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A Discretionary Lane Changing Decision Model Based On Fuzzy Inference System

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Dedication

This dissertation is dedicated to GOD and to my parents, for all their love, patience, kindness and support.

The members of my dissertation committee have generously given their time and expertise to better my work. I thank them for their contribution and their good-natured support.

A DISCRETIONARY LANE CHANGING DECISION MODEL BASED ON FUZZY INFERENCE SYSTEM

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Abstract

A lane changing event involves up to five vehicles: the subject vehicle, preceding and following vehicles in the original lane, and the preceding and following vehicles in the target lane. Understanding the behavior of the subject vehicle with respect to the surrounding vehicles is fundamental to the study of the safety of a lane change maneuver and for the modeling of lane changing behavior. First, the statistical properties of 10 lane changing parameters were defined and studied using the Next Generation SIMulation (NGSIM) vehicle trajectory data collected at the I-80 Freeway in Emeryville, California, and then tested with data collected at the U.S. Highway 101 in Los Angeles, California. The results show that all the parameters are positively correlated with each other; the gaps and distance are best described by the log-normal distribution; the time to collisions are best described by the Laplace probability distribution; the speed is best described by the logistic distribution. This dissertation then presents a Fuzzy Inference System (FIS) which models a driver's binary decision to or not to execute a discretionary lane changing move on freeways. It answers the following question "Is it time to begin to move into the target lane?" after the driver has decided to change lane and have selected the target lane. The system uses four input parameters: the gap between the subject vehicle and the preceding vehicle in the original lane, the gap between the subject vehicle and the preceding vehicle in the target lane, the gap between the subject vehicle and the following vehicle in the target lane, and the distance between the preceding and following vehicles in the target lanes. The input parameters were selected based on the outcomes of a drivers survey, and can be measured by sensors instrumented in the subject vehicle. The FIS was trained with NGSIM vehicle trajectory data collected at the I-80 Freeway in Emeryville, California, and then tested with data collected at the U.S. Highway 101 in Los Angeles, California. The test results show that the FIS system made lane change recommendations of "yes, change lane" with 82.2% accuracy, and "no, do not change lane" with 99.5% accuracy. These accuracies are better than the same performance measures given by the TRANSMODELER's gap acceptance model for

discretionary lane change, which is also calibrated with NGSIM data. The developed FIS has a potential to be implemented in lane change advisory systems, in autonomous vehicles, as well as microscopic traffic simulation tools.

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Chapter 1: Introduction

1.1 Background

A vehicle's two-dimensional motion on a highway surface may be decomposed into the longitudinal and lateral movements. The longitudinal movement in the same lane, in the presence of vehicles ahead (the preceding vehicle) and behind (the following vehicle), is termed by traffic flow researchers as car-following. On the other hand, the lateral movement, which is always accompanied with a longitudinal movement, is known as lane changing. Lane changing model is as important as car-following model as the fundamental building blocks in microscopic traffic simulation tools [FHWA, 1995; PTV 2007; Quadstone 2009; TSS 2002; Caliper 2011]. The impact of lane change on traffic safety has been frequently investigated [Winsum et al. 1999; Hunt 1994; Thiemann 2008; Zheng et al. 2014]. Obviously, driver workload and stress are likely to significantly increase during the lane change; this makes driving more error-prone, and thus, more dangerous. For instance, approximately 539,000 two-vehicle lane change crashes occurred in the U.S. in 1999 [Li et al. 2006]. The microscopic driving behavior is also related to macroscopic property of traffic flow [Laval and Daganzo 2006; Zhao et al. 2013]. In the advent of semi-autonomous and autonomous vehicles, the understanding and accurate modeling of car-following and lane changing behavior is critical to the safe operations of these vehicles and the surrounding traffic. Although car-following has been studied by researchers in more than 50 years, relatively fewer examinations on lane changing behavior have been made. The reason could be due to the facts that (i) a lane change involves two-dimensional motions; and (ii) there are relatively more (up to five) vehicles involved in a lane changing event. In contrast, car-following involves two vehicles, one following another in the same lane. Therefore, the study of lane change is more complex and challenging than car-following.

In general, there are two types of lane change in freeways: mandatory and discretionary. Mandatory lane change is also known as forced or necessary lane change. It occurs when a vehicle is trying to move from the left or center lane to the rightmost lane in order to exit the freeway. Mandatory lane change also happens when a vehicle has just entered the freeway from an on-ramp and is trying to move to the center or left lane to travel at a faster speed or to avoid a downstream exit lane. Discretionary lane change is also known as free lane change or desired lane change. It occurs when a driver is following another vehicle at a speed slower than his/her desired speed and therefore seeks to increase its speed by moving to an adjacent lane. Obviously, the motivations and resulting driving behavior for the two types of lane change are different. Therefore, a driver is expected have different decision rules and/or risking taking behavior for the two types of lane change.

A discretionary lane change might be modeled as a four-step process: (1) motivation; (2) selection of target lane; (3) checking for opportunity to move; and (4) the actual move, as shown in Figure 1.1 [Caliper 2011]. The beginning and end of the four steps are marked by times t_1, t_2, t_3, t_4 and t_5, respectively, where $t_1<t_2<t_3<t_4<t_5$. At time t_1, the driver begins to feel uncomfortable driving in the original lane. Between t_1 and t_2, external stimulus motivates him/her to want to change lane. At t_2, he/she has made up his mind to change lane, and begins to look for a target lane (on the left or on the right). At t_3, the target lane is selected. From t_3 onwards, the driver actively seeks an opportunity in the target lane to make a move. He/she begins the lateral move at t_4. The lateral move is completed at time t_5.

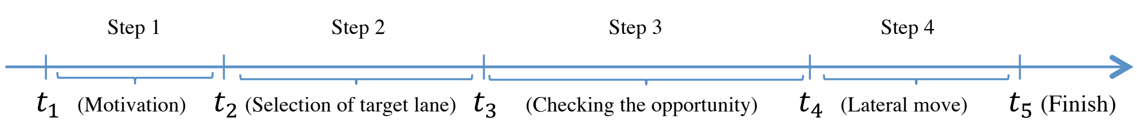


Figure 1.1: Steps in a discretionary lane change

The traditional lane changing decision models rely mainly on deterministic mathematical equations and/or rules to replicate drivers' decisions. These models do not consider the uncertainties of drivers' perception and decisions [McDonald et al. 1997; Das and Bowels 1999].

Traditional lane changing decision models are based on crisp magnitudes of parameters [Das and Bowels 1999; Das et al. 1999]. This is in contrast to the real world in which drivers make their decisions based on imprecise perceptions of the surrounding traffic [Ma 2004]. In recent years, several approaches have become popular to address the inadequacies of traditional models. Because of their theoretical benefits and proven performance, there is strong interest in approaches which are based on Artificial Intelligence (AI), particularly fuzzy logic. Fuzzy logic incorporates a degree of uncertainty in the decision making process and therefore, reflects the drivers' natural or subjective perceptions of the inputs which influence their decisions. Therefore, the fuzzy logic approach is used in this research to model the lane changing decision process from t_3 to t_4.

There are several issues in the existing lane changing models. The first issue is that the models are largely based on how the modelers perceive drivers would make lane changing decisions, rather than on the general user's driving experience. Only a few developers of the existing lane changing models have identified factors and developed lane changing rules based on video evidence e.g., Hidas, [2002, 2005], or by interviewing drivers e.g., [Sun and Elefteriadou 2010].

A second issue is that a lane change decision is often modeled as a one-player (the lane changer) decision-making process. However, our observations and experience tell a different story: in heavy traffic, a typical lane change decision making process involves at least two players – the lane changer and the follower in the target lane. This is because the follower in the target lane is often required to make decisions as a result of someone else's lane change decision. Thus, at least two decision making players and processes are involved in the lane changing process in heavy traffic.

Another issue with the existing models is that failed lane changing attempts are often ignored in calibrating and validating the models due to the lack of data; thus, current lane change models do not have the capability of reproducing failed attempts [Laval and Leclercq 2006].

A final note on lane changing modeling is that a proposed model should be developed for either for freeways or for urban streets. Although lane changes on freeways and those on urban streets have different necessities, few models are developed specifically for either freeways or urban streets.

In this dissertation, the issues of driver feedback, failed lane changing attempts will be addressed. A lane changing decision model will be developed for freeways driving.

1.2 Objective

The objective of this research is to develop an improved discretionary lane changing decision model using the fuzzy logic approach. More specifically, a Fuzzy Inference System (FIS) is constructed to replicate a driver's decisions in the third step to the four-step discretionary lane changing process; that is, from t_3 to t_4, checking for an opportunity in the target lane to begin a lateral move. The model will answer the question "Is it time to start moving into the target lane?"

1.3 Significance of Research

Compared to past researches, this research will be the first one to conduct a driver survey to select drivers' discretionary lane changing decision parameters, and construct fuzzy sets, fuzzy rules based on the results of the questionnaire survey. This research will also be the first one to construct fuzzy membership functions using the statistics of vehicle interactions during discretionary lane changing maneuvers extracted from a national database of vehicle trajectories (NGSIM database). With these approaches, the developed FIS model is expected to be more accurate than the past models.

