ sequences}} p\left(O_T, S_T \mid s_0, X\right) \tag{3.6}$$

3.1.3 One Step State Dependency

In this section, we propose an intermediate approach to capturing the state dependency. In this approach, the assumption of the evolution of two processes is still relevant. The observable state is the consequence of the previous decisions, which are the underlying hidden states. The particularity of this approach is that every future state does not depend upon which states the chain was in before the current state. It is assumed that future state transitions and actions depend only on the current state and are independent of all previous states.

Under the above assumptions, the joint probability of a latent state (s_t), the previous latent state (s_{t-1}) and the observed actions (o_t) of a given vehicle at time t is given by:

$$p\left(o_t, s_t, s_{t-1} \mid X\right) = p\left(o_t \mid s_t, X\right) p\left(s_t \mid s_{t-1}, X\right) p\left(s_{t-1} \mid X\right) \tag{3.7}$$

Where, $p(s_{t-1} \mid X)$ is calculated recursively using Equation (3.8):

$$p(s_{t-1} \mid X) = \sum_{i \in TL_{t-2}} p(s_{t-1}^i | s_{t-2}^i, X) p(s_{t-2}^i | X) \tag{3.8}$$

Therefore given the initial probabilities $p(s_0 \mid X)$, these values can be calculated for any t.

The marginal probability of an observation is given by:

$$p\left(o_t \mid X\right) = \sum_{s_t} \sum_{s_{t-1}} p\left(o_t, s_t, s_{t-1} \mid X\right) \tag{3.9}$$

Finally, the joint probability of the sequence of observations is calculated by:

$$p\left(O \mid X\right) = \prod_{t=1}^{T} \sum_{s_t} \sum_{s_{t-1}} p\left(o_t \mid X\right) \tag{3.10}$$

It is important to note that $p(s_{t-1} | X)$ is calculated recursively, therefore the Equation (3.10) depends on the initial conditions.

One of the difficulties with the two last formulations is the initial conditions (s_0). In most cases it is assumed that the initial conditions are either observed or represent a steady state. However, there are many cases where the first time a subject is observed does not correspond to any natural starting point and instead, it is determined by the location and capabilities of the data collection system. Therefore, it is necessary to find a method to overcome this limitation, as it will be explained in the next sections.

3.1.4 Initial Conditions

In dynamic panel data models with unobserved effects, the treatment of the initial observations is an important theoretical and practical problem.

Before parameters generating a stochastic process with dependence among time-ordered outcomes can be estimated, the process must be somehow initialized. In applied work, two initial conditions are typically invoked:

- The pre-sample history of the process is truly exogenous.
- The process is assumed to be in equilibrium.

If the process has been in operation prior to the time it is sampled, as it happens in our case, or if the disturbance term of the model is serially correlated, the initial conditions are not exogenous variables. Treating them as exogenous variables, results in inconsistent parameter estimates.

For linear models with an additive unobserved effect, the problems can be solved by using an appropriate transformation, such as differencing, to eliminate the unobserved effects, and then chooses instruments based on sequential conditional moment assumptions.

Solving the initial conditions problem is notably more difficult in nonlinear models. Generally, there are no known transformations that eliminate the unobserved effects and result in usable moment conditions. Previous research has focused on three different ways of handling initial conditions. The first approach is to treat the initial condition for each cross-sectional unit as nonrandom variables. Unfortunately, norandomness of the initial conditions, s_0, implies that s_0 is independent of unobserved heterogeneity, υ. Even when we observe the entire history of the process, the assumption of independence between υ and s_0 is very strong. Another approach is to allow the initial condition to be random, and then to use the joint distribution of all outcomes on the response (including that in the initial time period) conditional on unobserved heterogeneity and observed strictly exogenous explanatory variables. The main complication with this approach is specifying the distribution of the initial condition given unobserved heterogeneity. The third approach, proposed by Heckman (1981) is to approximate the conditional distribution of the initial condition. This avoids the practical problem of not being able to find the conditional distribution of the initial value.

Specifically the following procedure is proposed and examined by Heckman (1981):

1. Approximate the utility function at the initial observations in the sample to individual n, by:

$$\begin{aligned} U_n^O(t) &= f(s_t, X_t) + \alpha\upsilon_n + \varepsilon_n(t) \\ U_n^O(t=0) &= f^*(X_0) + \alpha\upsilon_n^* + \mu_n(0) \end{aligned} \tag{3.11}$$

   Where $U_n^O(t)$ and $U_n^O(t=0)$ are the utilities functions of the alternative $O = \{1,...,i,...I\}$ to individual n at time t and at the special case of time $t=0$ respectively where the previous state can not be modeled. $\mu_n(0)$ is assumed to be i.i.d distributed with mean zero.

2. Permit $\mu_n(0)$ to be freely correlated with $\varepsilon_n(t),\ t = 0,...T$ and $\operatorname{cov}(\varepsilon_t, \varepsilon_{t-1}) = 0$.
3. Estimate the model by the method of maximum likelihood without imposing any restriction between the parameters of the structural system and the parameters of the approximate reduced form probability function for the initial state of the sample.

3.2 Application to the Lane Changing Model

3.2.1 Model Structure

Driver behavior can be characterized as sequence of basic actions each associated with a particular state of the driver-vehicle environment and characterized by a set of observable states. In the lane change process, the observable state is the lane change (change right, change left, no lane change) and the hidden state is the target lane.

The lane change models proposed by Toledo et al. (2003) and Choudhury (2005) are static models. They assume that all state dependences are captured by the explanatory variables. This approach is based on the concept of a partial short-term plan. To illustrate this approach, consider the situation described in Figure 3.1: suppose that vehicle B is a slow-moving vehicle and that the goal of vehicle A is to overtake it. The short-term plan may consist of the following steps:

- Change to the left lane.
- Accelerate and pass vehicle B.
- Change back to the right lane.

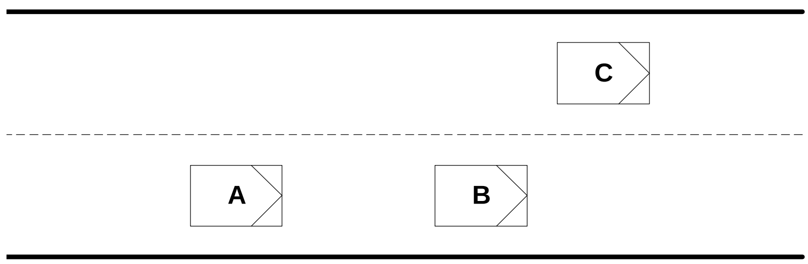


Figure 3.1 - A lane changing situation illustrating partial short-term planning

Vehicle A will perform the first step: change to the left lane and then re-evaluate the situation and decide what to do next. For example, depending on the behavior of vehicle C, vehicle A may continue with the previous plan, or abandon the goal of overtaking vehicle B and follow vehicle C in the left lane.

This approach captures the effect of evolving conditions on driving behavior at the expense of assuming that all state dependencies are captured by the explanatory variables. This assumption may not be restrictive since explanatory variables that are derived from the positions and speeds of the subject vehicle and surrounding vehicles are important in all driving behavior models. The values of these variables depend on the past actions of the vehicle (e.g. the current speed and position of a vehicle are a function of previously applied accelerations) and so, capture the effects of previous actions and states. The computational burden associated with the partial short-term approach is low since calculation of the likelihood function requires $2T\,|\,s\,|$ probability calculations. In spite of the fact that this approach captures the effect of evolving conditions on driving behavior, it is also assumed that at each point in time the driver assesses the situation and selects the immediate action, and as it was explained earlier it is not a real assumption.

Another possible modeling approach, which was presented in section 3.1.2, would be to define latent states as combinations of a short-term goal and a short-term plan and capture the dynamics of the behavior by modeling state dependencies. The first problem in the analysis of a full state-dependency as was described above is the exponential increase in possible trajectories (states). This complexity could be discussed with the help of an example. Consider a vehicle that is observed in a two lane roadway for three consecutive time periods during which time it did not change lanes.

To simplify the discussion further, we consider two possible states "Right lane" or "Current lane" of the decision tree. The lane changing decision tree reduces to the one shown in Table 3.1. Since the driver did not change lanes, he/she may be in state "Right lane and gap reject" or in state "Current Lane" during these three times.

Table 3.1 - Possible States during the three successive time periods.

Time period	Lane change	Possible states (arrows show state to state transitions)	
1	No	Right lane/ reject gap	Current lane
2	No	Right lane/ reject gap	Current lane
3	No	Right lane/ reject gap	Current lane

The number of possible sequences in the summation of Equation (3.6) is $|s|^T$, where $|s|$ is the number of possible states. The total number of probabilities to calculate is $2T|s|^T$. Except for degenerate cases with a very small set of possible states or a very short observation period, modeling all possible combinations of states is prohibitively expensive. From the mentioned above, it is not a viable method of analysis.

To overcome the limits mentioned above, we will propose an intermediate approach to modeling driver behavior capturing the effect of evolving conditions on driving behavior (state dependency).

The decision to initiate a lane change and the acceptance of gaps to complete it are affected by neighborhood variables and driver characteristics as well as the decision state of the driver. To implement such an approach, we assume that the driver has a number of states, each with its own associated interstate transition probabilities. We must make observations of the driver's state, and make a response based on the model applied to the current state. But the internal states of the driver are not directly observable, thus we must use an indirect estimation process on the observed behavior (e.g., staying in the current or changing lanes). We have adapted the expectation-maximization methods developed for use with HMMs to perform this estimation task. The likelihood of any state in our dynamic model makes use of the estimate of the current state to adjust the transition probabilities.

The observed sequence of states is probabilistically related to the hidden process. We model such processes using a HMM where there is an underlying hidden Markov process changing over time, and a set of observable states which are related somehow to the hidden states.

Figure 3.2 shows the application of this methodology to the lane changing model for a two lane case. Latent states are shown as ovals and observed states are represented as rectangles. The target lane is the lane the driver perceives as best to be in. The decision process is latent since the target lane choice is unobservable. For example, we may observe that a driver stays in his current lane, but we cannot observe the reason that caused him to stay there: The driver may have chosen not to pursue a lane change at all or he may have chosen to move to another lane but could not complete the lane change. Thus lane selection is a latent process which evolves from state to state and generates a sequence of hidden states. A desired lane change is executed when the driver evaluates the adjacent gap in the target lane and decides whether this gap is acceptable (Right Lane), otherwise the driver does not execute the lane change (Current lane). This process generated the observable lane action state.

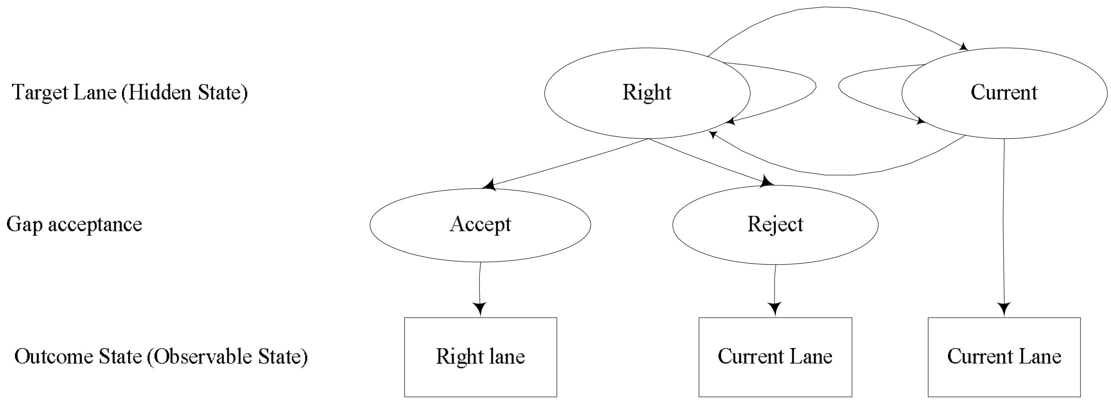


Figure 3.2 - Structure of the proposed lane changing model

However, there is still a difficulty with this formulation: the initial conditions (s_0). In most cases it is assumed that the initial conditions are either observed or represent a steady state. However, in our case, the first time a vehicle is observed does not correspond to any natural starting point that would support this assumption. Instead, it is determined by the location and capabilities of the data collection system, as explained in the data chapter.

The lane changing model explains the choice of the driver in two dimensions: the target lane choice and the gap acceptance. Lane utility functions may depend on explanatory variables as it will be explained in the next chapter. Variables should reflect the conditions in the immediate neighborhood in each lane (e.g. relative leader speed in each lane and presence of heavy vehicles), path plan considerations (e.g. the distance to a point where the driver must be in certain lane(s) and the number of lane changes needed in order to be in these lanes) and knowledge of the system (e.g. avoiding the left lane before a permissive left turn or avoiding an on-ramp merging lane). In most cases information about the characteristics of drivers and their vehicles (e.g. aggressiveness, vehicle's speed and acceleration capabilities and level of driving skill) is not available. Therefore, it is necessary to introduce individual-specific latent variables in the utilities to capture these correlations. Different choice models are obtained depending on the assumption made about the distribution of the error terms. It can be assumed that conditional on the value of the latent variable, the error terms of different utilities are independent. Mathematically, this specification is given by:

$$U_n^{lanei}(t) = \beta^{lanei} X_n^{lanei}(t) + \rho\delta_n^{lanei}(t-1) + \alpha^{lanei}\upsilon_n + \varepsilon_n^{lanei}(t) \qquad (3.12)$$

Where, $U_n^{lane\ i}(t)$ is the utility of the alternative of choosing lane i to individual n at time t. $X_n^{lane\ i}(t)$ is a vector of explanatory variables. $\beta^{lane\ i}$ is a vector of parameters. $\delta_n^{lanei}(t-1)$ is the state dependence variable. ρ is the state dependence parameter. υ_n is an individual-specific latent variable assumed to follow some distribution in the population. $\alpha^{lane\ i}$ is the parameter of υ_n. $\varepsilon_n^{lanei}(t)$ is a generic random term with i.i.d. distribution across the choices, individuals and time. $\varepsilon_n^{lanei}(t)$ and υ_n are independent of each other.

3.2.2 The Target Lane Model

Next the specification of the models is presented in detail in order to explain the two choices that the drivers make within the lane changing model: the target lane choice and the gap acceptance decision.

At the first level, the driver chooses a target lane (TL), which is the lane with the highest utility. The target lane choice set constitutes of all the available lanes in the roadway. The total utility of lane i as a target lane to driver n at time t can be expressed by:

$$U_n^{TL}(t) = V_n^{TL}(t) + \alpha^{TL}\upsilon_n + \varepsilon_n^{TL}(t) \qquad \forall TL = \{Lane1, Lane2, Lane3, Lane4\} \qquad (3.13)$$

Where $V_n^{TL}(t)$ is the systematic component of the utility and $\alpha^{TL}\upsilon_n + \varepsilon_n^{TL}(t)$ is the error term associated with the target lane utilities. υ_n is an individual specific error term that captures correlations between the observations of a single driver over time (individual-specific latent variables). α^{TL} is the parameter of υ_n. $\varepsilon_n^{TL}(t)$ is a generic random term.

The systematic utilities are given by:

$$V_n^{TL}(t) = \beta^{TL} X_n^{TL}(t) + \rho \delta_n^{TL}(t-1) \qquad \forall TL = \{Lane1, Lane2, Lane3, Lane4\} \tag{3.14}$$

Where, $X_n^{TL}(t)$ is a vector of explanatory variables affecting the utilities of the lanes and β^{TL} is the corresponding vector of parameters. $\delta_n^{TL}(t-1)$ is the state dependence variable. ρ is the state dependence parameter.

The utilities of a target lane may be affected by general lane attributes, such as density and speed of traffic in the lane, traffic composition (e.g. percentage of heavy vehicles), etc. Moreover, special lane-specific attribute may be included in the utility function. For example, the exclusive lane-specific variables are included in the utility of a lane if the lane in considerations is a tolled lane.