This research will demonstrate the potential of FIS in modeling discretionary lane changing decisions on freeways. In addition, the FIS will outperform the existing TRANSMODELER's gap acceptance model (which is developed for discretionary lane change, and calibrated with the same data sets used in this research). This research will demonstrate that FIS has better accuracy than this competitor in making “yes, change lane” and “no, do not change lane” recommendations.

Once developed, the model may be programmed into traffic simulation models as part of the lane changing module, or in lane changing advisory systems in actual vehicles. It also has the potential to be programmed into autonomous vehicles. The research has the potential to improve freeway safety by reducing the number of crashes due to incorrect lane changing decisions.

1.4 Scope

This research is limited to the following scope:

1. The FIS developed so far is for passenger cars as the subject vehicles;
2. It only concerns with discretionary lane change;
3. In this research, only NGSIM database will be used. Because the NGSIM data does not include demographic and psychological information of the drivers, the developed lane changing decision model does not include the motivation to change lane and the selection of the target lane. However the motivation will be included as part of the questionnaire survey (and the target lane can be infer from the stated motivation). This additional information will be collected but not analyzed as part of this dissertation. It may be used for future research.

1.5 Outline of Dissertation

In Chapter 2, the existing lane changing models are classified into models in microscopic traffic simulation tools, conventional lane changing models and fuzzy logic based lane changing models, according to their characteristics and applications. The lane changing decision models are reviewed and the general procedure for model development and the parameters considered by each model are identified. In addition, the strengths and weaknesses of the lane changing decision models are summarized. Finally, the major limitations of the existing lane changing decision models are highlighted.

This literature review is followed by a description of the NGSIM database used in this research in Chapter 3 and the processing of the NGSIM database. Furthermore, the data is analyzed statistically. The statistical correlations and probability distributions of the data later help the author in selecting the parameters, the maximum and minimum value of the fuzzy membership functions.

An exclusive FIS lane changing model is introduced and developed in Chapter 4. This chapter first reports a survey conducted to understand drivers' lane changing behavior and to understand the important lane changing parameters used by drivers in practice. This chapter then outlines the approach for developing a fuzzy logic lane changing model by defining fuzzy sets, fuzzy membership functions, fuzzy rules, composition of rules and defuzzification to have crisp outputs.

The FIS lanes changing models is tested in Chapter 5 with the use of two data sets (Datasets A and B) derived from the processed NGSIM database. Furthermore, a comparison of performance between the developed FIS model and the lane changing model in the TANSMODELER simulation tool is made.

Finally, Chapter 6 summarizes the findings of this dissertation, potential applications, contributions, limitations and discusses future research directions.

Chapter 2: Literature Review

This chapter reviews discretionary lane changing models, with special focuses on driver's decision making process and the parameters used to make a decision. This first sub-section reviews lane changing models in microscopic traffic simulation tools. Conventional and fuzzy lane changing models are reviewed in the next sub-sections. At the end of this chapter the lane changing parameters are summarized.

2.1 Lane Changing Models in Microscopic Traffic Simulation Tools

This section reviews the lane changing models in popular microscopic traffic simulation tools: FRESIM, VISSIM, PARAMICS, AIMSUN and TRANSMODELER.

The lane changing model in FRESIM [FHWA 1995] is described in its predecessor INTRAS's development report [Wicks and Lieberman 1980]. There are two types of lane change in FRESIM: free lane change and forced lane change. A free lane change is sought when a subject vehicle is traveling below its *desired speed* and it can gain speed by moving to an adjacent lane. If the above condition is met, a binary decision to change lane is generated according to a pre-defined probability and assigned to the subject vehicle. Once a decision has been made to change lane, to successfully execute a free lane change, the subject vehicle must satisfy the following rules: (i) the *lead headway* in the target lane must satisfy a "non-collision constraint"; and (ii) the *lag headway* in the target lane must also satisfy the non-collision constraint. Considering only two lane changing parameters without giving any scientific reason could be the other weakness.

VISSIM [PTV 2007] classifies lane changes into free lane change and necessary lane change. In the case of a free lane change, the VISSIM's lane changing model checks if the available *distance* between the subject vehicle and the following vehicle in the target lane satisfies the "desired safety distance". It also checks to make sure that the *time headway* between the subject vehicle and the following vehicle in the target lane exceeds the "minimum time headway". For a lane change in a queue, the model also checks the *time headway* between the subject vehicle and the preceding vehicle in the target lane.

PARAMICS does not distinguish between mandatory lane change and discretionary lane change. The lane changing model in PARAMICS is based on the gap acceptance theory [Duncun n.d.]. A vehicle is allowed to move from its original lane to the target lane if both (i) the *gap* (in distance unit) between the subject vehicle and the preceding vehicle in the target lane; and (ii) the *gap* (in distance unit) between the subject vehicle and the following vehicle in the target lane must exceed their respective minimum threshold values. The minimum threshold values are functions of *relative speed* of the following and preceding vehicle in the target lane and *desired headway*. PARAMICS requires considerable input data.

AIMSUN [TSS 2002] describes a vehicle's lane changing decision making process in terms of necessity, desirability and possibility to change lane. The necessity to change lane includes the need to overtake the existing leader to travel at a faster speed. Therefore it is broader than the causes of mandatory lane change. If it is necessary to change lane, the AIMSUN's logic checks if an adjacent lane's *speed* and *gap* are desirable (i.e., faster speed, and longer gap between the preceding and following vehicles). If the conditions are both necessary and desirable, the logic next looks for a *gap* in the target lane to make a safe maneuver. To distinguish between discretionary and mandatory lane changes, AIMSUN divides a freeway segment upstream of an off-ramp into three zones, where discretionary lane changes take place in the most upstream zone. The length of the zones is a function of the *speed limit* and individual vehicle's *desired speed*. AIMSUN was found to be highly sensitive to the reaction time value.

TRANSMODELER [Caliper 2011] uses the discrete choice approach in the modeling of a driver's lane changing decision. The TRANSMODELER software considers two types of lane change: discretionary and mandatory. A discretionary lane change is considered when a driver is dissatisfied with the current speed. There are two discretionary lane changing models: neighboring lane model and target lane model. The neighboring lane model, as its name suggests, has the target lanes adjacent to the original lane. In contrast, the target lane model moves the subject vehicle by more than one lane. In the neighboring lane model, the logit model calculates the probabilities of a driver selecting each available lane (left or right adjacent lane). Once a target lane has been selected, the subject vehicle seeks a suitable gap in the target lane to merge into. The gap acceptance parameters (attributes) considered are *lead gap* and *lag gap*. The coefficients of the gap acceptance parameters have been calibrated with NGSIM data [Caliper 2011].

The gap acceptance model was the only one that could be compared to the FIS because this model determines t_4 (the moment of start of lane changing move) and calibrated with NGSIM data. Once a vehicle has decided to change lanes, it will look for a gap in the selected target lane and decide whether it is safe to execute the lane change. Whether the gap is considered acceptable by the subject vehicle is determined by a gap acceptance model that compares the measured gap against the minimum "acceptable" gap required. The gap acceptance model divides the gap in the target lane into two gaps: a *lead gap* (G_{PA}) and a *lag gap* (G_{FA}).

There are three gap acceptance models in TRANSMODELER. The first is a linear model and the second is a non-linear model. The third is a model developed and calibrated with NGSIM data. All the three models are a function of the lead and lag gaps. The third model is described in detail here because it will be used to compared with the proposed FIS model.

The model calibrated with NGSIM data is based on the gaps between the subject vehicle and the lead and lag vehicles in the target lane. The critical gaps are calculated by the following formula [Choudhury 2007]:

$$G_i^g = \exp\left(\beta^g X^g + \alpha^g V_i + \varepsilon_i\right) \qquad (2.1)$$

where:

G_i^g = Minimum acceptable lead or lag gap g for driver i;

g = {lead, lag};

i = time instance;

which the formula could be rewritten as:

$$G_i^{lead} = \exp\,(\beta_0^{lead} + \beta_1^{lead} X_1^{lead} + \beta_2^{lead} X_2^{lead} + \beta_3^{lead} X_3^{lead} + \alpha^{lead} V_i + \varepsilon_i) \quad (2.2)$$

$$G_i^{lag} = \exp\,(\beta_0^{lag} + \beta_1^{lag} X_1^{lag} + \beta_2^{lag} X_2^{lag} + \alpha^{lag} V_i + \varepsilon_i) \quad (2.3)$$

where:

β_0^{lead} = Constant = 1.0;

β_0^{lag} = Constant = 1.5;

β_1^{lead} = Coefficient of X_1^{lead} = 1.541;

β_1^{lag} = Coefficient of X_1^{lag} = 1.426;

β_2^{lead} = Coefficient of X_2^{lead} = 6.21;

β_2^{lag} = Coefficient of X_2^{lag} = 0.64;

β_3^{lead} = Coefficient of X_3^{lead}= 0.13;

X_1^{lead} = Max {0, $(V_S - V_{PA})$};

X_1^{lag} = Max {0, $(V_S - V_{FA})$};

X_2^{lead} = Min {0, $(V_S - V_{PA})$};

X_2^{lag} = V_{FA};

X_3^{lead} = V_S;

V_S = Speed of the subject vehicle;

V_{FA} = Speed of the following vehicle after lane changing;

V_{PA} = Speed of the preceding vehicle after lane changing;

α^{lead} = Coefficient of the individual driver-specific variable V_i = -0.008;

α^{lag} = Coefficient of the individual driver-specific variable V_i = -0.205;

V_i = Individual driver-specific random variable which is assumed to have a normal distribution with mean 0 and variance 1. V_i is the same for one vehicle and different with the other vehicles. $-3 \leq V_i \leq 3$,

ε_i = Random term associated with the driver at i. which is assumed to have a normal distribution with mean 0 and variance 0.854.

Critical lead and lag gaps calculated from the above formulas are called G_i^{lead} and G_i^{lag}, respectively. On the other hand, lead and lag gaps measured from the actual driving are denoted by $G_{PA}$and G_{FA}, respectively. These two gaps should be compared to make a lane changing decision.

IF

$$G_{PA} > G_i^{lead} \text{ AND } G_{FA} > G_i^{lag}$$

THEN

Decision = 1 or "yes, change lane"

ELSE

Decision = 0 or "no, do not change lane"

2.2 Conventional Lane Changing Models

Gipps [1986] is perhaps one of the earliest to document a lane change study in a signalized street. The driver's decision making framework consists of the possibility, necessity and desirability to change lane. He then proposed a lane changing model encompassing mandatory and discretionary lane changes. The decision parameters for discretionary lane change included the subject vehicle's *safe speed*, the *relative speed* between the following and preceding vehicles in the target lane, and *gap* (headway between preceding and following vehicle). The contribution of Gipps is in the formulation of the decision process. The decision making framework is later used in AIMSUN. However, he only conducted an experiment via computer simulation. Gipps did not mention why he only considered distance and speed as lane changing parameters and even no framework for estimation of the model's parameters was proposed. He assumes that the lane changing occurs when a gap of sufficient length is available and it is safe to change lane which causes some limitations in congested traffic conditions.

After observing video recordings of 73 lane changing maneuvers in arterials in Sydney, Australia, Hidas [2005] concluded that the accepted gaps in the target lane is closely related to the *relative speed* between the preceding and following vehicles. He classified lane changes into free, forced and cooperative lane changes based on the *space gap in front* and *space gap behind* the subject vehicle in the target lane. Regardless of the type of lane change, the logic proposed by Hidas [2005] makes use of *space gap in front* and *space gap behind*. He considered gap as the main important parameter for his model only with no reason.

Kesting et al. [2007] used a linear combination of *accelerations* of the subject vehicle, the follower in the original lane and the follower in the target lane to form an incentive criterion for lane change. This lane changing model is based purely on acceleration rates.

Yeo et al. [2008] proposed an oversaturated freeway flow algorithm which consists of a lane change model. The algorithm has two types of lane change: mandatory and discretionary. The purpose of a discretionary lane change is for the subject vehicle to increase speed or to improve its position in the traffic stream. The parameters for discretionary lane change are *average speed difference*, *average speed of vehicles in the target lane*, *free-flow speed* of subject vehicle and *speed* of the subject vehicle.

Schakel et al. [2012] combined incentives to follow a route, to gain speed and to keep right into a single lane change desire value, from which three types of lane change (free, synchronized and cooperative) are distinguished. The proposed lane changing model, which is based on the gap acceptance concept, incorporates car-following acceleration/deceleration in decision making. The lane change decision making process included seven parameters: *relax headway*, *route desire*, *anticipated speed*, *speed desire*, *keep-right desire*, *combine desires*, and *gap-acceptance*. The model has been calibrated with loop detector data collected at the A20 Motorway near Rotterdam, Netherlands.

Hill and Elefteriadou [2013] studied the lane changing behavior of drivers in instrumented vehicles driving on I-4 Freeway in Orlando, Florida, and I-95 Freeway in Jacksonville, Florida. The *time for a lane changing maneuver*, *desired speed*, *lead gap* (defined as the distance between the subject vehicle and the preceding in the target lane) and *lag gap* (defined as the distance between the subject vehicle and the following in the target lane) were recorded for 321 discretionary lane changes. They found that the Gamma distribution provided the best fit for the lag gap. However, the Johnson SI distribution provided the best fit for the lead gap.

Hou et al. [2014] proposed a model of mandatory lane change using Bayes classifier and decision trees. Vehicle trajectory data from the NGSIM database were used to develop and to test the model. Time mean speed was the only parameter that the author used to make the model.

2.3 Fuzzy Logic Lane Changing Models

The models reviewed in Sections 2.1 and 2.2 do not incorporate the inconsistencies and uncertainties of drivers' perception and decisions. These models are based on crisp parameters magnitudes. Most of the traditional lanes changing decision models (as reviewed above) use crisp mathematical equations and conventional logic to represent drivers' knowledge of the surrounding traffic and to model the drivers' lane changing decisions. Random terms are included in some of these models to capture the variation of the parameters. The random terms are mainly Gumbel or normally distributed [Ahmed 1999; Choudhury et al. 2007; Toledo 2009].

However, drivers make decisions based on their imprecise perceptions of the surrounding traffic. In recent years, fuzzy logic based approaches have been applied to lane change models because they overcome the shortcoming of rigid conventional models. One of the benefits of fuzzy logic is that it incorporates uncertainty in the model and therefore, reflects the natural or subjective perception of real parameters [Ma 2004].

Das and Bowles [1999] and Das et al. [1999] proposed a fuzzy logic lane changing model in a new microscopic simulation methodology called Autonomous Agent SIMulation Package (AASIM). The major motivation of using a fuzzy knowledge based approach to model drivers' decisions is that fuzzy models provide an effective means to change highly nonlinear systems into IF-THEN rules. In addition, fuzzy logic is well equipped to handle uncertainties in real world traffic situations. They classified the lane changing maneuvers as MLC (Mandatory Lane Change) and DLC (Discretionary Lane Change). The DLC rules of AASIM reflect a binary decision (to change lane or not) which is based upon two explanatory parameters. These two explanatory parameters are the driver's speed satisfaction level, and the level of congestion in the left or right adjacent lanes. The inputs to the fuzzy rules are *gap* size and *vehicle speed in the target lane*, and *headway to the front vehicle in the current lane*. In AASIM, no specific lane changing decision model was considered for each vehicle type.

Moridpour et al. [2009; 2012] proposed a fuzzy logic model of lane changing for heavy vehicles. *Front space gap*, *rear space gap* and the *average speed of the surrounding vehicles* in the current lane are the parameters which used in the model. The microscopic analysis of the lane changing maneuvers has showed that the fuzzy logic model more accurately replicated the microscopic lane changing behavior of the heavy vehicle drivers. Not considering light vehicles (cars) besides of not considering the parameters in the target lane could be the weaknesses of the study.

McDonald et al. [1997], Brackstone et al. [1998] and Wu et al. [2000] have developed a fuzzy logic motorway lane changing simulation model and have established fuzzy sets and systems for their model. To model the lane changing decision, they classified the lane changing maneuvers into two categories: (a) lane changes to the near-side (shoulder) lane, mainly performed to prevent disturbing the fast-moving vehicles that approach from the rear; and (b) lane changes to the off-side (median) lane, mainly performed with the aim of gaining speed advantages. Their decision model uses two parameters: (a) pressure from the rear, which is *the time headway of the rear vehicle*; and (b) *gap* satisfaction in the near-side lane, the period of time during which it would be possible for the subject vehicle driver to stay in the selected gap in the near-side lane, without reducing speed. To establish the off-side lane-changing decision model, they defined two parameters: (a) overtaking benefit, the speed advantage when an off-side lane-changing maneuver is executed; and (b) opportunity, which reflects the safety and comfort of the lane-changing maneuver, measured by the time headway to the first lag vehicle in the off-side lane. They estimated the number of lane changing maneuvers and the percentage of lane occupancy for each lane at different traffic flow rates. The estimated results were then compared with the observations in the field data. The results showed that the differences between the observed and estimated measurements are in the range of 0–11%. Fuzzy rules are constructed to make use of *time headways of the rear vehicle*, and *time headway to the first lag vehicle in the faster lane* as inputs.

2.4 Lane Changing Parameters

After considering the mentioned studies on lane changing, the lane changing parameters are summarized in Table 2.1. This table does not included parameters such as tailgated, gap (headway between preceding and following vehicle) and speed limit of highway that are only used only in one model. The acceleration terms are excluded because it is difficult for a driver to perceive a second order term in making a lane change decision. The remaining parameters are renamed to make the terms more consistent in this dissertation. Seven of the eight parameters may be derived from the NGSIM vehicle trajectory data. The maximum, safe or desired speed of vehicle (or driver) cannot be deduced from the NGSIM data and therefore this parameter is not used in the dissertation.

Table 2.1: Summary of Lane Changing Parameters Reviewed.