The driver's target lane choice may be affected by the variables associated with the surrounding vehicles, such as speed and type of the vehicles in the neighborhood. The value of these neighborhood variables is indicated by the current position of the vehicle. For example, if the front vehicle in the current lane has a very high speed compared to the driver's desired speed, the driver is likely to prefer the current lane over other lanes; it means the current lane is likely to have a higher utility.

The driver may be consistent in his behavior. Thus, another important variable that may affect the driver's target lane is the target lane that the driver previously chose. For example, suppose that the right lane is the target lane chosen by the driver in the previous time. Therefore, the right lane is likely to have a high utility capturing the consistency on the driver's behavior and the dependency on the target lane over the two consecutive time periods.

There are up to four components that compose the systematic utility of a lane:

- Utility component consisting of the characteristics of the lane.
- Utility derived from the relative position of the lane with respect to the current lane.

- Utility derived from the state dependence.
- Utility component derived from the path plan of the vehicle.

Different choice models are obtained depending on the assumption made about the distribution of the error terms $\varepsilon_n^{TL}(t)$. Assuming that these random terms are independently and identically Gumbel distributed, choice probabilities for the various lanes, conditional on the individual specific error term (υ_n) are given by a Multinomial Logit model:

$$P(TL_t \mid TL_{t-1}, \upsilon_n) = \frac{\exp(\beta_{it}^{TL} X_t^{TL} + \rho\delta^{TL_{t-1}} \mid \upsilon_n)}{\sum_{j \in TL} \exp(\beta_{jt}^{TL} X_t^{TL} + \rho\delta^{TL_{t-1}} \mid \upsilon_n)} \tag{3.15}$$

$$\forall TL = \{Lane1, Lane2, Lane3, Lane4\}$$

Where, $\beta_t^{TL} X_t^{TL} + \rho\delta^{TL_{t-1}} \mid \upsilon_n$ is the conditional systematic utility of the alternative lane.

3.2.3 The Gap Acceptance Model

In the target lane model the driver may choose to stay in the current lane or to target changing either to the right lane or to the left lane. Next, conditional on the target lane choice, the driver decides by evaluating the gaps, whether or not to change lanes immediately using the adjacent gap. Following the model proposed by Toledo et al. (2003) and Choudhury (2005), this work uses the same gap acceptance model structure used in their works.

The adjacent gap in the target lane is defined by the lead and lag vehicles in that lane as shown in Figure 3.3. The lead gap is the clear spacing between the rear of the lead vehicle and the front of the subject vehicle. Similarly, the lag gap is the clear spacing between the rear of the subject vehicle and the front of the lag vehicle. Note that one or both of these gaps may be negative if the vehicles overlap.

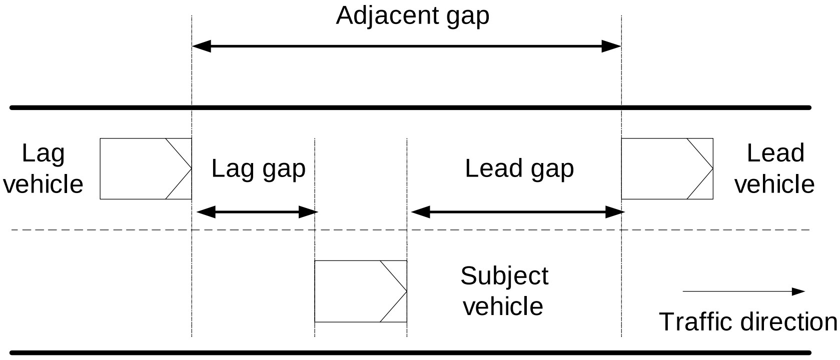


Figure 3.3 - The subject, lead and lag vehicles and the gaps they define

Critical gaps vary for different individuals and with the situation. The driver's critical gaps are the minimum acceptable gaps. They are modeled as random variables whose means are functions of explanatory variables. The available lead and lag gaps are compared to these ones. An available gap is accepted only if it is greater than the critical gap. The individual specific error term captures correlations between the critical gaps of the same individual over time. Critical gaps are assumed to follow a lognormal distribution to ensure that they are always positive, they are:

$$\ln\left(G_n^{lead\ TL,cr}(t)\right) = \beta^{lead} X_n^{lead\ TL}(t) + \alpha^{lead}\upsilon_n + \varepsilon_n^{lead}(t) \tag{3.16}$$

$$\ln\left(G_n^{lag\ TL,cr}(t)\right) = \beta^{lag} X_n^{lag\ TL}(t) + \alpha^{lag}\upsilon_n + \varepsilon_n^{lag}(t) \tag{3.17}$$

Where, $G_n^{lead\ TL,cr}(t)$ and $G_n^{lag\ TL,cr}(t)$ are the lead and lag critical gaps in the target lane, measured in meters. $X_n^{lead\ TL}(t)$ and $X_n^{lag\ TL}(t)$ are vectors of explanatory variables affecting the lead and lag critical gaps, respectively. β^{lead} and β^{lag} are the corresponding vectors of parameters. $\varepsilon_n^{lead}(t)$ and $\varepsilon_n^{lag}(t)$ are normally distributed random terms associated with the critical gaps: $\varepsilon_n^{lead}(t) \sim N\left(0, \sigma_{lead}^2\right)$ and $\varepsilon_n^{lag}(t) \sim N\left(0, \sigma_{lag}^2\right)$. α^{lead} and α^{lag} are the parameters of the individual specific random term υ_n for the lead and lag critical gaps, respectively.

The gap acceptance model assumes that both the lead gap and the lag gap must be acceptable in order for the vehicle to change lanes. The probability of changing lane, conditional on the individual specific term and the target lane is therefore given by:

$$
\begin{aligned}
&P_n\left(\text{change to target lane}|TL_t,\upsilon_n\right)=P_n\left(l_t^{TL}=1\,|\,TL_t,\upsilon_n\right)= \\
&P_n\left(\text{accept lead gap }|TL_t,\upsilon_n\right)P_n\left(\text{accept lag gap }|TL_t,\upsilon_n\right)= \\
&P_n\left(G_n^{lead\,TL}(t)>G_n^{lead\,TL,cr}(t)\ |TL_t,\upsilon_n\right)\cdot P_n\left(G_n^{lag\,TL}(t)>G_n^{lag\,TL,cr}(t)\ |TL_t,\upsilon_n\right)
\end{aligned}
\tag{3.18}
$$

Where, TL is the target lane (which requires a lane change). l_t^{TL} is the lane changing indicator for the target lane (the lane changing action):

$$
l_t^{TL}=\begin{cases}1 & \textit{a change to lane TL is performed at time t}\\ 0 & \textit{otherwise}\end{cases}
$$

$G_n^{lead\,TL}(t)$ and $G_n^{lag\,TL}(t)$ are the available lead and lag gap in the target lane, respectively. $G_n^{lead\,TL,cr}(t)$ and $G_n^{lag\,TL,cr}(t)$ are the corresponding critical gaps.

Assuming that critical gaps follow a lognormal distribution, the conditional probability that the lead gap is acceptable is given by:

$$
\begin{aligned}
&P_n\left(G_n^{lead\,TL}(t)>G_n^{lead\,TL,cr}(t)\ |TL_t,\upsilon_n\right)= \\
&P_n\left(\ln\left(G_n^{lead\,TL}(t)\right)>\ln\left(G_n^{lead\,TL,cr}(t)\right)\ |TL_t,\upsilon_n\right)= \\
&\Phi\left[\frac{\ln\left(G_n^{lead\,TL}(t)\right)-\left(X_n^{lead\,TL}(t)\beta^{lead}+\alpha^{lead}\upsilon_n\right)}{\sigma_{lead}}\right]
\end{aligned}
\tag{3.19}
$$

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

Similarly the conditional probability that the lag gap is acceptable is given by:

$$
\begin{aligned}
&P_n\left(G_n^{lag\,TL}(t) > G_n^{lag\,TL,cr}(t)\ |TL_t, \upsilon_n\right) = \\
&P_n\left(\ln\left(G_n^{lag\,TL}(t)\right) > \ln\left(G_n^{lag\,TL,cr}(t)\right)\ |TL_t, \upsilon_n\right) = \\
&\Phi\left[\frac{\ln\left(G_n^{lag\,TL}(t)\right) - \left(X_n^{lag\,TL}(t)\beta^{lag} + \alpha^{lag}\upsilon_n\right)}{\sigma_{lag}}\right]
\end{aligned}
\tag{3.20}
$$

The gap acceptance decision is affected by neighborhood variables and path plan variables, which are captured by explanatory variables like the subject vehicle's speed, relative speeds with respect to the lead and lag vehicles in the target lane, traffic density and indicators for the urgency of the lane change (e.g. the distance to the point the lane change must be completed).

Decisions made at lower levels of the driving behavior decision process are conditional on those made at higher levels (e.g. gap acceptance decisions are conditional on the target lane choice). The effects of lower level choices on higher-level decisions may be captured by introducing the expected maximum utility (*EMU*) of the alternatives at the lower level in the specification of higher-level choices.

3.2.4 Treatment of the Initial Conditions in the Lane Changing Models

As it was explained above, the treatment of the initial observations is an important theoretical and practical problem. Next, the treatment of the initial conditions in the lane changing models is presented.

First, the utility function at the initial observations in the sample to individual n is approximated by:

$$
U_n^{TL}(t=0) = f^*(X_0) + \alpha\upsilon_n^* + \mu_n(0) \tag{3.21}
$$

Where $U_n^{\mathrm{TL}}(t=0)$ is the utility function of the alternative of choosing *lane i* as a target lane to individual n at the special case of time $t=0$ where the previous state can not be modeled. $\mu_n(0)$ is assumed to be i.i.d distributed with mean zero.

The conditional systematic component of the utility of *lane i* for the initial observation is different from the others observations, thus all the parameters for this observation are allowed to be different, too. The systematic component of the utility is given by:

$$V_n^{TL}(0) \mid \upsilon_n = \beta^{*TL} X_n^{TL}(0) \qquad \forall TL = \{Lane1, Lane2, Lane3, Lane4\} \tag{3.22}$$

Where, $X_n^{TL}(0)$ is the vector of explanatory variables for the special case of $t = 0$. β^{*TL} is the corresponding vector of parameters for the initial observations.

Then the model is estimated by the method of maximum likelihood without imposing any restriction between the parameters of the structural system and the parameters of the approximate reduced form probability function for the initial state of the sample.

3.3 The Likelihood Function

In this section, the likelihood function of lane changing actions observed in the trajectory data is presented.

As discussed in a previous section, there is an important limitation in the dataset; explanatory variables related to the driver/vehicle characteristics and to the driver's path plan are not available. For example, the path plans of drivers exiting the freeway downstream of the observed section are unknown.

In order to overcome the lack of driver/vehicle characteristics data, the driver/vehicle specific latent variables are introduced in the model. These variables capture correlations between the decisions made by the same driver over time. The individual specific error term υ_n is included in the specification of the target lane and in the gap acceptance utility functions. The parameters associated with this variable in the various model components are estimated jointly, and so, capture correlations between these decisions, which may be attributed to unobserved driver/vehicle characteristics.

Variables related to the path plan, such as the distance to an off-ramp the driver needs to use are not available for vehicles that exit the freeway downstream of the observed section. In order to capture the effect of these variables, a distribution of the distance from the downstream end of the road section being studied to the exit points is used. It is used a discrete distribution of the distances, based on the locations of off-ramps downstream of the section. The alternatives considered are the first, second and subsequent off-ramps. The probability mass function of distances beyond the downstream end of the section to the off-ramps used by drivers is given by:

$$p\left(d_n\right)=\begin{cases}\pi_1 & first\ downstream\ exit\left(d^1\right)\\ \pi_2 & second\ downstream\ exit\left(d^2\right)\\ 1-\pi_1-\pi_2 & otherwise\left(d^3\right)\end{cases} \tag{3.23}$$

Where, π_1 and π_2 are the parameters to be estimated. They are the proportions of drivers using the first and second downstream off-ramp, respectively. d^1, d^2 and d^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 (d^1 and d^2) are measured directly from geometric information. For the subsequent exits an infinite distance is used ($d^3=\infty$), which corresponds to an assumption that drivers that use this exits ignores path plan consideration in the lane choice. The parameters of this distribution are estimated jointly with the other parameters of the model. In this way in stead of handling with missing data and unobserved driver/vehicle characteristics, the likelihood function can be formulated.

The joint probability density of a combination of target lane (TL) observed for driver n at time t , TL for driver n at time $t-1$ and lane action (l) observed for driver n at time t, conditional on the individual specific variables, υ_n , and the distance to the exit point, d , is given by:

$$P_n\left(TL_t,TL_{t-1},l_t|d_n,\upsilon_n\right)=P_n\left(TL_t\,|\,TL_{t-1},d_n,\upsilon_n\right)P_n\left(l_t\,|\,TL_t,\upsilon_n\right)P_n(TL_{t-1}\,|\,d_n,\upsilon_n) \tag{3.24}$$

Where, $P_n\left(TL_t \mid TL_{t-1}, d_n, \upsilon_n\right)$ and $P_n\left(l_t \mid TL_t, \upsilon_n\right)$ are given by Equations (3.15) and (3.18), respectively. $P_n(TL_{t-1} \mid d_n, \upsilon_n)$ is calculated recursively using Equation (3.25):

$$P_n(TL_{t-1} \mid d_n, \upsilon_n) = \sum_{i \in TL_{t-2}} P_n(TL_{t-1}^j | TL_{t-2}^i, d_n, \upsilon_n) P_n(TL_{t-2}^i | d_n, \upsilon_n) \tag{3.25}$$

Therefore given the initial probabilities $P_n(TL_0 \mid d_n, \upsilon_n)$, these values can be calculated for any t.

Only the lane changing actions are observed. The marginal probability of the lane action is given by summing the target lane out of the joint probability:

$$P_n\left(l_t | d_n, \upsilon_n\right) = \sum_{j \in TL_t} \sum_{i \in TL_{t-1}} P_n(TL_t^j, TL_{t-1}^i, l_t | d_n, \upsilon_n) \tag{3.26}$$

The behavior of driver n is observed over a sequence of T consecutive time intervals. With the assumption that, conditional on d_n and υ_n, these observations are independent, the joint probability of the sequence of observations is the product of the probabilities given by:

$$P_n\left(\mathbf{l} | d_n, \upsilon_n\right) = \prod_{t=1}^{T} \sum_{j \in TL_t} \sum_{i \in TL_{t-1}} P_n(TL_t^j, TL_{t-1}^i, l_t | d_n, \upsilon_n) = \prod_{t=1}^{T} P_n(l_t | d_n, \upsilon_n) \tag{3.27}$$

Where, $\mathbf{l}$ are the sequences of lane changing decisions. It is important to note that $P_n(TL_{t-1} \mid d_n, \upsilon_n)$ was calculated recursively, therefore Equation (3.27) depends on the initial conditions.

The unconditional individual likelihood function is acquired by integrating (or summing, for the discrete variable d_n) the conditional probability over the distributions of the individual specific variables:

$$L_n = \int_{\upsilon} \sum_{d} P_n(\mathbf{l} \mid d_n, \upsilon_n) p(d) f(\upsilon) d\upsilon \tag{3.28}$$

Where, $p(d)$ is given by Equation (3.23) and $f(\upsilon)$ is the standard normal probability density function.

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

$$L = \sum_{n=1}^{N} \ln\left(L_n\right) \tag{3.29}$$

The maximum likelihood estimates of the model parameters are found by maximizing this function. In this work, the Broyden-Fletcher-Goldfarb-Shanno (BFGS) optimization algorithm implemented in the statistical estimation software GAUSS (Aptech Systems 1994) was used. BFGS is a quasi-Newton method, which maintains and updates an approximation of the Hessian matrix based on first-order derivative information (see, for example, Bertsekas 1999). GAUSS implements a variant of BFGS due to Gill and Murray (1972), which updates the Cholesky decomposition of the Hessian (Aptech Systems 1995).