Simulation model and/or reference	Front gap (distance)	Rear gap (distance)	Lead time to collision	Lag time to collision	Distance in target lane	Max, safe, free-flow or desired speed	Current speed of subject vehicle	Relative speed
FRESIM			Yes	Yes		Yes		
VISSIM		Yes		Yes				
PARAMICS	Yes	Yes						Yes
AIMSUN					Yes	Yes	Yes	
TransModeler	Yes	Yes						
Gipps (1986)					Yes		Yes	Yes
McDonald (1997); Brackstone (1998); Wu (2000)				Yes	Yes			
Das (1999); Das and Bowles (1999)			Yes		Yes			Yes
Hidas (2005)	Yes	Yes						
Yeo (2008)						Yes	Yes	Yes
Schakel(2012)			Yes	Yes	Yes	Yes	Yes	Yes
Moridpour (2009; 2012)	Yes	Yes						Yes
Hill and Elefteriadou (2013)	Yes	Yes				Yes		

As mentioned in Introduction, there are five vehicles in a lane change scenario. The active player is the subject vehicle *S*. This vehicle moves from its original lane to the target lane. Figure 2.5 shows the critical instant in a lane changing maneuver when *S* crosses the lane markers. The vehicle in front of *S* in the original lane is called the preceding vehicle before lane change, denoted as *PB*. The vehicle behind *S* in the original lane is called the following vehicle before lane change, denoted as *FB*. After the lane change, the subject vehicle inserts itself in the target lane between the preceding vehicle (denoted as *PA*) and the following vehicle (denoted as *FA*). The longitudinal positions of *S*, *PB*, *FB*, *PA*, *FA*, measured with reference to the center of each vehicle, are represented by Y_S, Y_{PB}, Y_{FB}, Y_{PA}, Y_{FA}, respectively. The lengths of *S*, *PB*, *FB*, *PA* and *FA* are denoted as L_S, L_{PB}, $L_{FB,}$ L_{PA} and L_{FA} respectively. There are 10 possible parameters which are described below.

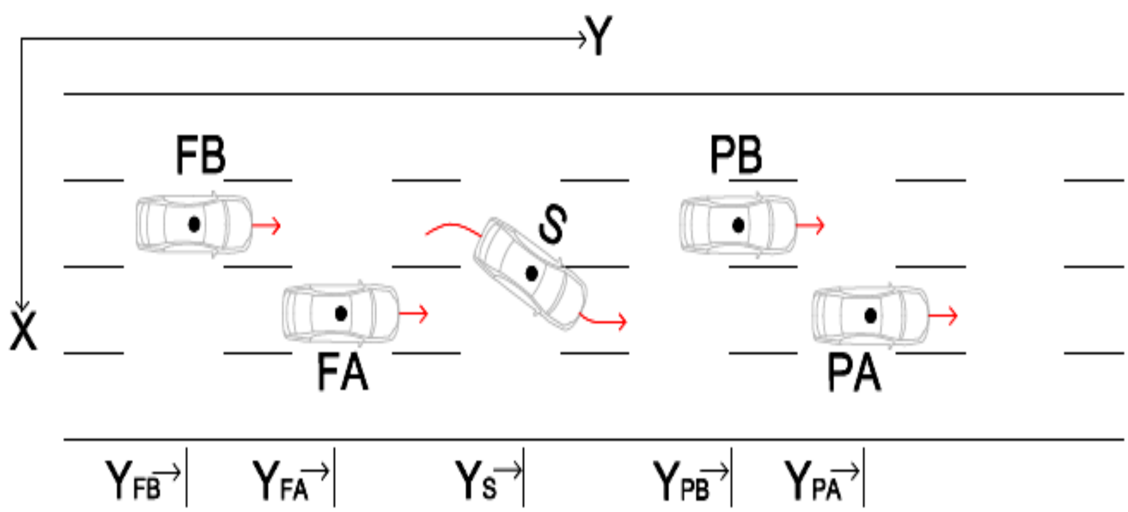


Figure 2.1: Vehicles and their positions during a lane change.

The following parameters are of interest and are defined in this dissertation as:

- Front gap before lane change (in meters):

$$G_{PB} = \left(Y_{PB} - \frac{1}{2}L_{PB}\right) - \left(Y_S + \frac{1}{2}L_S\right), \qquad G_{PB} \geq 0 \tag{2.4}$$

- Rear gap before lane change (in meters):

$$G_{FB} = \left(Y_S - \frac{1}{2}L_S\right) - \left(Y_{FB} + \frac{1}{2}L_{FB}\right), \qquad G_{FB} \geq 0 \tag{2.5}$$

- Front gap after lane change (in meters):

$$G_{PA} = \left(Y_{PA} - \frac{1}{2}L_{PA}\right) - \left(Y_S + \frac{1}{2}L_S\right), \qquad G_{PA} \geq 0 \tag{2.6}$$

- Rear gap after lane change (in meters):

$$G_{FA} = \left(Y_S - \frac{1}{2}L_S\right) - \left(Y_{FA} + \frac{1}{2}L_{FA}\right), \qquad G_{FA} \geq 0 \tag{2.7}$$

- Lead time-to-collision before lane change (in seconds):

$$T_{PB} = \frac{G_{PB}}{V_S - V_{PB}}, \qquad -\infty \leq T_{PB} \leq +\infty \tag{2.8}$$

- Lag time-to-collision before lane change (in seconds):

$$T_{FB} = \frac{G_{FB}}{V_{FB} - V_S}, \qquad -\infty \leq T_{FB} \leq +\infty \tag{2.9}$$

- Lead time-to-collision after lane change (in seconds):

$$T_{PA} = \frac{G_{PA}}{V_S - V_{PA}}, \qquad -\infty \leq T_{PA} \leq +\infty \tag{2.10}$$

- Lag time-to-collision after lane change (in seconds):

$$T_{FA} = \frac{G_{FA}}{V_{FA} - V_S}, \qquad -\infty \le T_{FA} \le +\infty \qquad (2.11)$$

- Distance (in meters):

$$D = \left(Y_{PA} - \frac{1}{2}L_{PA}\right) - \left(Y_{FA} + \frac{1}{2}L_{FA}\right), \qquad D \ge 0 \qquad (2.12)$$

The speed of the subject vehicle V_S (in meter/second) is also analyzed.

In defining the gaps and headways, the subscript *P* denotes the preceding vehicle, *F* denotes the following vehicle; while *B* represent the lane before lane change (the original lane), and *A* represent the lane after lane change (the target lane). In addition to the parameters identified in the literature review, the gaps and headways before a lane change are added in the analysis so as to study the proximity of the three associated vehicles (*S*, *PB*, *FB*) immediately before the subject vehicle leaves its original lane. The headways are defined such as a positive value indicates a risk of collision. This is similar to time-to-collision in traffic conflict analysis. Ten potential parameters are listed in Table 2.2.

Table 2.2: Parameters that describe vehicle interactions in a lane change.

Notation	Definition	Unit	Range
G_{PB}	Gap between vehicle *S* and vehicle *PB*	m	≥0
G_{FB}	Gap between vehicle *S* and vehicle *FB*	m	≥0
G_{PA}	Gap between vehicle *S* and vehicle *PA*	m	≥0
G_{FA}	Gap between vehicle *S* and vehicle *FA*	m	≥0
D	Distance between vehicle *PA* and *FA*	m	≥0
T_{PB}	Time-to-collision between vehicle *S* and vehicle *PB*	s	-∞ to +∞
T_{FB}	Time-to-collision between vehicle *S* and vehicle *FB*	s	-∞ to +∞
T_{PA}	Time-to-collision between vehicle *S* and vehicle *PA*	s	-∞ to +∞
T_{FA}	Time-to-collision between vehicle *S* and vehicle *FA*	s	-∞ to +∞
V	Speed of vehicle *S*	m/s	≥0

2.5 Summary

There are several issues with the current lane changing models. The first issue is that the models are largely based on how the modelers perceive drivers would make lane changing decisions, rather than drivers' personal experience. Very few articles describe how the input parameters for the lane changing models were selected and of the few which reported the parameter selection process and the reasons of their selection, none was based on feedback provided by drivers. Among the existing lane change models, only a few have identified parameters and developed lane changing rules based on video evidence, e.g., Hidas, [2002, 2005], or by interviewing drivers e.g., Sun and Elefteriadou, [2011, 2012].

Another issue with the existing models is that failed lane changing attempts are often ignored in the model calibration and validation processes. Thus, current lane change models may not have the capability of reproducing failed attempts with sufficient accuracy [Laval and Leclercq, 2008]. At the minimum, the capability has not been validated and reported.

A final note on lane change modeling is that a proposed model should be developed specifically either for freeways or for urban streets. This is because lane changes on freeways and those on urban streets have different motivations.

Additional important findings from the literature review, which affect the decisions on the FIS design in the subsequent chapters are (i) some of the parameters (e.g., desired speed) cannot be estimated autonomously by sensors embedded in vehicles, or are related to the driver's psychology which render the model implementation difficult if not impossible; (ii) some models use relative speed as an input, which is not a direct measure of risk compared to time-to-collision; (iii) different models use of different sets of input parameters, some of which are not available, or can be derived from available data, such as the NGSIM database; (iv) for most of the models, the computational steps or knowledge base necessary for the implementation are not clearly described, which causes difficulty in implementing these models for comparative evaluation.

Because of the complexity of the lane changing behavior, all of the above research issues cannot be addressed in this dissertation. This dissertation focuses on:

1- Conducting a survey to ask respondents (drivers) about the parameters used and to understand which parameters are the most important ones;
2- Developing model for one player and the player is the subject vehicle;
3- Developing a model only for freeways;
4- Using parameters which are available and can be computed from the NGSIM directly.

Chapter 3: Vehicle trajectory dataset

The NGSIM database used in this research is explained in this chapter. The database provides sufficient vehicle lane changing maneuvers to support the development of a lane changing decision model on freeways. In this chapter, the available passenger car lane changing maneuvers are processed and the parameters (as defined in Chapter 2) analyzed statistically. Also, a correlation analysis is performed to find out which lane changing parameters are related to each other. At the end, probability distributions are fitted to the data to later help the author in selecting the maximum and minimum value of the fuzzy membership function.

3.1 NGSIM Database

The vehicle trajectory data analyzed in this chapter and later used to develop the FIS was taken from the NGSIM database. The NGSIM project is a data collection effort funded by Federal Highway Administration (FHWA) for the development and/or validation of new traffic models. In this research, the vehicle trajectory date collected at a segment of I-80 Freeway (Eisenhower Highway) in Emeryville, California [Cambridge 2005a] and a segment of U.S. Highway 101 (Hollywood Freeway) in Los Angeles, California [Cambridge 2005b] was used. For each of the freeway segments, vehicle motions were captured by several video cameras located on top of a tall building. The video images were post-processed to extract vehicle trajectory data at 0.1 second intervals. The data was downloaded from the NGSIM project website for further processing as described in Section 3.2.

The I-80 Dataset, as shown in Figure 3.1, was collected over a 1650 ft. segment, in the northbound direction between the Powell Street on-ramp and Ashby Street off-ramp. This segment of the freeway has six lanes between the ramps. The available data was collected on April 13, 2005 from 4:00-4:15 p.m., 5:00-5:15 p.m. and 5:15-5:30 p.m. In this dissertation, the data from 4:00-4:15 p.m. was used because it has the highest number of lane changes among the three 15-minute periods.

The U.S. 101 data was collected over a 2100 ft. segment, in the southbound direction between the Ventura Boulevard on-ramp and Cahuenga Boulevard off-ramp. This segment of the freeway also has six lanes between the ramps. The available data was collected on June 15, 2005 from 7:50-8:05 a.m., 8:05-8:20 a.m. and 8:20-8:35 a.m. In this dissertation, the data from 7:50-8:05 a.m. was used because it also has the highest number of lane changes among the three 15-minute periods.

For each of the freeway segments, vehicle motions were captured by several video cameras placed on top of a tall building. The video images were post-processed to extract vehicle trajectory data at 0.1 second intervals, and make available to researches via the NGSIM project website [Cambridge 2005a, 2005b].

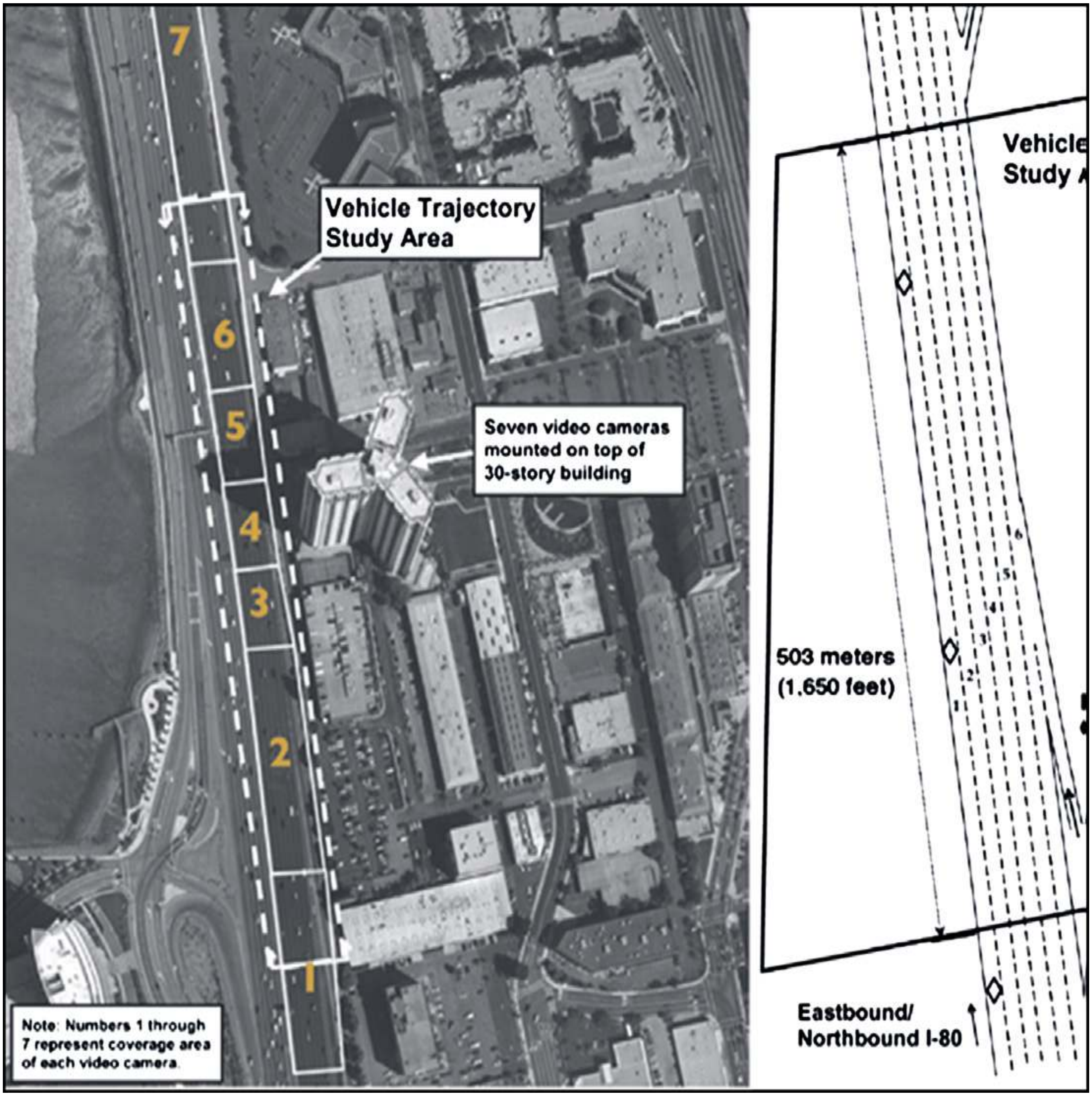


Figure 3.1: The I-80 Dataset Collection Site.

[http://ops.fhwa.dot.gov/trafficanalysistools/ngsim.htm]

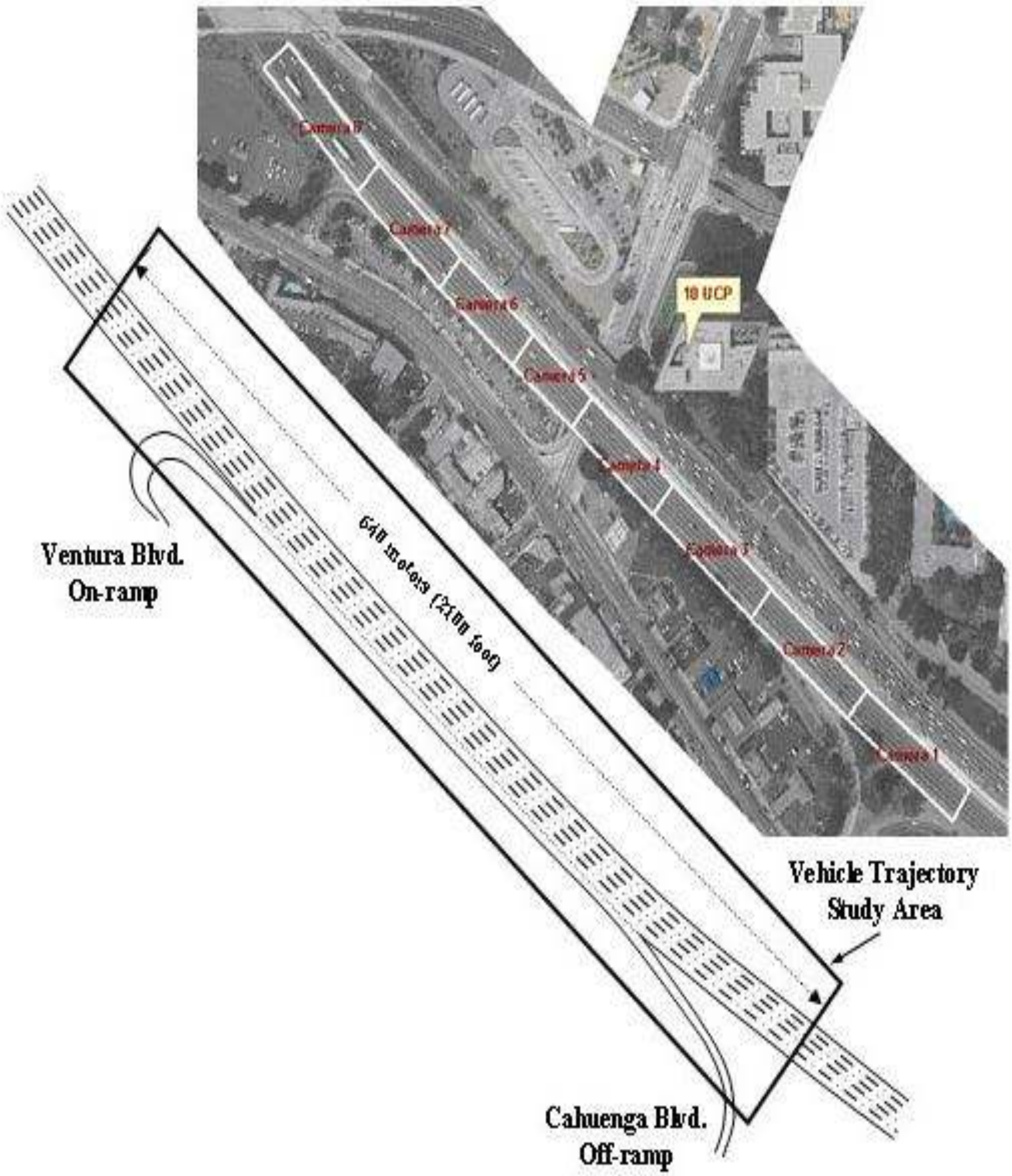


Figure 3.2: The US 101 Dataset Collection Site.