The integrals in the likelihood function were calculated numerically using the Gauss-Legendre quadrature method (Aptech Systems 1994). Numerical integration is expected to perform better than Monte-Carlo integration in the application at hand because of the presence of the reaction time dimension: Monte-Carlo integration would require explanatory variable values, lagged by the reaction time, to be calculated for each draw. In contrast, with numerical integration only the explanatory variables values for the (much fewer) points used for the integration need to be calculated.

The likelihood function is not globally concave. For example, if the signs of all the coefficients of the individual-specific error term υ_n are reversed, the solution is unchanged due to its symmetric distribution function. To avoid obtaining a local solution, different starting points were used in the optimization procedure.

3.4 Summary

In this chapter, mathematical formulations of the different components of the lane changing model were presented. The proposed modeling of lane changing allows behaviors that were not modeled previously, such as the state dependency behavior to facilitate lane changing to be captured.

At the beginning of the chapter different possible modeling structures that allow capturing state dependency were discussed. A model specification that accounts for a full state dependency was presented. However this model is computationally demanding. Another alternative specification, a static model, which is based on the concept of partial short-term plan, was proposed. This approach captures the effect of evolving conditions on driving behavior in an indirect way. It assumes that drivers make repeated instantaneous decisions. State dependencies are not explicitly modeled, but it is assumed that they are captured by the change in the explanatory variable values.

Finally, a lane changing model that captures drivers' lane changing behavior under the assumption of stability on the behavior was developed using HMM structures within the model.

Similarly to past models, several mechanisms are available within the model structure to capture inter-dependencies between the various decisions made. Decisions made at lower levels of the driving behavior decision process are conditional on those made at higher levels. In addition, individual-specific latent variables may be introduced in the various choice models to capture correlations between the decisions made by a given driver that are the result of unobserved driver and vehicle characteristics.

In the proposed target lane model, the driver selects the lane with the highest utility as his target lane and makes lane changes based on this choice. A lane change occurs in the direction implied by the target lane depending on gap availability. Furthermore, the choice of the driver is dependent on the target lane that the driver chose in the past.

The state dependence creates dependence on the initial conditions. However, in this model the dependence is on the latent state and therefore the initial conditions are not observable. Furthermore, the first time a subject is observed does not correspond to any natural starting point and instead, it is determined by the location and capabilities of the data collection system. To overcome the limitation, we adapted an approach proposed by Heckman (1981), which approximates the distribution of the initial condition, conditional on the individual-specific error term. Therefore, the utility function for the initial observations for each driver is allowed to differ from that of the other observations.

At the end of the chapter, the joint likelihood function for the target lane selection and gap acceptance observed in the trajectory data has been derived.

Chapter 4

Data for Model Estimation

In this chapter, the data requirements for estimation of the model are discussed. Also, the characteristics of the collection site and the dataset used for model estimation in this thesis are summarized.

4.1 The Collection Site

Trajectory data, which consists of observations of the positions of vehicles at discrete points in time, provides useful information about the explanatory variables used for the proposed target lane model. Trajectory data points are equally spaced in time with short time intervals between them, typically 1 second or less. Speeds, accelerations and lane changes are extracted from the time series of positions. Additional explanatory variables required by the model, such as relations between the subject and other vehicles (e.g. relative speeds, time and space headways, lengths of gaps in traffic) may also be inferred from the raw dataset. The driver specific attributes are however not directly measurable but these characteristics can be captured by introduction of latent variables to capture correlations among different decisions made by the same driver.

The dataset used in this study was collected in 1983 by FHWA in a four-lane section of Interstate 395 (I-395) Southbound in Arlington, Virginia, through video cameras. It is 997 meters in length and includes an on-ramp and two off-ramps. The section is shown schematically in Figure 4.5. An hour of data at a rate of 1 frame per second was collected through aerial photography of the section. A detailed technical description of the systems and technologies used for data collection and reduction is found in FHWA (1985). The dataset, smoothed by Toledo (2003) using a local regression procedure, contains observations of the position, lane and dimensions of every vehicle within the section every 1 second.

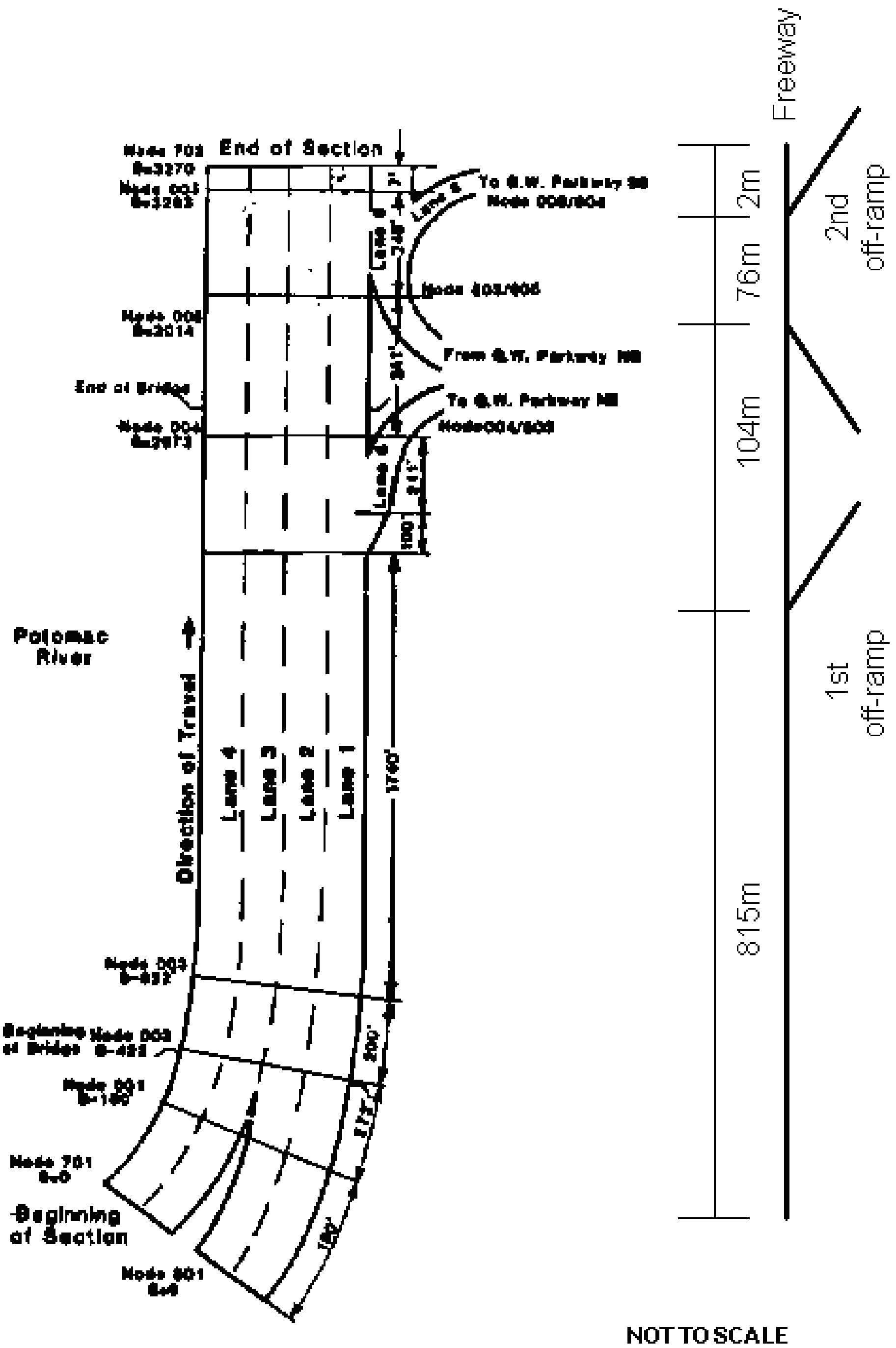


Figure 4.1 - The I-395 data collection site

This dataset is particularly useful for estimation of lane changing models because of the geometric characteristics of the site: it is 997 meters long with two off-ramps and an on-ramp. It is one of the longest sites for which trajectory data is available, and so, is best suited to capture short-term planning, anticipation and non-myopic considerations. The ramps within the site provide path plan information for the various vehicles. Moreover, the fact that three distinct path plans (i.e. staying in the freeway or taking the first or second off-ramp) are represented within the site creates the variability that is needed to capture these effects.

4.1.1 Characteristics of the Estimation Dataset

The vehicle trajectory data of the various vehicles in the section and the speeds and accelerations derived from these trajectories are used to generate the required variables.

The resulting estimation dataset includes 442 vehicles for a total of 15632 observations at a 1 second time resolution. On average a vehicle was observed for 35.4 seconds (observations). All the vehicles are first observed at the upstream end of the freeway section. At the downstream end, the majority of traffic (76%) stays in the freeway. The 8% and 16% of vehicles, which exit the section using the first and second off-ramps (shown in Figure 4.1) respectively, are useful to capture the effect of the path plan on driving behavior. The breakdown of the destinations of vehicles is shown in Table 4.1.

Table 4.1 - Breakdown of vehicles by destination

Destination	# of vehicles
Freeway	337 (76%)
1 st ramp	35 (8%)
2 nd ramp	70 (16%)

Lane-specific variables like lane density, lane speed, and percentage of heavy vehicle have been calculated from the raw dataset. The variation of lane-specific variables across the different lanes is summarized in Table 4.2.

Table 4.2 - Variations of Lane-specific Variables

	Lane 1	Lane 2	Lane 3	Lane 4	Segment
Average Density d/s, veh/km/lane	28.41	28.29	28.64	26.56	29.22
Average Density u/s, veh/km/lane	29.86	30.06	30.52	28.29	29.22
Average Speed, m/sec.	14.22	15.79	16.23	17.50	15.75

The same dataset has been used by Toledo (2003) and Choudhury (2005) in estimating lane changing models. The detailed characteristics of the dataset documented by them are summarized below:

Speeds in the section range from 0.4 to 25.0 m/sec. with a mean of 15.6 m/sec.. Densities range from 14.2 to 55.0 veh/km/lane with a mean of 31.4 veh/km/lane. 2% of the vehicles are categorized as heavy vehicles (length over 9.14 meters or 30 feet).

Acceleration observations vary from -3.97 to 3.99 m/sec^2. Drivers are accelerating in 52% of the observations. The level of service in the section is D-E (HCM 2000). The vehicles the subject interacts with and the variables related to these vehicles are shown in Figure 4.2. Relative speeds with respect to various vehicles are defined as the speed of these vehicles less the speed of the subject. Table 4.3 and 4.4 summarize statistics of the variables related to the subject vehicle and the vehicle in front respectively.

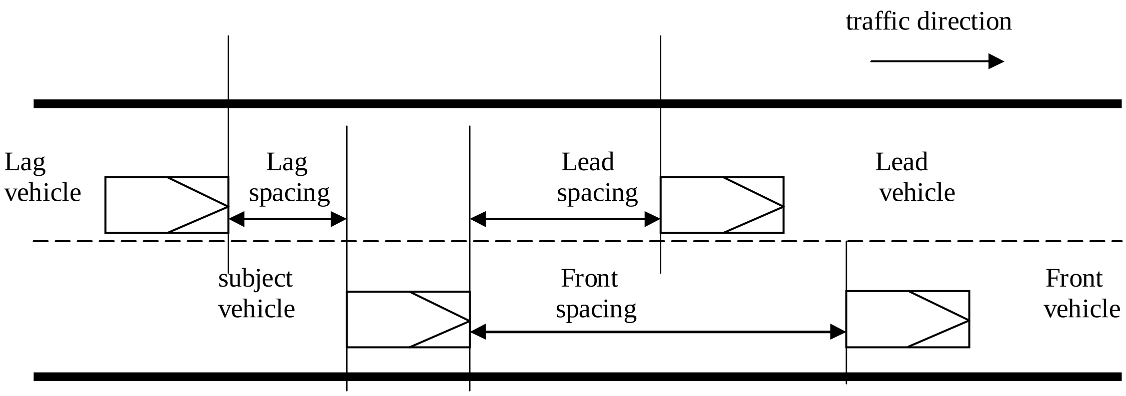


Figure 4.2 - The subject, front, lead and lag vehicles and related variables

Table 4.3 - Statistics of variables related to the subject vehicle

Variable	Mean	Std	Median	Minimum	Maximum
Speed (m/sec)	15.6	3.1	15.8	0.4	25
Acceleration (m^2/sec)	0.05	1.21	0.05	-3.97	3.99
Positive	0.96	0.76	0.78	0	3.99
Negative	-0.93	0.75	-0.74	-3.97	0
Density (veh/km/lane)	31.4	6.5	30.8	14.2	55.0

Table 4.4 - Statistics of relations between the subject and the front vehicle

Variable	Mean	Std	Median	Minimum	Maximum
Speed (m/sec)	15.8	3.2	16.0	0.2	25.0
Relative speed (m/sec)	0.2	1.7	0.2	-8.6	9.7
Spacing (m)	26.6	21.2	20.4	1.4	250.5
Time headway (sec)	2.0	1.4	1.7	0.3	27.3

The distributions of speed and acceleration in the data are shown in Figure 4.3.

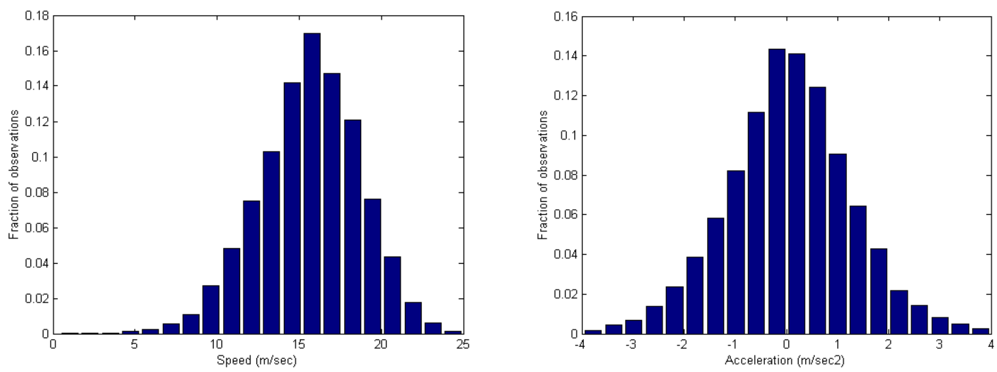


Figure 4.3 - Distributions of speed and acceleration in the data

The distributions of density and time headway in the data are shown in Figure 4.4.

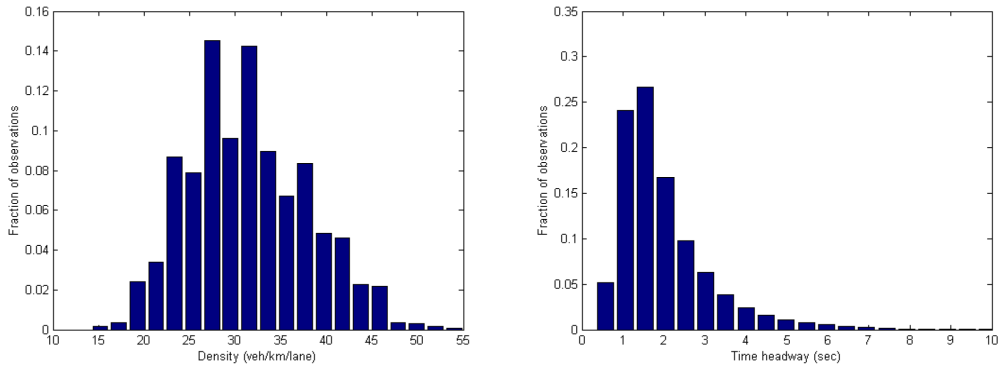


Figure 4.4 - Distributions of density and time headway in the data

Lane selection and gap acceptance behaviors are captured by observing lane changes drivers perform. An important factor in these behaviors is drivers' desire to follow their path. In this dataset drivers have three possible destinations, each with a corresponding path following behavior:

- Exiting the section through the first off-ramp.
- Exiting the section through the second off-ramp.
- Staying in the freeway at the downstream end of the section.