[http://ops.fhwa.dot.gov/trafficanalysistools/ngsim.htm]

3.2 Data Processing

The NGSIM data was processed by means of MATLAB (MathWorks 2014). The vehicle trajectory data was processed as follows:

- Only passenger cars were selected as the subject vehicles. Trucks and motorcycles, which were believed to have different lane changing behavior, and also have smaller sample sizes, were not considered.
- Only the subject vehicles originally travelled in lanes 2, 3 and 4 were considered. Vehicles in lanes 5 and 6 were not considered so as to eliminate the possibility of drivers executing mandatory lane changes after entering from the upstream on-ramp or to exit at the downstream off-ramp. Similarly, subject vehicles in lane 1 were not considered as it is a high occupancy vehicle lane.
- Vehicles making multiple lane changes were excluded. This was because any lateral movement of more than one lane is more likely a mandatory move.
- For each identified *S*, the time t_4 was taken as the first instance when the front center of the *S* had lateral velocity of at least 0.2 m/s. This criteria is taken from Wang et al. [2014].
- Once t_4 has been determined, the positions of vehicles *PB*, *FB*, *PA*, *FA*, that surrounded *S* were identified, and the input parameters were calculated at t_4-0.4, t_4-0.3, t_4-0.2, t_4-0.1 and t_4 seconds respectively, according to the procedure recommended by Punzo et al. [2011]. The average parameter values from t_4-0.4 to t_4 (five 0.1 second intervals) were used as the values perceived by the driver at t_4. The reasons for taking the average value over 0.5 second are (i) to reduce the error caused by using instantaneous values in the NGSIM data; (ii) to be more consistent with driver's perception time; and (iii) to be consistent with other research that has used NGSIM data, for example Siuhi and Kaseko [2010].
- The method of averaging data was repeated at 0.5 second intervals at, before and after t_4. Therefore, every *S* has multiple input vectors for the FIS at 0.5 second intervals.

- The Observed Maneuver (*OM*) was coded as 1 for lane change at t_4, and 0 for all other vectors. The observed maneuvers of $OM = \{0, 1\}$ were used to compare with FIS's recommendations to evaluate the FIS's performance.
- The above steps were repeated for passenger cars in lanes 2, 3 and 4 that did not change lane.

Because a lane changing event involves five vehicles (as shown in Figure 2.1), not all the five vehicles may appeared in the data collection segment and captured by the video cameras. Therefore, it may not be possible to calculate all the parameters for a lane change from the available NGSIM data. For example, if a subject vehicle changed lane near the downstream end of a freeway segment, the preceding vehicles (*PB* and *PA*) may already have left the camera view.

In this case, it is impossible to calculate the parameters associated with these two vehicles.

3.3 Descriptive Statistics

Table 3.1 lists the descriptive statistics of the 10 parameters analyzed. The gaps and distance are processed to 0.001 m precision; headways are processed to 0.1 second precision while speed is processed to 0.01 m/s precision. After data processing, the I-80 Dataset and U.S. 101 Dataset each has approximately sample size of 160 (from 15 minutes of video). The sample sizes for the different parameters are different, because not all the five vehicles involved in a lane change appear in NGSIM's camera view. For the same parameter, the mean and maximum values obtained from the I-80 Dataset are smaller than the corresponding values in the U.S. 101 Dataset. For example, for G_{FA}, the rear gap after lane change, the I-80 Dataset has a mean of 16.377 m while the U.S. 101 Dataset has a mean of 21.77 m. This is because the traffic condition in the I-80 data set was more congested than the traffic condition in the U.S. 101 Dataset. In the I-80 Dataset, the traffic volume was 8144 vph and the average space mean speed was 17.86 mph. In the U.S. 101 Dataset, the volume was 8642 vph and the average space mean speed was 25.66

mph. With using @RISK software [Palisade 2013], the processed data was fitted with a probability distribution.

Table 3.1: Descriptive statistics of lane changing parameters

(a) I-80 Dataset 4:00 p.m. to 4:15 p.m.

Parameters	G_{PB}	G_{FB}	G_{PA}	G_{FA}	T_{PB}	T_{FB}	T_{PA}	T_{FA}	D	V_S
Unit	m	m	m	m	s	s	s	s	m	m/s
Sample size	163	158	153	146	163	149	161	153	149	163
Min value	3.032	0.697	0.101	0.166	-185.2	-183.7	-179.0	-77.54	5.12	1.503
Max value	76.893	46.705	105.45	57.741	182.61	182.52	75.92	81.98	153.61	13.879
Mean	15.867	14.166	12.76	16.377	-0.190	1.59	-2.66	4.29	30.00	7.885
Median	13.906	13.244	8.75	12.806	3.34	0.828	-0.732	3.44	25.82	7.788
Std deviation	9.325	7.490	13.37	12.379	39.49	48.03	23.77	20.73	18.72	2.256

(b) U.S. 101 Dataset 7:50 a.m. to 8:05 a.m.

Parameters	G_{PB}	G_{FB}	G_{PA}	G_{FA}	T_{PB}	T_{FB}	T_{PA}	T_{FA}	D	V_S
Unit	m	m	m	m	s	s	s	s	m	m/s
Sample size	152	163	140	159	141	144	141	155	141	171
Min value	2.650	3.976	0.700	0.310	-117.8	-118.0	-142.5	-177.9	10.49	6.311
Max value	82.948	101.351	116.67	122.01	180.55	157.56	167.44	143.61	139.48	23.692
Mean	19.712	26.286	19.29	21.77	6.80	-7.51	-0.100	-4.25	43.45	14.953
Median	14.998	22.748	13.39	17.90	5.74	-11.17	-3.81	-1.95	38.54	14.833
Std deviation	13.585	16.048	18.30	17.71	39.86	40.61	34.60	36.68	22.40	3.602

3.4 Correlation Analysis

A correlation analysis was performed for all the parameters in each data set. The purpose of the correlation analysis was to examine if there is any strong relationship between any two parameters so that some of the parameters that have strong correlations with each other may be excluded as subsequent input to the FIS lane changing decision model. In a correlation analysis, all the parameters must have the same sample size and be paired. The data was then filtered such that only the lane changes which produced all the parameter values were used in the correlation analysis. This filtering resulted in sample sizes of 122 for the I-80 Dataset and 142 for the U.S. 101 Dataset. The correlation coefficients, or r value, calculated by MINITAB [2010], are presented in Table 3.2. All the r values are significantly different from 0, with p-values all less than 0.001.

The minimum r value for both I-80 and U.S. 101 Datasets are 0.736. This indicates that some of the 10 parameters in both dataset are strongly correlated. The differences in the correlation matrices between the two data sets are indications that drivers in these two sites have different lane changing behavior.

Figure 3.2 shows the scatter plots of the parameters produced by MINITAB. The scatter plots of two parameters in each data set are presented in a 10 by 10 matrix. The diagonal elements of the matrix indicate the parameter names in the horizontal and vertical axles. The scatter plots visualize the correlations as listed in Table 3.2. Visually, all gap parameters for the I-80 Dataset and U.S. 101 Dataset are strongly correlated.

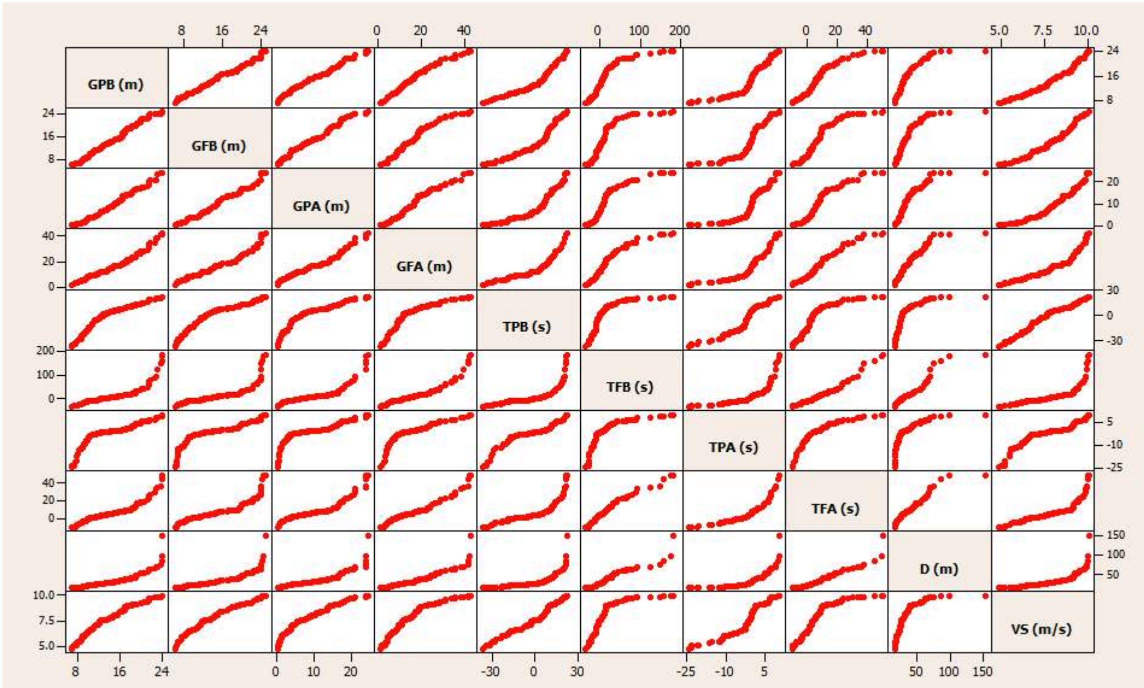
Table 3.2: Correlation matrices of lane changing parameters

(a) I-80 Dataset 4:00 p.m. to 4:15 p.m.