Table 4.5 describes the distribution of observed lane changes by direction (right, left) and by destination. It is worth noting that many of the vehicles that exit the section through the off-ramps are observed in the right-most lane at the upstream end of the section. This indicates that they may have started considering the path plan constraint earlier. As a result the coefficients of explanatory variables related to the path plan may be biased towards aggressive behaviors since the more timid drivers are discounted in the dataset.

Table 4.5 - Distribution of lane changes by direction and destination

Destination	Right	Left
Total	123	74
Freeway	71	71
1 st ramp	12	0
2 nd ramp	40	3

Table 4.6 - Statistics describing the lead and lag vehicles

Variable	Mean	Std	Median	Minimum	Maximum
Relations with Lead vehicle					
Relative Speed (m/sec)	0.2 (0.0)	2.6 (2.9)	0.5 (0.1)	-17.3 (-17.5)	8.1 (15.5)
Lead spacing (m)	22.2 (19.6)	21.9 (39.9)	14.1 (13.0)	0.04 (-18.1)	117.9 (268.9)
Relations with Lag vehicle					
Relative speed (m/sec)	-0.4 (0.0)	2.2 (2.7)	-0.3 (0.0)	-6.7 (-15.0)	5.2 (14.1)
Lag Spacing (m)	23.1 (18.6)	20.6 (23.0)	16.6 (12.0)	1.7 (-18.1)	110.1 (232.6)
Statistics are for the accepted gaps only, in parenthesis for the entire dataset					

The relations between the subject and the lead and the lag vehicles in the lanes to its right and to its left, affect the gap acceptance and gap choice behaviors. Table 4.6 summarizes statistics of the accepted lead and lag gaps (i.e. the gaps vehicle changed lanes into). Accepted lead gaps vary from 0.04 to 117.9 meters, with a mean of 22.2 meters. Accepted lag gaps vary from 1.7 to 110.1 meters, with a mean of 23.1 meters. No significant differences were found between the right and left lanes. Relative speeds are defined as the speed of the lead vehicle or the lag vehicle less the speed of the subject. Statistics for the entire dataset are also shown. With these statistics, negative spacing values indicate that the subject and the lead vehicle partly overlap (this is possible because they are in different lanes). As expected, the mean accepted gaps are larger than the mean gaps in the traffic stream. Similarly, lead relative speeds in accepted gaps are larger than in the mean of the dataset and lag relative speeds are smaller in the entire dataset (i.e. on average, in accepted gaps the subject vehicle is slower relative to the lead vehicle and faster relative to the lag vehicle compared to the entire dataset).

The distributions of relative speeds and spacing, with respect to the front, lead and lag are shown in Figure 4.5 and Figure 4.6, respectively.

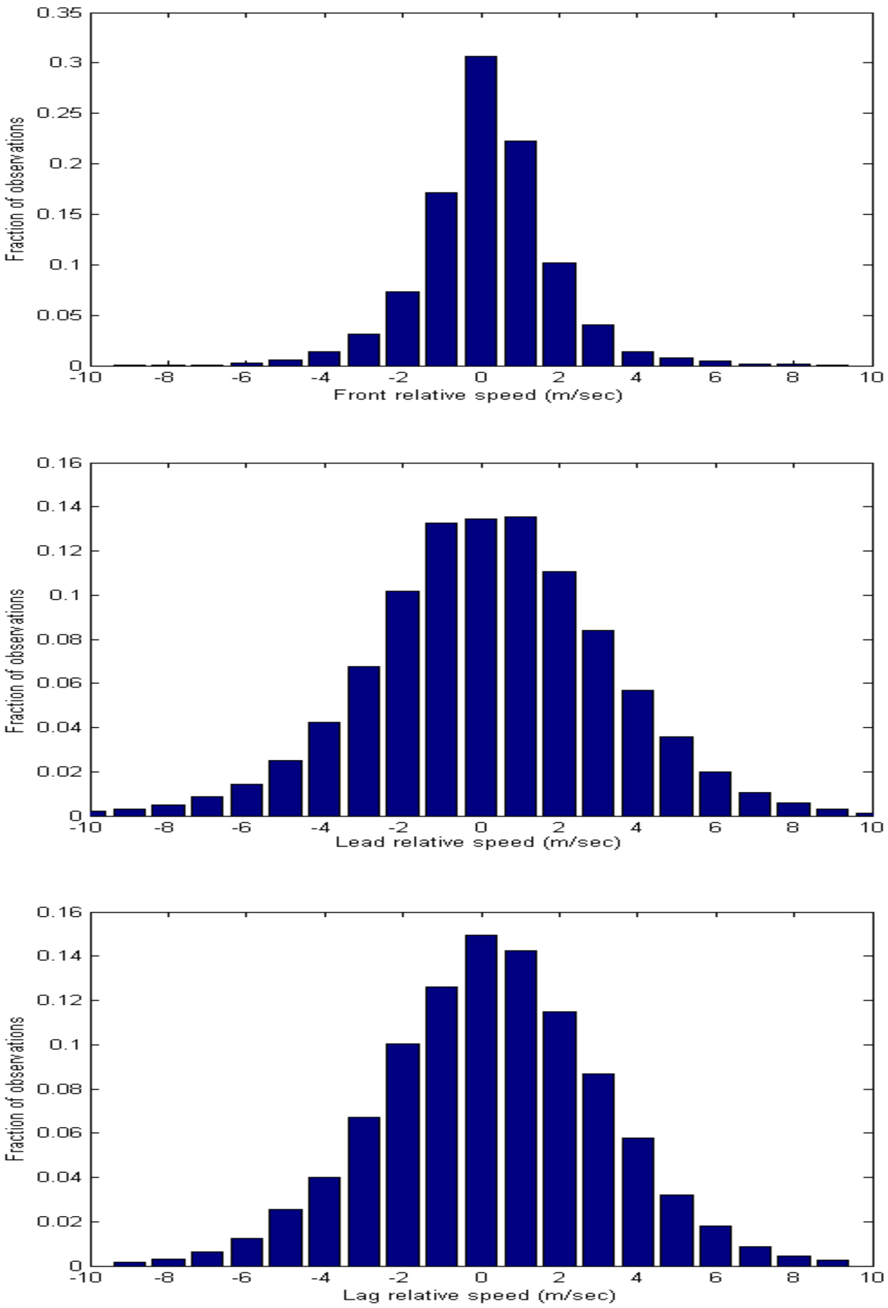


Figure 4.5 - Distributions of relative speed with respect to the front, lead and lag vehicles

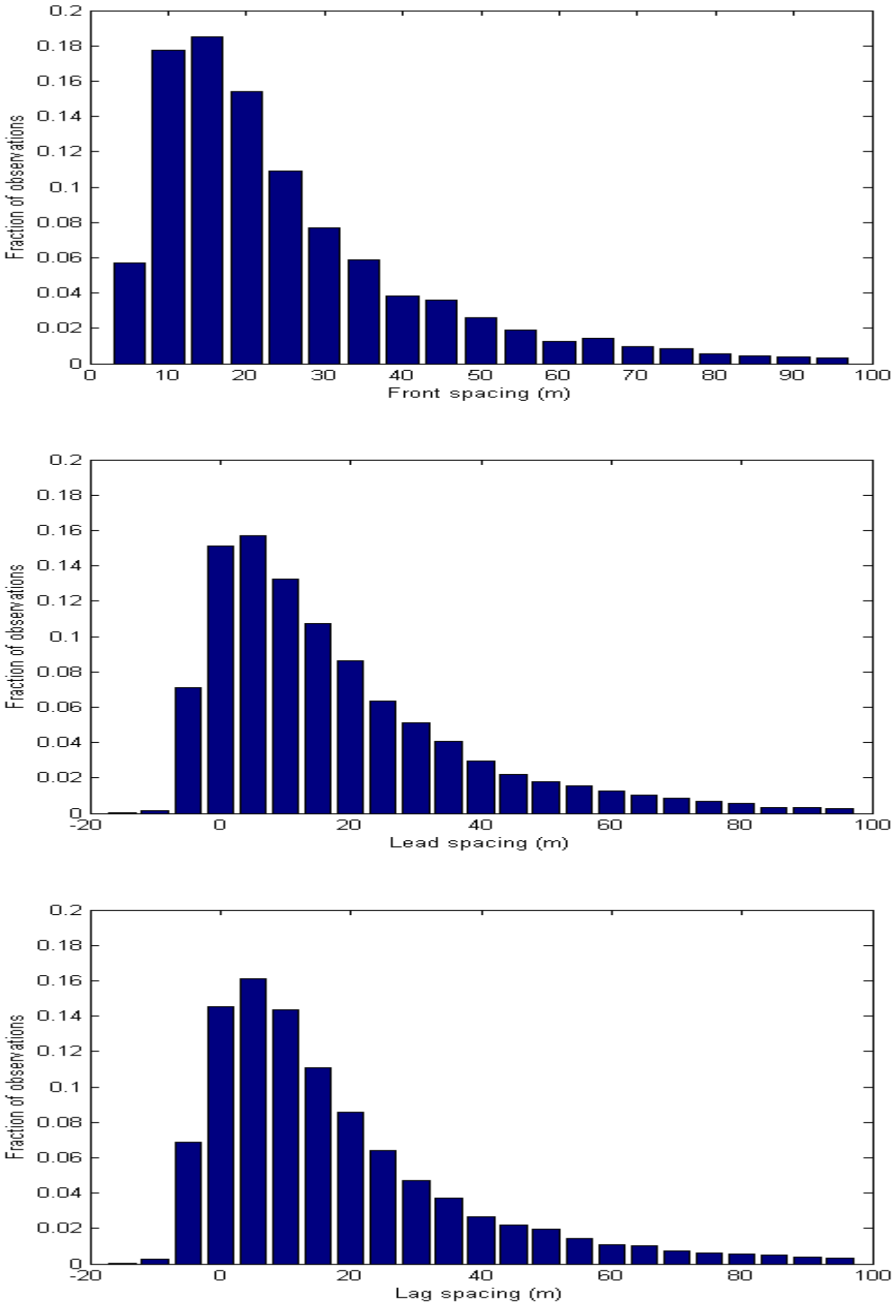


Figure 4.6 - Distributions of spacing with respect to the front, lead and lag vehicles.

4.2 Initial Observations

As was explained in chapter 3, the estimation of the model allows the utility function of the initial observation to differ from the subsequent ones. Therefore, we next present summary statistics for the initial observation for each driver.

In the dataset, all the vehicles are first observed at the upstream end of the freeway section that it is situated 815 m upstream of the first off ramp. Table 4.6 summarizes statistics of the variables related to the subject vehicle and the vehicle in front for the initial observations.

Table 4.7 - Statistics of variables related to the subject vehicle and the vehicle in front for the initial observations

Variable	Mean	Std	Median	Minimum	Maximum
Speed (m/sec)	15.5	3.0	15.7	6.0	22.3
Relations with the front vehicle					
Speed (m/sec)	15.6	3.1	16.0	6.1	24.5
Relative speed (m/sec)	0.1	1.9	0.2	-8.3	7.5

As we can see, the values we obtain for the initial observations are in the same range of the other observations. On one hand the speeds in the section range from 0.4 to 25.0 m/sec. with a mean of 15.6 m/sec. and on the other hand the speeds for the initial observation range from 6 to 22.3 m/sec. with a mean of 15.5 m/sec. From the mention above we can conclude that the Initial Observation has the same behavior that the other observations. This conclusion allows to us to suppose that the first observation of our data will constitute the initial observation of it. This statement permits to us to build our model in a simpler way.

4.3 Summary

In this chapter, the data requirements for estimation of the proposed model were discussed. Trajectory data, which consists of observations of the positions of vehicles at discrete points in time, is a useful basis to infer variables that may explain driving behavior.

The characteristics of the collection site and the dataset used for model estimation in this thesis were summarized. Trajectory data from I-395 Arlington, VA was used to estimate the model parameters. This dataset is particularly useful for estimation of the model because of the geometric characteristics of the site: the site is 997 meters long with two off-ramps and an on-ramp and therefore includes weaving sections that may exhibit behaviors represented in the proposed lane changing model, such as short-term planning and anticipation and capture the effect of the path plan on driving behavior.

The data represents a wide range of traffic conditions. Speeds range from 0.4 to 25.0 m/sec. Densities range from 14.2 to 55.0 veh/km/lane. The level of service in the section is D-E.

The values for the initial observation variables are in the same range of the other observations, which allows us to assume that the there is no difference between the behavior of the initial observation and the behavior of the other observations.

Chapter 5

Estimation Results

In this chapter, estimation results of the proposed lane changing model using the Arlington, VA dataset are described. All components of the model were estimated jointly using a maximum likelihood estimation procedure. Statistical assessment and behavioral interpretation of the results are presented. A discussion of the estimation results of the various components is also presented.

5.1 Estimation Results

The estimation results of the proposed lane changing model with the data from I-395 section are presented in Table 5.1. All components of the model were estimated jointly using a maximum likelihood estimation procedure as described in a previous chapter. However, in order to simplify the presentation, estimation results for the various components of the model are discussed separately. The discussion order follows the hierarchy of the hypothesized decision-making process: the target lane model is presented first, followed by the gap acceptance model.

Table 5.1 - Estimation results of the lane changing model

	Variable	Parameter values	T-statistic
Target lane Model			
Lane Attributes	Lane 1 constant	-1.859	-3.43
	Lane 2 constant	-0.649	-2.034
	Lane 3 constant	-0.034	-0.18
	Current lane dummy (CL)	3.264	14.10
	More than one lane change from the CL	-4.132	-1.97
Neighborhood Variables	Front vehicle spacing, m.	0.026	4.09
	Relative front vehicle speed, m/sec.	0.134	2.67
Path-plan Variables	Path plan impact, more than one lane change required to the next exit.	-2.604	-5.98
	Next exit dummy, lane change(s) required.	-1.624	-3.04
	Exponent of remaining distance, θ_{MLC}.	-1.283	-2.67
	Probability of taking 1st exit, π_1	0.0002	0.01
	Probability of taking 2nd exit π_2	0.047	2.044
Heterogeneity	Coefficient of aggressiveness, Lane 1, α^{lane1}.	1.143	3.02
	Coefficient of aggressiveness, Lane 2, α^{lane2}.	0.270	0.96
	Coefficient of aggressiveness, Lane 3, α^{lane3}.	1.803	6.46
	Coefficient of aggressiveness, Lane 4, α^{lane4}.	0.453	1.84
State Dependence Variable	Persistence dummy, ρ	0.131	4.53
Initial Conditions Variables	Initial Current lane dummy	4.804	1.84
	Initial Path plan impact, more than one lane change required	-1.309	-1.99
	Initial Front vehicle spacing, m	-0.017	-1.92
Lead Critical Gap			
Constant		1.706	6.03
Relative lead speed positive, Max (ΔS_{nt}^{lead},0) , m/sec		-6.323	-3.31
Relative lead speed negative, Min (ΔS_{nt}^{lead},0) , m/sec		-0.155	-2.51
Heterogeneity coefficient of lead gap, α^{lead}		0.099	0.35
Standard deviation of lead gap, σ^{lead}		0.939	4.18
Lag Critical Gap			
Constant		1.429	5.63
Relative lag speed positive, Max (ΔS_{nt}^{lag},0) , m/sec		0.512	5.84
Heterogeneity coefficient of lag gap, α^{lag}		0.211	1.27
Standard deviation of lag gap, σ^{lag}		0.775	5.87

5.1.1 The Target Lane Model

This model describes drivers' choice of lane they would want to travel in. The target lane choice, are affected by different classes of variables:

- Lane-specific variables: These variables include distance of the lane with respect to the current lane (indicated by the number of lane changes required to reach the lane), position of the lane in the roadway, special attributes of the lane if any (e.g. exclusive lane or not).
- Neighborhood variables: These variables describe the subject vehicle and its relations with surrounding vehicles. Variables in this group include relative speeds and spacing with respect to the vehicle in front of in neighboring lanes.
- Path plan variables: These variables capture the effect of the path plan on drivers' decisions. Variables in this group include distances to the point where the driver must be in specific lanes to follow his path, the number of lane changes required to be in the correct lanes and indicators of whether the driver needs to take the next off-ramp.
- Driver specific attributes: The lane changing behavior is also likely to be affected by the individual driving style, capabilities and preferences of the driver. These variables capture considerations and preferences that are based on the driver's knowledge and experience with the transportation system, individual characteristics of the driver, such as aggressiveness, and of the vehicle, such as speed and acceleration capabilities.
- State dependence variable: The decisions drivers make over time are not independent. This variable captures the effect of the dependence in the lane changing decisions drivers make over time such as the lane the driver chose as his target lane in the previous time. Then, this variable captures the stability and persistence of the drivers' behavior.

As it was explained above, a group of variables are those capturing the lane-specific conditions. The estimated values of the lane-specific constants imply that, everything else being equal, the lane 1 – the right-most lane – is the most undesirable. Lanes that are more to left are more desirable. This may be the result of drivers' preference to avoid the merging and weaving activity that takes place in that lane.

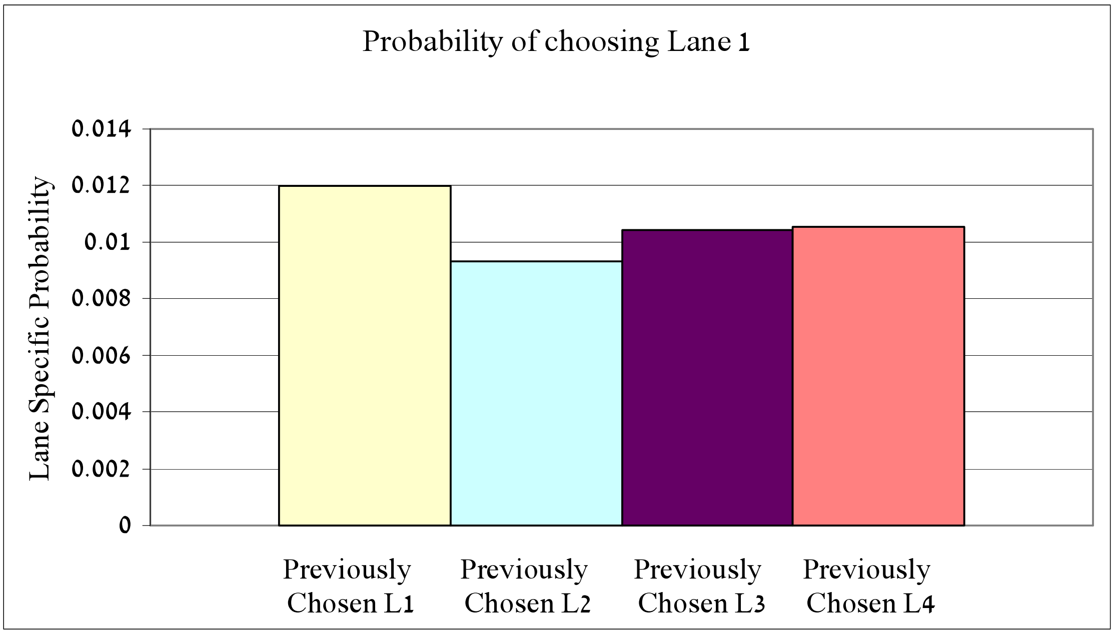
Some of the lane-specific variables are dependent on the current lane of the vehicle. The coefficient of the current lane dummy captures the inertia preference to stay in the current lane. As expected, the sign of this coefficient is positive. Moreover, the value and the sign of the coefficient of the variable that captures the influence of more than one lane changes required from the current lane to the target lane denotes the disutility associated with choosing target lanes that require more than one lane-changing maneuver.

The variable that captures the state dependence indicates that the utility of a lane increases if the target lane chosen by the driver is the same target lane chosen in the previous time period. As expected the sign of this coefficient is positive. This implies that drivers are persistent in trying to complete a lane change. When the driver assesses the situation and selects the immediate action, he takes into account the decisions made earlier. This dummy variable is defined:

$$\delta_n^{i,TL}(t-1) = \begin{cases} 1 & \textit{lane i was the chosen lane at t-1} \\ 0 & \textit{otherwise} \end{cases} \tag{5.1}$$

With the assumption that all the four lanes have the same attributes and the driver is currently in lane 2, Figure 5.1 shows the variation of the probabilities of choosing a target lane depending on the target lane that was chosen in the previous time. As expected, the figures show that the probability of choosing a lane is the highest if this lane was previously chosen and lower if another lane was previously chosen as a target lane. Furthermore, we can appreciate from the figures below that the probability of choosing a lane is higher if the previously chosen lane had a lower probability of being previously chosen. An explanation may be that the probability of continuing with the plan increases with its quality. If the driver chose a weak plan (one that has a low choice probability), the probability of aborting it and choosing another one is higher compared to when the previously selected plan is strong. To illustrate this, suppose that the driver is currently in lane 2. The probability of choosing lane 2 is the highest if the driver also decided to stay in this lane in the previous time period. However, if the previously chosen lane is not lane 2, the probability of choosing lane 2 in the current time period is highest if lane 4 was previously chosen and lowest if lane 3 was previously chosen. This is also the reverse order of the probabilities of choice of these lanes.

From the above example we can conclude that the probability of giving up a previously chosen target lane is lower when that lane has a high choice probability.



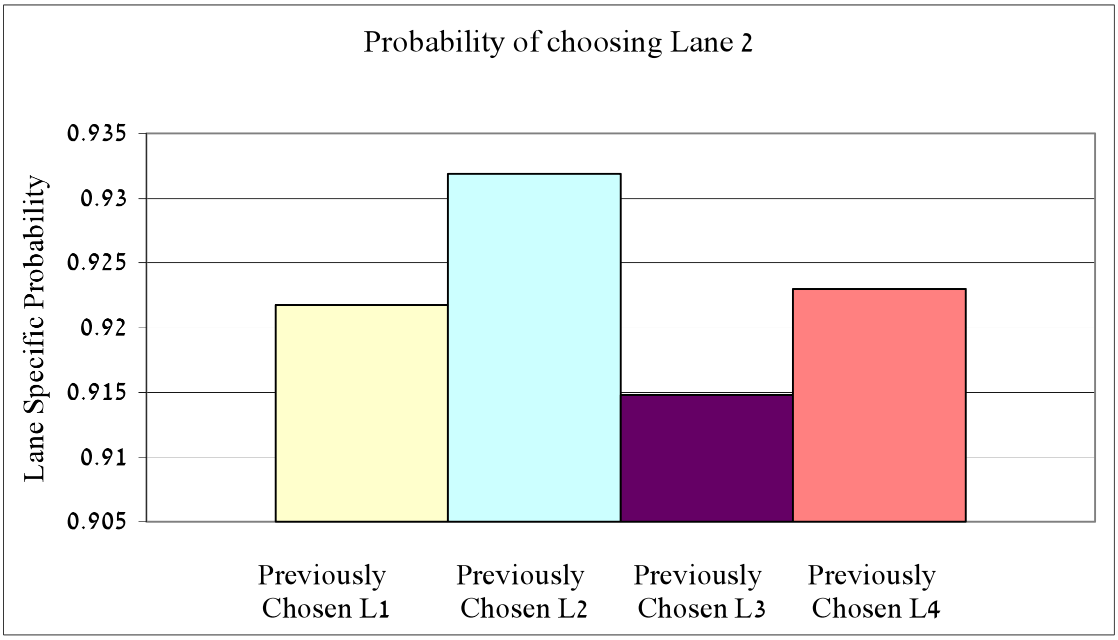
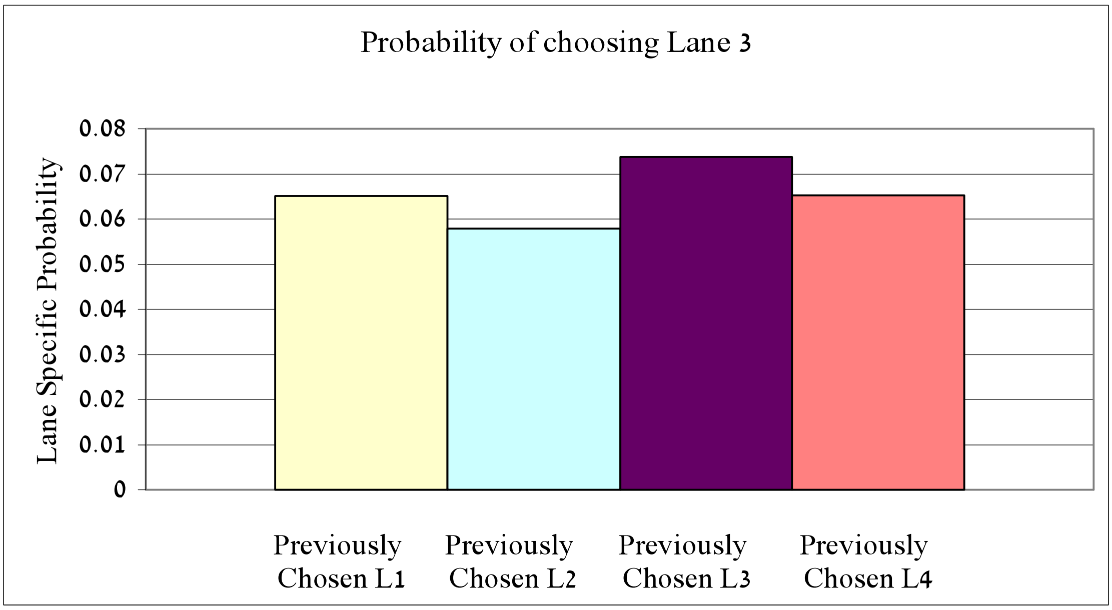


Figure 5.1 - Variation of the probability of choosing a lane, depending on the previously chosen lane when the current lane is Lane 2



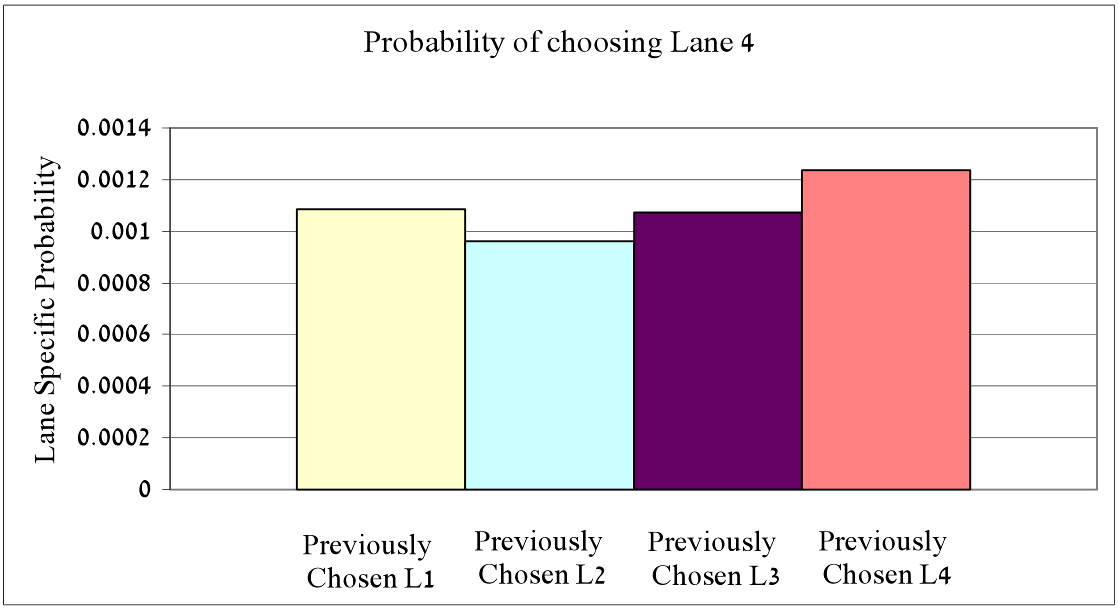


Figure 5.1 - Variation of the probability of choosing a lane, depending on the previously chosen lane when the current lane is Lane 2 (cont.)

Another group of variables are those capturing driving conditions in the immediate and extended neighborhood of the vehicle. The speed and spacing of the front vehicle (only appearing in the utility of the current lane) capture the likely satisfaction of the driver with conditions in the current lane. As expected, the sign of these coefficients are positive, thus the utility of the current lane increases with the speed of the front vehicle and with the spacing between the two vehicles. This implies that the subject is less likely to perceive the front vehicle as a constraint when the front vehicle speed is higher and the spacing is larger.

The effect of the path plan is captured by a group of variables, which combine a function of the distance to the point where the driver needs to be in a specific lane (i.e. in order to take an off-ramp) and the number of lane changes required to be in the correct lane. The path plan impact variables indicate that the utility of a lane decreases with the number of lane changes the driver needs to perform in order to maintain the desired path. The estimation dataset is from a four-lane freeway, in which the off-ramps are in the right-most lane. As expected, the utility of a lane decreases if the driver needs to perform lane changes from it in order to maintain the desired path. This effect is magnified as the distance to the off-ramp decreases (θ^{MLC} = -1.2830). The use of a power function to capture the effect of the distance from the off-ramp guarantees that at the limits, the path plan impact approaches 0 when $d_n^{exit}(t) \to +\infty$ and approaches $-\infty$ when $d_n^{exit}(t) \to +0$.

Figure 5.2 shows the variation of the probability of choosing lane 1 when the driver needs to take the next exit and his current lane is Lane 2, as a function of the distance from the off ramp for the following two different cases: lane 1 was the targeted lane in the previous time and another lane (lane 2, 3 or 4) was the targeted lane in the previous time period.

In the example, Lane 1 is the closest to the exit. We can note that when the driver is far from the desired exit, the probability of choosing lane 1 as the target lane is low. As the distance to exit decreases, the probability of choosing lane 1 gradually increases. When the driver is very close to the exit the probability of lane 1 becomes as highest as possible.

Moreover, we can appreciate in the figure that with the assumption that the driver is at the same distance from the off ramp, the probability of choosing lane 1 is higher if the driver already decided to change to this lane in the previous time period.

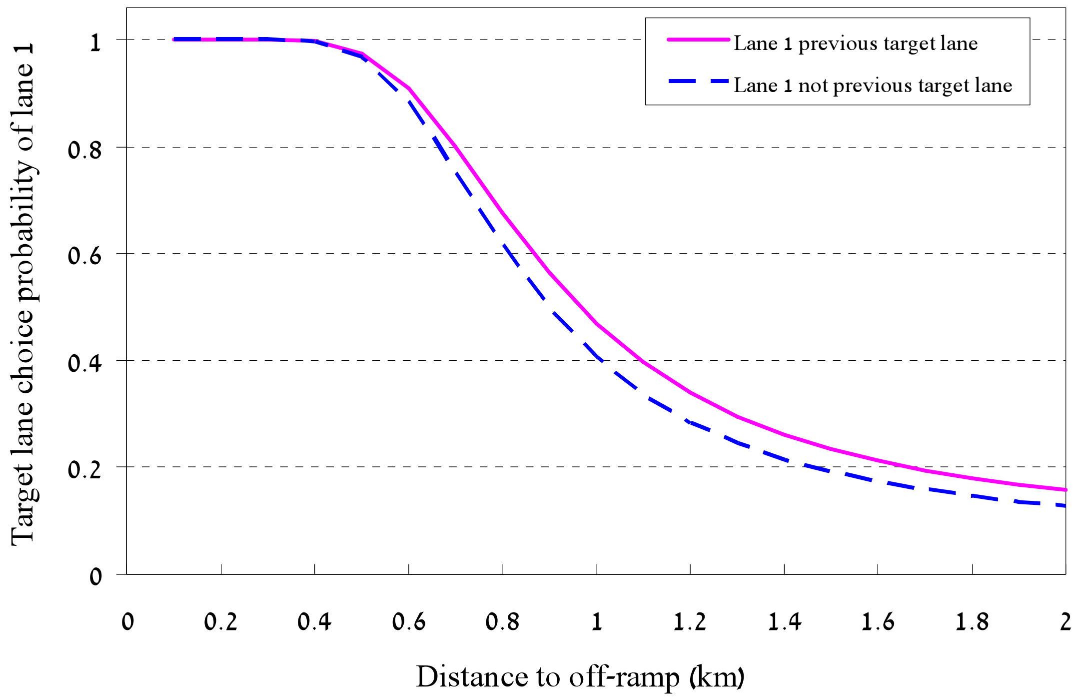


Figure 5.2 – Predicted Probabilities of choosing the target lane closest to an off-ramp used in the path.