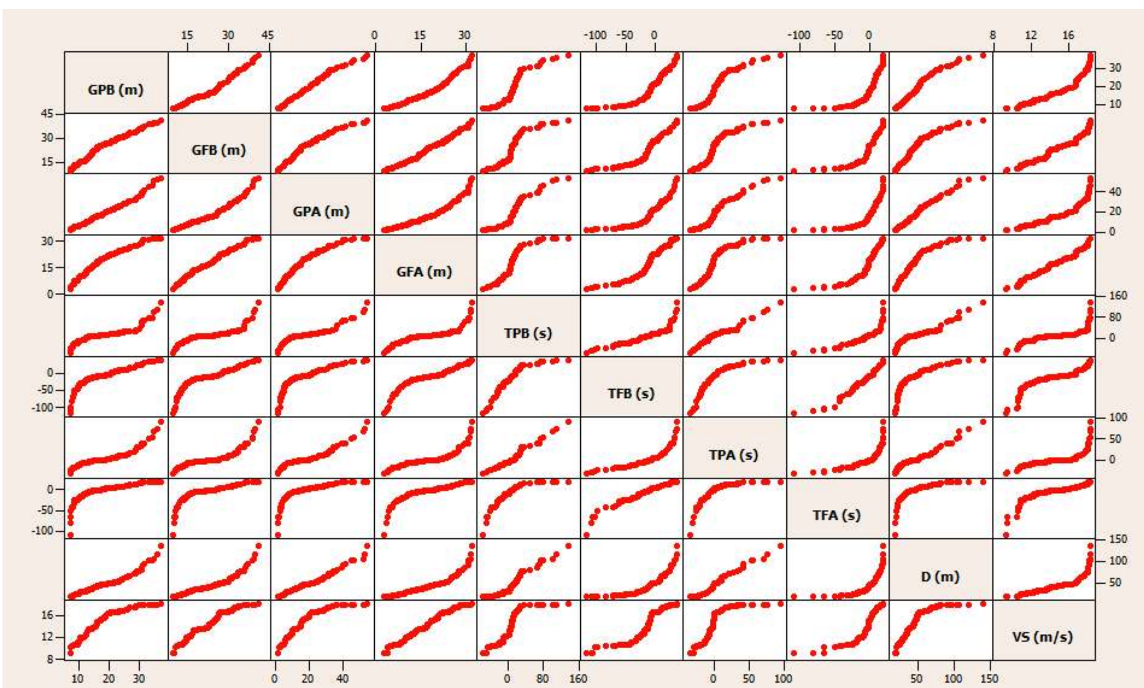
Parameters	G_{PB}	G_{FB}	G_{PA}	G_{FA}	T_{PB}	T_{FB}	T_{PA}	T_{FA}	D	V_S
G_{PB}	1	0.996	0.995	0.984	0.942	0.867	0.889	0.935	0.871	0.979
G_{FB}	0.996	1	0.993	0.976	0.942	0.843	0.884	0.918	0.856	0.981
G_{PA}	0.995	0.992	1	0.985	0.917	0.875	0.857	0.934	0.879	0.966
G_{FA}	0.984	0.976	0.985	1	0.891	0.932	0.860	0.975	0.921	0.939
T_{PB}	0.942	0.942	0.917	0.891	1	0.741	0.948	0.836	0.739	0.982
T_{FB}	0.867	0.843	0.875	0.932	0.741	1	0.754	0.980	0.957	0.790
T_{PA}	0.889	0.884	0.857	0.860	0.948	0.754	1	0.846	0.736	0.935
T_{FA}	0.935	0.918	0.934	0.975	0.836	0.980	0.846	1	0.957	0.879
D	0.871	0.856	0.879	0.921	0.739	0.957	0.736	0.957	1	0.796
V_S	0.979	0.981	0.966	0.939	0.982	0.790	0.935	0.879	0.796	1

(b) U.S. 101 Dataset 7:50 a.m. to 8:05 a.m.

Parameters	G_{PB}	G_{FB}	G_{PA}	G_{FA}	T_{PB}	T_{FB}	T_{PA}	T_{FA}	D	V_S
G_{PB}	1	0.984	0.994	0.974	0.912	0.871	0.932	0.780	0.974	0.947
G_{FB}	0.984	1	0.972	0.995	0.895	0.898	0.893	0.821	0.944	0.980
G_{PA}	0.994	0.972	1	0.958	0.936	0.853	0.957	0.760	0.989	0.922
G_{FA}	0.974	0.995	0.958	1	0.891	0.925	0.877	0.857	0.925	0.991
T_{PB}	0.912	0.895	0.936	0.891	1	0.889	0.980	0.821	0.958	0.846
T_{FB}	0.871	0.898	0.853	0.925	0.889	1	0.846	0.973	0.833	0.915
T_{PA}	0.932	0.893	0.957	0.877	0.980	0.846	1	0.753	0.981	0.823
T_{FA}	0.780	0.821	0.760	0.857	0.821	0.973	0.753	1	0.736	0.860
D	0.974	0.944	0.989	0.925	0.958	0.833	0.981	0.736	1	0.880
V_S	0.947	0.980	0.922	0.991	0.846	0.915	0.823	0.860	0.880	1



(a) I-80 Dataset



(b) U.S. 101 Dataset

Figure 3.2: Matrix plots of lane changing parameters

3.5 Probability Distributions

The processed data as reported in Table 3.1 had been fitted with probability distributions using @RISK [Palisade, 2013]. For each parameter, at least 10 distributions were considered. The Akaike Information Criterion (AIC) was used to select the distributions that provide the best fit to the observed data. AIC is an indicator for the goodness of fit that takes into account the number of estimated distribution parameters. For each lane changing parameter, the top three distributions that best fit the observed data are listed in Table 3.3. All the distributions listed in Table 3.3 provide good fit to the data, with *p*-values all smaller than 0.01.

From the results of distribution fitting presented in Table 3.3, the 10 lane changing parameters studied have different probability distributions that provide the best fit. It is preferably to have one probability distribution that can describe the gaps (G_{PB}, G_{FB}, G_{PA}, *and* G_{FB}), times to collision (T_{PB}, T_{FB}, T_{PA}, T_{FB}), distance (D) and speed (V_S) respectively. Laplace distribution provides the best fit to all the times to collision. Therefore, it is chosen as the recommended distribution. To select one probability distribution for the gaps, a numeric scoring system was used, in which the distributions that provide the best, second best and third best fits were assigned scores of three, two and one, respectively. The distribution that has the highest total score was recommended. Both the log-logistic and lognormal distributions have the same total score. The lognormal distribution is recommended because it appears in the top three lists for all the gap parameters. As for distance D, there is a clear winner which is the lognormal distribution. As for the subject vehicle's speed V_S, the logistic distribution is selected as it appears in the top three distribution list of both the I-80 Dataset and U.S. 101 Dataset. The recommended probability distributions are listed in Table 3.3. The distribution parameters, calculated from the method of moment, are also listed in the table.

The lognormal distribution has a probability density function of

$$f(x|\lambda, \zeta) = \frac{1}{\sqrt{2\pi}\zeta x} e^{-\frac{1}{2}\left(\frac{\ln x - \lambda}{\zeta}\right)^2} \quad X > 0 \tag{3.1}$$

Where λ ($\lambda > 0$) is the location parameter while ζ ($\zeta > 0$) is the scale parameter. The Laplace distribution has a probability density function of

$$f(x|\mu, b) = \frac{1}{2b} e^{\frac{|x-\mu|}{b}} \quad -\infty \leq X \leq \infty \tag{3.2}$$

which is symmetrical about its mean μ. The variable μ is known as the location parameter while b ($b > 0$) is known as the scale parameter. The part of the Laplace distribution with $X \geq \mu$ has the same shape as the exponential distribution. The logistic distribution has a probability density function of

$$f(x|\mu, s) = \frac{e^{-\frac{x-\mu}{s}}}{s\left(1+e^{-\frac{x-\mu}{s}}\right)^2} \quad X > 0 \tag{3.3}$$

The logistic distribution has two parameters: μ, the location parameter, and s ($s > 0$), the scale parameter. The recommended probability distributions are listed in Table 3.3.