Drivers' perception and awareness of path plan considerations is likely to be a function of the geometric elements of the road. In particular, drivers are more likely to respond to constraints that involve the next road element they will encounter. In the road section used for estimation, such behavior would present itself for drivers who exit the freeway using the next off-ramp, as opposed to drivers who will use subsequent exits. As with the impact of the distance, explanatory variables are generated by interaction of a next-exit dummy variable with the number of lane changes required. As expected, the estimated coefficient for this variable is negative and then, the utility of a lane decreases if there is more than one lane change required in order to take the next exit.

The last group of variables is those capturing the driver specific attributes. The heterogeneity coefficients, $\alpha^{lane\ 1}$, $\alpha^{lane\ 2}$, $\alpha^{lane\ 3}$ and $\alpha^{lane\ 4}$, capture the effects of the individual specific error term υ_n on the target lane choice, thus accounting for correlations between observations of the same individual due to unobserved characteristics of the driver/vehicle. $\alpha^{lane\ 1}$ and $\alpha^{lane\ 3}$ are more positive compared with

$\alpha^{lane\ 2}$ and $\alpha^{lane\ 4}$. In the data collection site there are two roads that are merged. Then, we can understand that lane 1 and lane 3 are the right-most lanes of each one of the roads that met in this section. The estimated parameters are positive and so, υ_n can be interpreted as positively correlated with the driver's timidity. A timid driver (i.e. $\upsilon_n > 0$) is more likely to choose the right lane over the left one compared to a more aggressive driver.

In summary, the target lane utilities are given by:

$$\begin{aligned} U_{nt}^{i} = {} & \beta^{i} + 0.026\Delta X_{nt}^{i,front}\delta_{nt}^{i,CL} + 0.134\Delta S_{nt}^{i,front}\delta_{nt}^{i,adj/CL} \\ & + 3.264\delta_{nt}^{i,CL} - 4.132\delta_{nt}^{i,\Delta CL>1} \\ & - 2.604\left[d_{nt}^{exit}\right]^{-1.283}\Delta Exit^{i} - 1.624\delta_{nt}^{next\ exit}\delta_{nt}^{i,\Delta EXIT\geq 1} \\ & + 0.131\delta_{n}^{i,TL} + \alpha^{i}v_{n} + \varepsilon_{nt}^{i} \end{aligned} \tag{5.2}$$

Where, β^i is the constant of $lane\ i$. $\Delta X_{nt}^{i,front}$ and $\Delta S_{nt}^{i,front}$ are the spacing and relative speed of the front vehicle in $lane\ i$, respectively. $\delta_{nt}^{i,adj/CL}$ is an indicator with value 1 if i is the current or an adjacent lane, and 0 otherwise. Similarly, $\delta_{nt}^{i,CL}$ has value 1 if i is the current lane, and 0 otherwise. $\delta_{nt}^{i,\Delta CL>1}$ is an indicator with value 1 if the lane i involves more than one lane changes from the current lane, and 0 otherwise. d_{nt}^{exit} is the distance to the exit driver n intends to use. $\Delta Exit^i$ is the number of lane changes required to get from lane i to the exit lane. $\delta_{nt}^{next\ exit}$ is an indicator with value 1 if the driver intends to take the next exit, and 0 otherwise. $\delta_{nt}^{i,\Delta EXIT\geq 1}$ is an indicator with value 1 if there is involved a lane change in order to take the next exit (lane i is not the exit lane) , and 0 otherwise. $\delta_{n}^{i,TL}$ is an indicator with value 1 if the target lane in time t is the same target lane that was chosen in time $t-1$.

5.1.2 The Gap Acceptance Model

The gap acceptance behavior is conditioned on the driver targeting either the right lane or the left lane. In these cases, the driver is assumed to evaluate the available adjacent gap in the target lane and decide whether to change lanes immediately or not.

In order for the gap to be acceptable both the lead and lag gaps, shown in 5.3, must be acceptable. Otherwise, it is not safe for the driver to do lane changing.

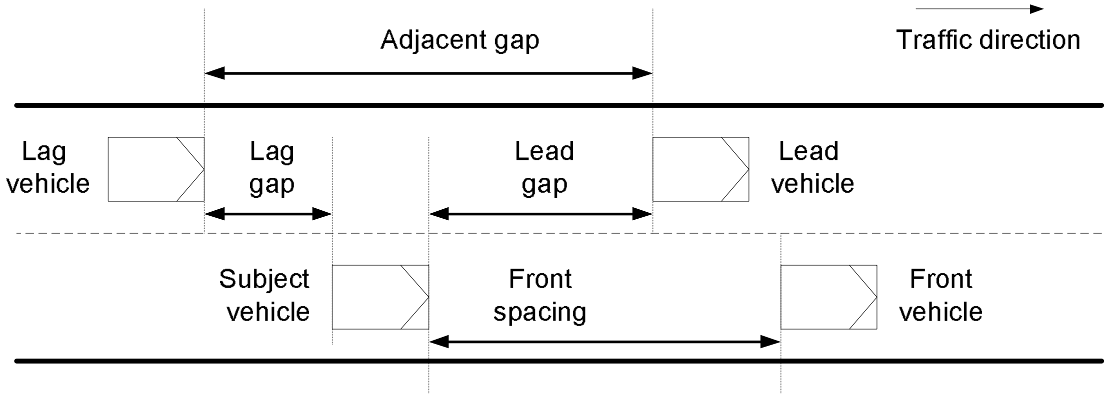


Figure 5.3 - The subject, front, lead and lag vehicles and related variables

Both the lead and lag critical gap are a function of the subject relative speed with respect to the corresponding vehicles. Relative speed with respect to a vehicle is defined as the speed of that vehicle less the speed of the subject.

The lead (or lag) gap is acceptable only if the available gap is larger than an unobservable critical lead (or lag) gap, which is the minimum acceptable gap. In order to ensure that critical gaps are always positive, they are assumed to follow a lognormal distribution:

$$\ln\left(G_n^{lead\,TL,cr}(t)\right) = \beta^{lead} X_n^{lead\,TL}(t) + \alpha^{lead}\upsilon_n + \varepsilon_n^{lead}(t) \tag{5.3}$$

$$\ln\left(G_n^{lag\,TL,cr}(t)\right) = \beta^{lag} X_n^{lag\,TL}(t) + \alpha^{lag}\upsilon_n + \varepsilon_n^{lag}(t) \tag{5.4}$$

Where, $G_n^{leadTL,cr}(t)$ and $G_n^{lagTL,cr}(t)$ are the lead and lag critical gaps in the target lane, measured in meters. $X_n^{lead\,TL}(t)$ and $X_n^{lag\,TL}(t)$ are vectors of explanatory variables affecting the lead and lag critical gaps, respectively. β^{lead} and β^{lag} are the corresponding vectors of parameters. $\varepsilon_n^{lead}(t)$ and $\varepsilon_n^{lag}(t)$ are the random terms associated with the critical gaps for driver *n* at time *t*. These error terms are normally distributed: $\varepsilon_n^{lead}(t) \sim N\left(0,\sigma_{lead}^2\right)$ and $\varepsilon_n^{lag}(t) \sim N\left(0,\sigma_{lag}^2\right)$. α^{lead} and α^{lag} are the parameters of the individual specific random term υ_n for the lead and lag critical gaps, respectively.

The estimated lead and lag gaps are given by equations (5.5) and (5.6) respectively:

$$G_n^{lead\,TL,cr}(t) = \exp\begin{Bmatrix} 1.706 - 6.323 Max\left(0, \Delta V_n^{lead,TL}(t)\right) - \\ -0.155 Min\left(0, \Delta V_n^{lead,TL}(t)\right) + 0.099\upsilon_n + \varepsilon_n^{lead}(t) \end{Bmatrix} \tag{5.5}$$
$$\varepsilon_n^{lead}(t) : \ N(0, 0.939^2)$$

$$G_n^{lag\,TL,cr}(t) = \exp\left\{1.429 + 0.512 Max\left(0, \Delta V_n^{lag,TL}(t)\right) + 0.211\upsilon_n + \varepsilon_n^{lag}(t)\right\} \tag{5.6}$$
$$\varepsilon_n^{lag}(t) : \ N\left(0, 0.775^2\right)$$

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

Inversely, 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. An explanation may be that drivers have a less reliable perception of the lag gap compared to the lead gap (due to the indirect observation of lag gaps through mirrors). Therefore, drivers may keep a minimum critical gap as a safety buffer.

Median lead and lag critical gaps, as a function of the relative speeds are presented in Figure 5.4.

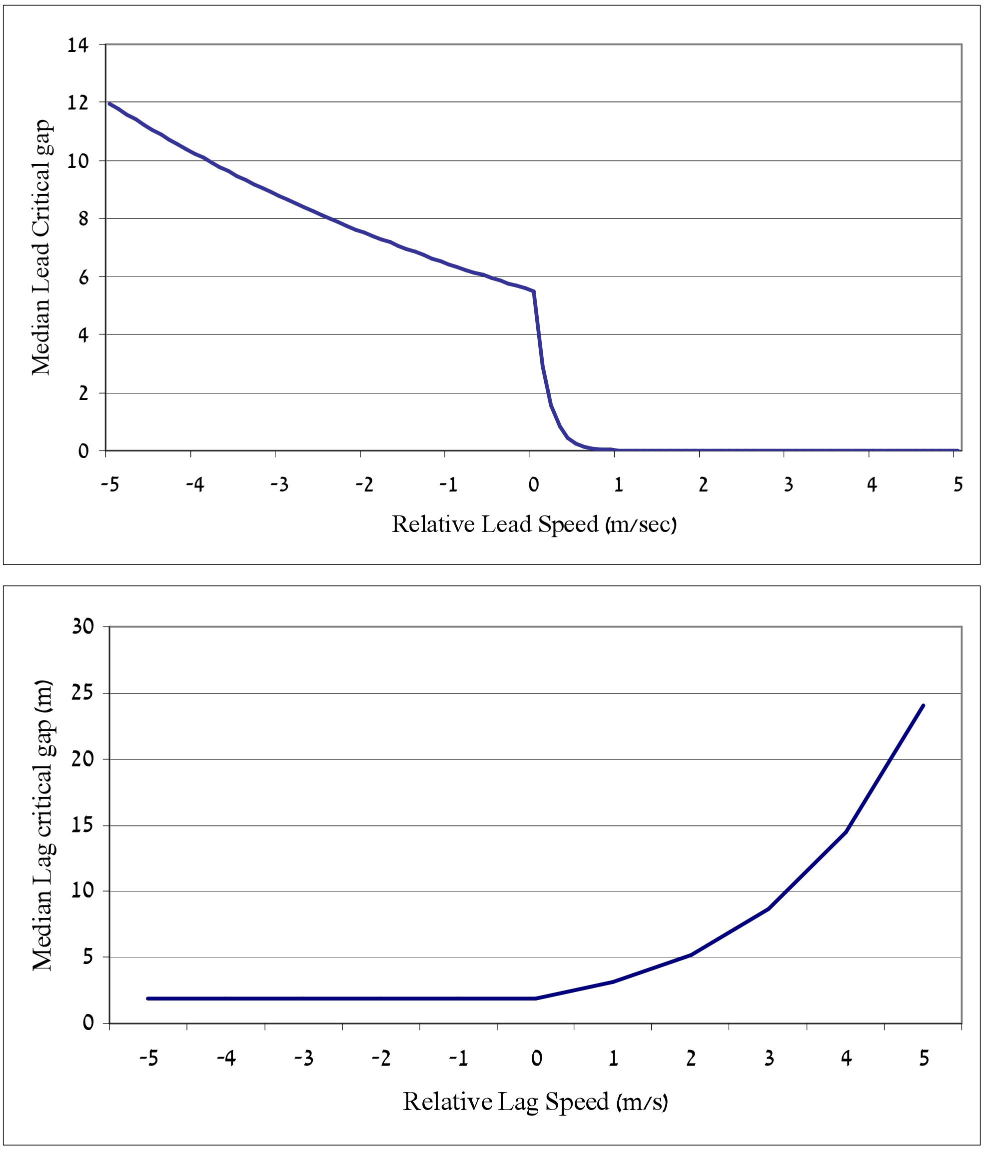


Figure 5.4 - Median lead and lag critical gaps as a function of relative speed

Estimated coefficients of the unobserved driver characteristics variable, υ_n, are positive for both lead and lag critical gaps. Hence, the variable can be interpreted as positively correlated with the characteristics of a timid driver who requires larger gaps for lane changing compared to more aggressive drivers who require smaller gaps for lane changing.

5.1.3 Statistical Test for Model Selection

In this section, model selection tests are performed based on the likelihood function values at convergence of different lane changing models: the explicit target lane model proposed by Choudhury (2005) but simplified; the lane changing model that takes into account the state dependence with initial values for all the variables and the lane changing model that takes into account the state dependence with initial values for some of the variables. Estimation results for the different models are presented in Appendix A.

The lane changing model that takes into account the state dependence extends the lane changing model with explicit target lane choice proposed by Choudhury (2005). The model with explicit target lane choice can be viewed as nested within the model with state dependence, and therefore classic statistical tests can be applied to select between them. Thus, likelihood ratio tests for model selection are applicable.

The likelihood ratio test (LRT) is a statistical test of the goodness-of-fit between two models. A relatively more complex model is compared to a simpler model to see if it fits a particular dataset significantly better. The LRT begins with a comparison of the likelihood scores of the two models:

$$LR = 2(L_u - L_r) \tag{5.7}$$

Where L_u is the likelihood score of a model (unrestricted model) and L_r is the likelihood score of the nested model (restricted model). This LR statistic approximately follows a chi-square distribution. To determine if the difference in likelihood scores among the two models is statistically significant, we next must consider the degrees of freedom. In the LRT, degrees of freedom are equal to the number of additional parameters in the more complex model.

The maximum likelihood values and numbers of parameters of the different models are presented in

Table 5.2.

Table 5.2 - Likelihood values of the estimated models

Model	Likelihood value	Parameters
Explicit Target Lane Choice Model	-880.35	25
State Dependence Model with initial values for all the variables	-874.97	38
State Dependence Model	-876.19	29

We first apply the LRT between the Explicit Target Lane Choice Model and the State Dependence Model with initial values for all the variables:

$$LR = 2(-874.97 + 880.35) = 10.76 \quad (5.8)$$

Degrees of freedom: 13

The critical value of chi-square distribution with 13 degrees of freedom and a probability of 0.90 of exceeding the critical value is 19.81.

Adding additional parameters always result in a higher likelihood value. However, when adding additional parameters is no longer justified in terms of significant improvement in fit of a model to a particular dataset. In our case, the results of this test show that the State Dependence Model with initial values for all the variables does not better fit the data than the Explicit Target Lane Choice Model.

Then, we apply the LRT between the Explicit Target Lane Choice Model and the State Dependence Model with initial values for some of the variables:

$$LR = 2(-876.19 + 880.35) = 8.32 \quad (5.9)$$

Degrees of freedom: 4

The critical value of chi-square distribution with 4 degrees of freedom and a probability of 0.90 of exceeding the critical value is 7.8.

In this case, the results show that the State Dependence Model (with initial values for some of the variables) better fits the data, and therefore should be selected for prediction.

5.2 Summary

In this chapter, estimation results of the target lane model using Gauss statistical estimation software has been presented.

Estimation results for the target lane model indicate significant influence of different types of variables: lane-specific attributes, captured for example by the position of the driver; variables that capture driving conditions in the immediate and extended neighborhood of the vehicle, for example the speed of the vehicle in front of the subject and the spacing between them; variables that relate to the path plan, which combine a function of the distance to the point where the driver needs to be in a specific lane (i.e. in order to take an off-ramp) and the number of lane changes required to be in the correct lane; variables capturing the driver specific attributes and the variable capturing the state dependence.

This last variable is the one that captures the effect of the dependence in the lane changing decisions drivers make over time such as the lane the driver chose as his target lane in the previous time. Then, this variable captures the stability and persistence of the drivers' behavior.

Gap acceptance decisions are affected by the subject relative speeds with respect to the lead and lag vehicle in the target lane.

The proposed target lane model includes state dependence. The estimation results indicate that the sign of this additional variable in the utility function is logical and matches the intuitive expectations.

Chapter 6

Conclusions

This chapter summarizes the research reported in this thesis and highlights the major contributions. Finally, directions for future research are also suggested.

6.1 Summary of the Work and Results

Lane changing is usually modeled in two steps: the decision to consider a lane change – lane selection process, and the decision to execute the lane change. Modeling the lane changing decision process is very complex due to its latent nature and the number of factors a driver considers before reaching a decision. The only observable part of this process is a successful lane change operation. The exact time at which a driver decides to change lanes cannot be observed. Most current models assume that drivers make repeated instantaneous decisions. At each point in time the driver assesses the situation and selects the immediate action independent of previous decisions. However, in reality, the decisions of a driver over time are interdependent. Interdependencies among decisions, particularly over the time dimension for the same driver are not captured in detail in most of the existing models. For example, the persistence of drivers to follow their originally chosen plans, which can lead to state-dependence, has been ignored in the state-of-the-art models.

A lane changing model that captures drivers' lane changing behavior under the assumption of stability of the behavior was presented in this work. This approach is justified by the estimation results for the target lane model, which indicates significant dependence in the lane changing decisions drivers make over time.

A random utility approach has been adopted to model both components of the model: the selection of a target lane and gap acceptance. 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. This driver-specific random term is included in all model components. Missing data due to the limitations of the data collection are also account for.

Drivers that target lane changing evaluate the available adjacent gap in the target lane to decide whether they can immediately change lanes or not. The gap acceptance model requires that both the lead gap and the lag gap are acceptable. Their decision is based on comparison of the available gaps to corresponding critical gaps, which are functions of explanatory variables. Critical gaps depend on the subject relative speeds with respect to the lead vehicle and the lag vehicle in the target lane.

Statistical tests show that the State Dependence Model does better fit the data than previous models and therefore should be selected for prediction.

6.2 Contributions

The objective of this research is to improve the modeling of driving behavior and in particular the influence of the state dependence in the drivers' behavior. More reliable simulation of traffic flow requires driving behavior models that capture stability in the driver's behaviors. This thesis contributes to state-of-the-art in driving behavior modeling in the following respects:

- Development of a framework for modeling the lane changing behavior taking into account the state dependence between observations of a given driver over time and the development of the detailed specifications of the various components within the driving behavior model;
- Most of the existing models where the HMM formalism was applied, did not use real data to estimate them, it was used data obtained from a driving simulator. Contrarily, the model developed herein is estimated with data that was collected in a freeway section from the real world;
- The parameters of the target lane model were estimated using trajectory data. Estimation results show that the state dependence variable is significant in lane selection. A significant improvement in goodness of fit is observed over previous models;

- Estimation results show that the proposed treatment of the initial conditions was successful;
- Most of the applications of the HMM structure for lane changing, focused in identifying the intention of the driver using observed behavior (i.e. acceleration, steering angle). These models could detect whether or not the driver is changing lanes at the time of the observation but did not explain why the lane changing is undertaking and so cannot predict lane changes ahead of time. The model proposed in this work, permits to explain the driver's behavior.

6.3 Future Research Directions

The emergence of microscopic traffic simulation tools in the last few years has brought about increasing interest in driving behavior modeling. Some of the directions in which further research is needed are presented below:

- Most of published estimation results of lane changing models are for freeway traffic. Similar models need to be developed for urban streets, in which other factors and considerations such as bus traffic and pedestrians may affect the behavior.
- There is a lack of information about individuals, such as the level of skill, driving abilities and character. A tool to collect the data about the own attitudes and characteristics of the drivers need to be developed in order to achieve a better understanding of the driver's behavior.
- The interaction between the lane-changing and acceleration behavior of the driver is also ignored in the current model. There is the need to develop more detailed driving behavior models based on the concept of generalized target lane capable of capturing interdependencies between lane-changing and acceleration behaviors.
- The lane-changing duration is omitted in this work. The acceleration behavior of the vehicle changing lanes and of other vehicles around it may be affected during the execution of lane changes, but this effect cannot be captured if lane

changes are instantaneous. Therefore, a model that capture the duration of lane changes needs to be developed.

- To enhance the ability of the models proposed in this thesis, the model should be implemented in microscopic traffic simulators. The impact on traffic flow characteristics and the performances of simulators need to be tested.

Appendix A

Estimation Results of Different Lane Changing Models

In this appendix, estimation results of the explicit target lane model proposed by (2005) but simplified and the lane-changing model that takes into account the state dependence with initial values for all the variables using the Arlington, VA data are presented.

A.1 Explicit Target Lane Model (Simplified)

The estimation results of the model structure proposed by Charisma (2005) using the trajectory data from Arlington, VA are presented in Table A.1.

Table A.1 - Estimation results of the explicit target lane model (simplified)

	Variable	Parameter values	T-statistic
Target lane Model			
Lane Attributes	Lane 1 constant	-1.931	-3.34
	Lane 2 constant	-0.683	-2.02
	Lane 3 constant	-0.049	-0.25
	Current lane dummy (CL)	3.449	15.38
	More than one lane change from the CL.	-4.281	-1.79
Neighborhood Variables	Front vehicle spacing, m.	0.024	3.95
	Relative front vehicle speed, m/sec.	0.136	2.71

	Variable	Parameter values	T-statistic
Path-plan Variables	Path plan impact, more than one lane change required to the next exit.	-2.484	-5.67
	Next exit dummy, lane change(s) required.	-1.525	-2.92
	Exponent of remaining distance, θ_{MLC}.	-1.091	-2.75
	Probability of taking 1st exit, π_1	0.0002	0.01
	Probability of taking 2nd exit π_2	0.057	2.20
Heterogeneity	Coefficient of aggressiveness, Lane 1, α^{lane1}.	1.143	1.35
	Coefficient of aggressiveness, Lane 2, α^{lane2}.	0.271	0.34
	Coefficient of aggressiveness, Lane 3, α^{lane3}.	1.788	8.41
	Coefficient of aggressiveness, Lane 4, α^{lane4}.	0.251	0.32
Lead Critical Gap			
Constant		1.667	5.92
Relative lead speed positive, Max (ΔS_{nt}^{lead},0) , m/sec		-6.376	-3.30
Relative lead speed negative, Min (ΔSntlead,0) , m/sec		-0.154	-2.49
Heterogeneity coefficient of lead gap, α^{lead}		0.099	0.34
Standard deviation of lead gap, σ^{lead}		0.931	4.35
Lag Critical Gap			
Constant		1.394	5.70
Relative lag speed positive, Max (ΔS_{nt}^{lag},0) , m/sec		0.513	5.93
Heterogeneity coefficient of lag gap, α^{lag}		0.211	1.21
Standard deviation of lag gap, σ^{lag}		0.754	5.79

A.2 State Dependence Model with Initial Values for all the Variables

The estimation results of the state dependence model structure using the trajectory data from Arlington, VA are presented in Table A.2. In this model it is proposed an initial value for every variable.

Table A.2 - Estimation results of the state dependence model with initial values for all the variables

	Variable	Parameter values	T-statistic
Target lane Model			
Lane Attributes	Lane 1 constant	-1.845	-3.54
	Lane 2 constant	-0.626	-2.04
	Lane 3 constant	-0.007	-0.04
	Current lane dummy (CL)	3.235	14.18
	More than one lane change from the CL.	-4.146	-2.05
Neighborhood Variables	Front vehicle spacing, m.	0.026	4.17
	Relative front vehicle speed, m/sec.	0.147	2.94
Path-plan Variables	Path plan impact, more than one lane change required to the next exit.	-2.617	-6.28
	Next exit dummy, lane change(s) required.	-1.610	-2.97
	Exponent of remaining distance, θ_{MLC}.	-1.309	-2.63
	Probability of taking 1st exit, π_1	0.0002	0.01
	Probability of taking 2nd exit π_2	0.046	1.99
Heterogeneity	Coefficient of aggressiveness, Lane 1, α^{lane1}.	1.063	0.03
	Coefficient of aggressiveness, Lane 2, α^{lane2}.	0.191	0.01
	Coefficient of aggressiveness, Lane 3, α^{lane3}.	1.704	8.59
	Coefficient of aggressiveness, Lane 4, α^{lane4}.	0.423	0.01

	Variable	Parameter values	T-statistic
State Dependence Variable	Persistence dummy, ρ	0.148	1.20
Initial Conditions Variables	Initial current lane dummy	4.801	1.91
	Initial relative front vehicle speed, m/sec	-0.118	-1.24
	Initial path plan impact, more than one lane change required	-0.763	1.60
	Initial Next exit dummy, lane change(s) required	-0.651	0.36
	Initial front vehicle spacing, m	-0.016	-1.94
	Initial Exponent of remaining distance, θ_{MLC}.	-2.512	-0.27
	Initial Probability of taking 1st exit, π_1	0.0002	0.001
	Initial Probability of taking 2nd exit π_2	0.046	0.001
	Initial lane1 constant	-1.752	0.051
	Initial lane2 constant	-0.982	-0.36
	Initial Lane3 constant	-0.665	-1.01
	Initial More than one lane change from the CL	-4.151	-0.01
Lead Critical Gap			
Constant		1.724	6.05
Relative lead speed positive, Max (ΔS_{nt}^{lead},0) , m/sec		-6.337	-3.29
Relative lead speed negative, Min (ΔSntlead,0) , m/sec		-0.156	-2.50
Heterogeneity coefficient of lead gap, α^{lead}		0.004	0.01
Standard deviation of lead gap, σ^{lead}		0.947	4.33
Lag Critical Gap			
Constant		1.467	5.77
Relative lag speed positive, Max (ΔS_{nt}^{lag},0) , m/sec		0.513	5.66
Heterogeneity coefficient of lag gap, α^{lag}		0.153	0.20
Standard deviation of lag gap, σ^{lag}		0.815	5.99

Bibliography

Ahmed K.I. (1999), Modeling Drivers’ Acceleration and Lane-changing Behavior, PhD Dissertation, Department of Civil and Environmental Engineering, MIT.

Ahmed K.I., Ben-Akiva M., Koutsopoulos H.N. and Mishalani R.G. (1996), Models of Freeway Lane-changing and Gap Acceptance Behavior, in Proceedings of the 13th International Symposium on the Theory of Traffic Flow and Transportation, pp. 501-515.

Aptech System (1994), GAUSS manual, Volume I and II, Maple Valley, WA.

Aptech System (1995), GAUSS applications: maximum likelihood estimation, Maple Valley, WA.

Behbahanizadeh K. and Hidas P. (1999), Microscopic Simulation of Lane-changing under Incident Conditions, in Proceedings of the 14th International Symposium on the Theory of Traffic Flow and Transportation, pp. 53-69.

Ben-Akiva M., Darda D., Jha M., Toledo T. and Koutsopoulos H., (2003) Calibration of microscopic traffic simulation models with aggregate data, Transportation Research Board, 82nd Annual Meeting.

Bertsekas D.P. (1999), Nonlinear programming. Athena Scientific, Belmont MA.

Bolduc D. (2000), Discrete choice models with panel data, Summer Course, MIT.

Choudhury C.F. (2005), Modeling lane-changing behavior in presence of exclusive lanes, Massachusetts Institute of Technology.

Daganzo C.F. (1981), Estimation of gap acceptance parameters within and across the population from direct roadside observation, Transportation Research 15B, pp. 1-15.

Dapzol N. (2005), Driver's behavior modeling using the Hidden Markov Model formalism. Young Researcher Seminar of the European Conference of

Transport Research Institute; Available at: http://www.ectri.org/YRS05/Papiers/Session-1/Dapzol.pdf (accessed November 2006)

FHWA (1985) Freeway Data Collection for Studying Vehicle Interactions, Technical Report FHWA/RD-85/108, Federal Highway Administration, US Department of Transportation, McLean, Virginia.

FHWA (1998), CORSIM User Manual (1.04 ed.), Federal Highway Administration, US Department of Transportation, McLean, Virginia.

Gipps P.G. (1986), A Model for the Structure of Lane-changing Decisions, Transportation Research, 20B, pp. 403-414.

Halati A., Lieu H. and Walker S. (1997), CORSIM – Corridor Traffic Simulation Model, in Proceedings of the Traffic Congestion and Traffic Safety in the 21st Century Conference, pp. 570-576.

Heckman J.J. (1981), Statistical models for discrete panel data. In C.F. Manski and D. McFadden (Ed.), Structural analysis of discrete data with econometric applications, pp. 114-178.

Heckman J.J. (1981), The incidental parameters problem and the problem of initial conditions in estimating a discrete time – discrete data stochastic process. In C.F. Manski and D. McFadden (Ed.), Structural analysis of discrete data with econometric applications, pp. 179-195.

Heckman J. and Navarro S. (2006), Dynamic discrete choice and dynamic treatment effects, Department of Economics, University of Chicago.

Kuge N., Yamamura T., Shimoyama O. and Liu A. (2000), A Driver Behavior Recognition Method Based on a Drive Model Framework, Massachusetts Institute of Technology. In Proceedings of the Society of Automotive Engineers World Congress 2000 (pp. 469–476). New York: Society of Automotive Engineers.

Pentland A. and Liu A. (1999), Modeling and Prediction of Human Behavior, Massachusetts Institute of Technology, Neural Computation 11, 229–242.

Rabiner L.R., Juang B.H. (1986), An Introduction to Hidden Markov Models, IEEE ASSP magazine, pp 4-16.

Toledo T., Koutsopoulos H. and Ben-Akiva M. (2003), Modeling Integrated Lane-changing Behavior, Transportation Research Record 1857, pp 30-38.

Toledo T. (2003), Integrated Driving Behavior Modeling, PhD Dissertation, Department of Civil and Environmental Engineering, MIT.

Toledo T. (2005), Driving Behaviour: models and challenges, Faculty of Civil and Environmental Engineering, Technion – Israel Institute of technology.

Toledo T., Choudhury C.F. and Ben-Akiva M. (2005), Lane-changing models with explicit target lane choice, Transportation Research Board 1934, pp. 157-165.

University of Leeds, A step by step tutorial on Hidden Markov Models. Available at: http://www.comp.leeds.ac.uk/roger/HiddenMarkovModels/html_dev/main.html (accessed November 2006)

Wikipedia, Available at: http://en.wikipedia.org/wiki/Hidden_Markov_Models (accessed April 2008)

Wooldridge J.M. (1999), A framework for estimating dynamic, unobserved effects panel data models with possible feedback to future explanatory variables, Department of Economics, Michigan State University

Wooldridge J.M. (2003), Simple solutions to the initial conditions problem in dynamic nonlinear panel data models with unobserved heterogeneity, Department of Economics, Michigan State University.

Yang Q. and Koutsopoulos H.N. (1996), A Microscopic Traffic Simulator for Evaluation of Dynamic Traffic Management Systems, Transportation Research, 4C, pp. 113-129.

Zou X. and Levinson D. (2006), Modeling Pipeline Driving Behaviors: A Hidden Markov Model Approach (I), TRB 2006 Annual Meeting.

Zhang Y., Owen L.E. and Clark J.E. (1998), A Multi-regime Approach for Microscopic Traffic Simulation, Transportation Research Board, 77th Annual Meeting.

Technion - Israel Institute of Technology
Transportation Research Institute

הטכניון - מכון טכנולוגי לישראל
המכון לחקר התחבורה

תלות מצב במודלים של החלפת נתיבים

מאת

רומינה כ"ץ
תומר טולדו

חיפה, אוגוסט 2008 **דו"ח מחקר מס' 326/2010**

Technion City, Haifa 32000, Israel
Tel. (04) 829 2901 טל.
Fax 972-4-822 5716 פקס
קרית הטכניון, חיפה 32000

הבעות תודה

מחקר זה נעשה בהנחיית דר' תומר טולדו בפקולטה להנדסה אזרחית וסביבתית בטכניון – מכון טכנולוגי לישראל.
ברצוני להביע את הערכתי לדר' תומר טולדו אשר היה לי הכבוד לעבוד איתו. כמו כן, ברצוני להודות לו על ההנחיה, ההכוונה המקצועית, הנגישות, התמיכה התמידית ועל היותו מקור השראה ועמוד השדרה של המחקר. התלהבותו ומאמציו להסביר כל נושא בצורה פשוטה, אפשרו לי להמחיש ולחוות את המודלים. השכלתי רבות ממנו במהלך המחקר הזה.
ברצוני להודות הן למשרד הקליטה על מימון התואר והן לחברה הלאומית לדרכים בישראל על התמיכה במימוש התואר.
מעל הכול, אני מבקשת להודות לבעלי גבריאל על הסבלנות האוהבת, על תמיכתו ועל מתן אוירה מלאת אהבה שאפשרו לי להתפתח. כמו כן, ברצוני להביע את תודתי העמוקה להוריי סליה וחיים על תמיכתם החמה והאינסופית והחיזוק התמידי שאפשר לי לתת את המרב שבי בכל דבר בחיי.
תודתי נתונה גם לאחי יונתן על היחס החברי והאוהב ולאחותי אסתר ומשפחתה הצעירה על היותם שם בכל עת להם נזקקתי.

תקציר

גודש התנועה מהווה בעיה גדולה הן בתחומים עירוניים והן בדרכים בין עירוניות. תופעה זו הינה בעלת השפעה כלכלית שלילית וגורמת הרעה של הניידות, הבטיחות ואיכות הסביבה. פיתוח רשת הדרכים על מנת להתגבר על בעיית הגודש ובתחומי המטרופולינים הגדולים בפרט, מגיע לידי מיצוי של כמעט מלוא הפוטנציאל של זכויות הדרך המוקצות לכך. יתרה מזו, באזורים רבים אילוצים סביבתיים מגבילים את סלילתם של דרכים חדשות או הרחבתן של דרכים קיימות בעתיד.

מתוך כך, בשנים האחרונות גברה החשיבות של ייעול הניהול וניצול מיטבי של התשתיות הקיימות במטרה למזער את הגודש ולמקסם את הבטיחות. מערכות גדולות של ניהול תנועה הוצעו ויושמו. מתודולוגיות ואלגוריתמים שמוצעים לניהול תנועה צריכים לעבור כיול ולהיבחן. ברוב המקרים ניסויי שדה אינם ישימים עקב עלויות גבוהות וחוסר בהסכמה ציבורית. יתר על כן, התועלת במבחני שדה אלו עלולה להיות נמוכה עקב חוסר היכולת לשלוט באופן מלא על התנאים בהם הם מבוצעים. לכן נחוצים כלים לביצוע הערכות אלו במעבדות.

בשנים האחרונות התפתח שימוש נרחב במודלים של מיקרו-סימולציה תנועתית המנתחים בצורה מפורטת את התנהגות הנהג. כתוצאה מכך התעורר צורך במודלים אמינים יותר. המודלים של הסימולציה התנועתית מהווים סינתזה של מודלים שונים השייכים לשתי קבוצות עיקריות: מודלים של בחירת מסלולים ומודלים של התנהגות בנהיגה. המודלים האחרונים חוזים את החלטת הנהג ביחס לתנועת רכבו תחת תנאי תעבורה שונים. תנועת הרכב היא בשני מימדים: תנועה לאורך – תאוצה / מהירות; ותנועה לרוחב – החלפת נתיב. מכאן ברור כי המודלים להחלפת נתיבים הינם מרכיב חשוב במיקרו-סימולציה תנועתית.

מודלים להחלפת נתיבים ממודלים בשני שלבים: בחירה של נתיב להחלפה וההחלטה לבצע החלפת נתיב (קבלת פערים). התהליך של מידול השלב של בחירת הנתיב להחלפה מורכב ביותר מאחר ומצד אחד הינו בלתי נצפה ומצד שני קיימים גורמים רבים המשפיעים על החלטת הנהג. החלק היחידי שניתן לצפייה בתהליך הינו הפעולה המוצלחת של החלפת נתיב. רוב המודלים הקיימים היום מניחים כי הנהגים בוחנים את המצב ומקבלים החלטות בכל רגע מחדש. כלומר, בכל רגע הנהג בוחן את המצב ומחליט על הפעולה המיידית בצורה בלתי תלויה בהחלטות קודמות. אך במציאות, קבלת ההחלטות לאורך הזמן אינן בלתי תלויות אחת מהשנייה. זוהי אחת המגבלות של המודלים הקיימים. בדרך כלל המודלים לא מצליחים לבטא את המורכבות של התנהגות הנהגים, הם לא תופסים את התלות ההדדית בין ההחלטות המתקבלות על ידי אותו נהג לאורך הזמן וכן מייצגים קבלת החלטות מיידית ואינם מבטאים את היכולת של הנהג להתמיד בביצוע ההחלטה שקיבל בזמן קודם.

מטרת המחקר הינה לשפר מודלים קיימים של התנהגות נסיעה על ידי שילוב מאפייני התנהגות כגון התמדה בהחלטות הנהג בעת נסיעתו במודלים של החלפת נתיבים. התנהגות ההתמדה הינה מקובלת באסטרטגיות להחלטות נסיעה (כגון תכנון מסלול, קביעת יעדים, לו"ז

וכו'). מתוך כך, ניתן להניח כי הנהג מתמיד ועקבי גם בניסיונו להשלים את החלפת הנתיב וכן להניח כי ההחלטות שהנהג מקבל לאורך הזמן אינן בלתי תלויות אלא שהינן קשורות בקשר הגיוני ועקבי.

המודל של מרקוב נסתר (Hidden Markov Model – HMM) מיועד לשימוש במקרים שבהם מעוניינים להתחשב במעבר בין המצבים השונים ומשמש למידול סדרות של נתונים. המודלים האלו מתבססים בשתי הנחות עיקריות: קיים הליך נסתר אשר מתפתח ממצב למצב ומאידך הבחינה של הפעולה הנצפית אשר מושפעת מהתהליך יכולה לתרום מידע על הליך זה. המצב הנצפה הינו התוצאה של ההחלטות הקודמות, אשר מהוות המצב הנסתר (Hidden State).

המחקר הנוכחי חוקר את היישום של ה-HMM במודלים של החלפת נתיבים במטרה לכלול את התנהגות התמדת הנהג במודלים. לצורך המחשת הנושא ולדוגמה, נניח שאנו צופים בנהג אשר בשני זמנים רצופים נשאר באותו נתיב, אך איננו יודעים הסיבה שגרמה לו להישאר באותו נתיב: הנהג החליט לא לבצע החלפת נתיב או ייתכן כי הנהג החליט לבצע החלפת נתיב אך לא הצליח לממש אותה. כך, ההליך של בחירת הנתיב הינו נסתר, עובר ממצב למצב ומייצר סדרה של מצבים נסתרים.

רוב העבודות שיישמו את ה-HMM במודלים של החלפת נתיבים, התמקדו בזיהוי כוונת הנהג על ידי צפייה בהתנהגות הנהג תוך כדי ביצוע הפעולה (כגון תאוצה, זווית כיוון הרכב וכו'). יתרה על כך, המודלים הקיימים הצליחו לזהות באם הנהג מבצע פעולה של החלפת נתיב או לא באותו רגע של הצפייה, אך הם לא הצליחו להסביר את המתרחש מאחורי ההתנהגות (למה הפעולה מתבצעת) ולכן הם לא הצליחו לחזות החלפת נתיבים בעתיד. המודל המוצע במחקר זה, מצליח להסביר את התנהגות הנהגים, לחזות החלפת נתיבים וכן מצליח לתפוס את ההתמדה הקיימת בהתנהגות.

ההחלטה לתחילת ההליך של החלפת נתיב וקבלת פערים מושפעים הן ממשתנים הקולטים את התכונות הקיימות סביב הנהג ושל הנהג עצמו והן ממצב ההחלטה של הנהג. במטרה ליישם את ההנחות המפורטות לעיל, עלינו להניח כי לנהג מספר מצבים נסתרים, כאשר לכל אחד מהם מיוחסות הסתברויות למעבר ממצב למצב. כמו כן, קיים צורך לצפות במצב בו נמצא הנהג ולתת מענה המתבסס במודל שיושם על המצב הנוכחי של הנהג. אך המצבים הפנימיים של הנהג אינם ניתנים לצפייה ולכן נוצר צורך להשתמש בהליך של אמידה בלתי ישירה דרך הפעולה הנצפית. לסדרה של הפעולות הנצפות קיים יחס הסתברותי המתקשר עם המצב הבלתי נצפה. ולכן, עלינו למדל את ההליך על ידי שימוש במודל של ה-HMM, אשר מתקיים בו הן הליך בלתי נצפה שמשתנה במהלך הזמן והן פעולות נצפות שקשורות למצבים הבלתי נצפים.

המודלים להחלפת נתיבים מסבירים את בחירת הנהג בשני מימדים: בחירת נתיב להחלפה וקבלת פערים. פונקצית התועלת של הנתיבים תלויה במשתנים מסבירים. המשתנים אמורים לבטא את התנאים השוררים בכל אחד מהנתיבים, את הצורך של הנהג לממש את תכנית המסלול ואת הידע וההכרות של הנהג עם קטע הכביש. בדרך כלל קיים חוסר במידע על תכונות הנהגים והרכבים (כגון תוקפנות, מיומנות בנהיגה, יכולת של הרכב להשיג מהירויות ותאוצה וכו'). לכן,

נעשה שימוש במודל במשתנה לטנטי שמבטא את התכונות האישיות של הנהג בפונקצית התועלת במטרה לקלוט את הקורלציות בין תצפיות של אותו נהג שנוצרות בגלל תכונות האופי שלו.

התלות במצב הקודם יוצרת תלות במצב ההתחלתי של כל המערכת. אך במודל המוצע התלות הינה במצב בלתי נצפה ולכן המצב ההתחלתי אינו נצפה. בנוסף לכך, התצפית הראשונה של בסיס הנתונים אינה תואמת להתחלה האמיתית של ההליך, אלא היא נקבעה על ידי המיקום והתכונות של מערכת איסוף הנתונים. במטרה להתגבר על בעיה זו, יושם הפיתרון המוצע על ידי Heckman (1981), אשר מבצע קירוב של המצב ההתחלתי כתלות בשגיאה הקשורה למשתנה לטנטי וספציפי של האינדיבידואל (הנהג). כך, המודל מאפשר לפונקצית התועלת של התצפית הראשונה להיות שונה מיתר התצפיות על מנת לתפוס בעקיפין את התלות במצב ההתחלתי הלא ידוע. .

בכדי לבצע החלפת נתיב נהג הרכב בוחן את הפערים הקיימים וממתין לפער מספיק גדול, על מנת לעבור אל הנתיב אליו הוא חפץ להגיע. ברגע שהפער נמצא מתאים על ידי הנהג (פער גדול יותר מהפער הקריטי) התחלת החלפת הנתיב מתבצעת (הנהג מחליף לנתיב השמאלי או הימני), אחרת הנהג אינו מבצע את החלפת הנתיב (הנהג נשאר בנתיב הנוכחי). התהליך הזה מפתח את הפעולה הנצפית של החלפת הנתיב.

המודל נאמד באמצעות בסיס נתונים של מסלולי נסיעה מפורטים של רכבים, אשר נאספו בשנת 1983 בקטע של כביש בין-ארצי (I-395) בוירג׳יניה באורך 997 מטר ובחתך של 4 נתיבים. הקטע כולל רמפה כניסה ושתי רמפות יציאה מקטע הדרך ומהווה קטע השתזרות שמאפשר לבחון את ההשפעות של תכנון המסלול על התנהגות הנהיגה. הנתונים נאספו באמצעות תצלום אוויר של הקטע במשך שעה ברזולוציה של תמונה אחת בשנייה. הנתונים המעובדים כוללים מידע על המיקום, הנתיב והמימדים של כל רכב בקטע בכל שנייה. הנתונים מייצגים תחום רחב של מצבי תעבורה. טווח המהירויות הינו בין 0.40 מ/שנייה ל-25 מ/שנייה. טווח הצפיפות הינו בין 14.2 רכב/ק״מ/נתיב ל-55.0 רכב/ק״מ/נתיב. רמת השרות בקטע הינה D-E.

בדיקת יכולת ההסבר של כל אחד מהמשתנים בוצעה בעזרת הסטטיסטי t (חלוקת המקדם שנאמד בסטיית התקן שלו) אשר חושב לכל אחד מהם. כמו כן, נבדק ההיגיון בגודלו ובכיוונו של ערך האומד של המשתנה בפונקצית התועלת. תוצאות האמידה של המודל של החלפת נתיב מראות כי החלטת הנהג להחלפת נתיבים מושפעת ממשתנים שונים כמפורט:

- משתנים המבטאים את תכונות הנתיבים, כגון מרחק של הנתיב הנוכחי עד לנתיב המיועד להחלפה והתכונות המיוחדות של הנתיב עצמו ;
- משתנים המבטאים את מאפייני התעבורה בנתיבים השונים, כגון המהירות של הרכב המקדים;
- משתנים המבטאים את תכנון המסלול, כגון האם הנהג חייב לצאת ביציאה הקרובה על מנת להמשיך בדרכו ליעד;
- משתנים המבטאים את תכונות הנהג כגון תוקפנות;

- משתנים המבטאים את התלות במצב הקודם, כגון הנתיב שהנהג בחר כנתיב להחלפה בתקופת הזמן הקודמת.

המשתנה האחרון שברשימה הינו המשתנה התופס את התלות הקיימת בין ההחלטות שהנהג מקבל במהלך הזמן. התוצאות מראות שהמשתנה הינו מובהק וכיוון ערך האומד שלו הינו חיובי בהתאם לצפוי. כלומר, במידה והנהג בחר בנתיב מסוים בתקופת זמן קודמת כך גדלה ההסתברות לבחור באותו נתיב בזמן הנוכחי. המשתנה מצליח לבטא את ההתמדה הקיימת בהתנהגות הנהג.

תוצאות האמידה של המודל גם מראות כי ההחלטות לבצע החלפת הנתיבים (קבלת הפערים) מושפעים מהמהירות היחסית של הרכב עצמו לרכבים הסובבים אותו בנתיב הסמוך בכיוון הנתיב המיועד להחלפה.

על מנת להגביר את כושר המודל המוצע יש לחקור את ההשפעה של החלפת נתיב על זרימת התנועה, על ידי הטמעת המודל במיקרו-סימולציה תנועתית. כמו כן, קיים צורך במחקרים נוספים בכדי לזהות השפעות עם בסיסי נתונים שונים ממקומות אחרים בעולם.

תוכן עניינים

תוכן עניינים (המשך)

רשימת איורים

רשימת טבלאות