Table 3.3: Fitted probability distributions of lane changing parameters

(a) I-80 Dataset 4:00 p.m. to 4:15 p.m.

Parameters	G_{PB}	G_{FB}	G_{PA}	G_{FA}	T_{PB}	T_{FB}	T_{PA}	T_{FA}	D	V_S
Unit	m	m	m	m	s	s	s	s	m	m/s
Best fit	Log-logistic	Log-normal	Gamma	Weibull	Laplace	Laplace	Laplace	Laplace	Log-normal	Logistic
2nd best fit	Pearson 5	Pearson 5	Inverse Gaussian	Log-normal	Logistic	Logistic	Logistic	Logistic	Pearson 5	Normal
3rd best fit	Log-normal	Inverse Gaussian	Log-normal	Gamma	Normal	Log-logistic	Weibull	Log-logistic	Log-logistic	Weibull
Recommended	Log-normal	Log-normal	Log-normal	Log-normal	Laplace	Laplace	Laplace	Laplace	Log-normal	Logistic
Log-normal location parameter λ	2.616	2.528	2.176	2.57	-	-	-	-	3.237	-
Log-normal scale parameter ζ	0.545	0.497	0.861	0.672	-	-	-	-	0.573	-
Laplace location parameter μ	-	-	-	-	-0.190	1.59	-2.66	4.29	-	-
Laplace scale parameter b	-	-	-	-	27.92	33.96	16.81	14.66	-	-
Logistic location parameter μ	-	-	-	-	-	-	-	-	-	7.885
Logistic scale parameter s	-	-	-	-	-	-	-	-	-	1.243

(b) U.S. 101 Dataset 7:50 a.m. to 8:05 a.m.

Parameters	G_{PB}	G_{FB}	G_{PA}	G_{FA}	T_{PB}	T_{FB}	T_{PA}	T_{FA}	D	V_S
Unit	m	m	m	m	s	s	s	s	m	m/s
Best fit	Pearson 5	Log-normal	Inverse Gaussian	Log-logistic	Laplace	Laplace	Laplace	Laplace	Log-normal	Logistic
2^{nd} best fit	Log-logistic	Pearson 5	Log-normal	Log-normal	Log-logistic	Log-logistic	Log-logistic	Logistic	Pearson 5	Pearson 5
3^{rd} best fit	Log-normal	Inverse Gaussian	Pearson 5	Pearson 5	Logistic	Logistic	Logistic	Normal	Pearson 5	Normal
Recommended	Log-normal	Log-normal	Log-normal	Log-normal	Laplace	Laplace	Laplace	Laplace	Log-normal	Logistic
Log-normal location parameter λ	2.78	3.11	2.639	2.827	-	-	-	-	3.654	-
Log-normal scale parameter ζ	0.634	0.563	0.801	0.713	-	-	-	-	0.485	-
Laplace location parameter μ	-	-	-	-	6.80	-7.51	-0.100	-4.25	-	-
Laplace scale parameter b	-	-	-	-	27.48	28.72	24.47	25.94	-	-
Logistic location parameter μ	-	-	-	-	-	-	-	-	-	14.953
Logistic scale parameter s	-	-	-	-	-	-	-	-	-	1.986

The histogram distributions of all the parameters were next plotted. Figure 3.3 plots the histogram distribution of G_{FA}, taken from I-80 Dataset, and the fitted distribution is lognormal. Visually, the distribution is well fitted. To ensure that the lognormal distribution chosen for G_{FA} is appropriate, the cumulative ascending fit was determined using @RISK. Figure 3.4 plots the cumulative ascending curve. The histogram distribution of T_{FA}, is shown in Figure 3.5, and the fitted distribution is Laplace. Visually, the distribution is well fitted. To ensure that the Laplace distribution is appropriate, the cumulative ascending fit was determined and is shown in Figure 3.6.

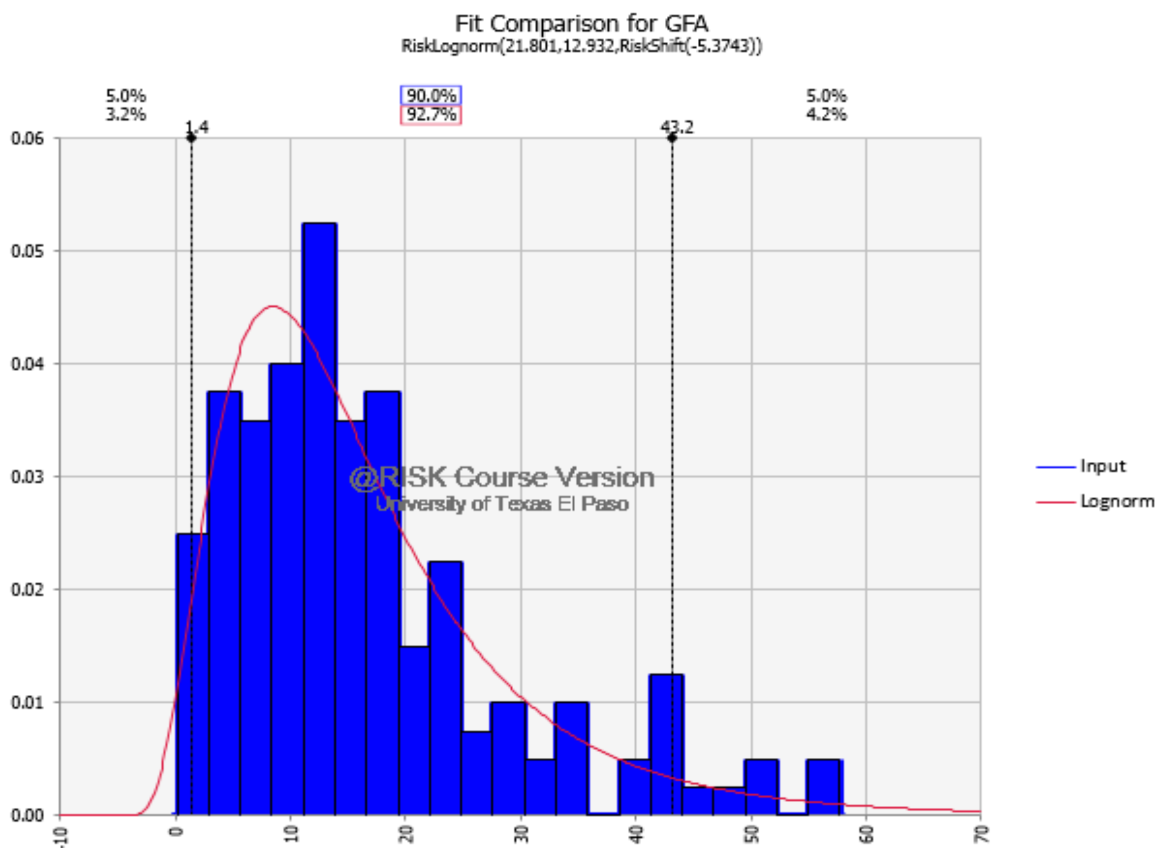


Figure 3.3: Observed and fitted probability distributions of G_{FA} from I-80 Dataset

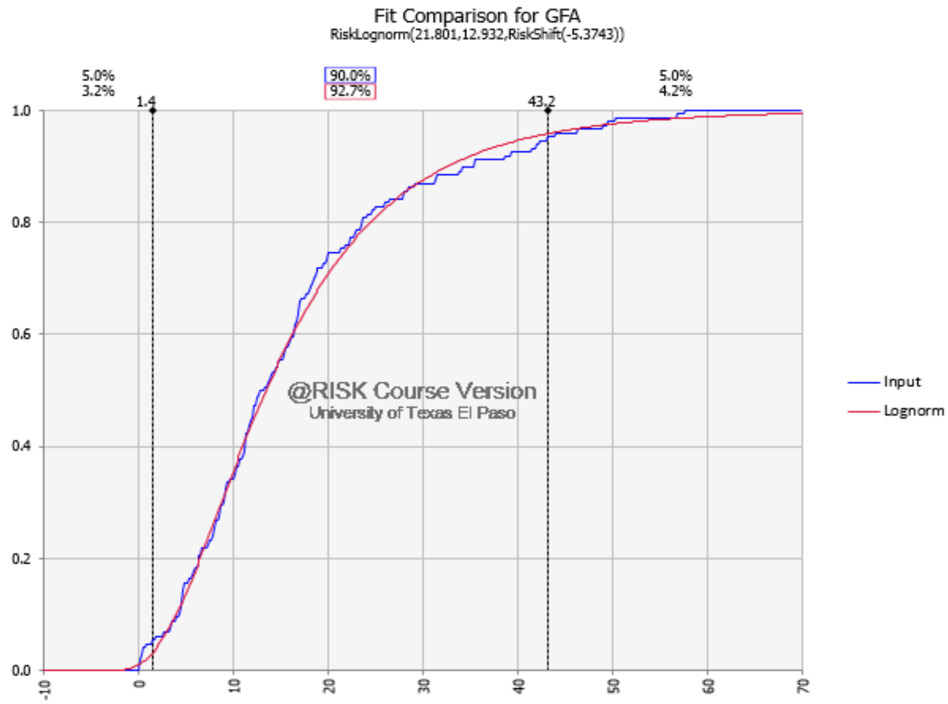


Figure 3.4: Observed and fitted cumulative ascending of *GFA* from I-80 Dataset

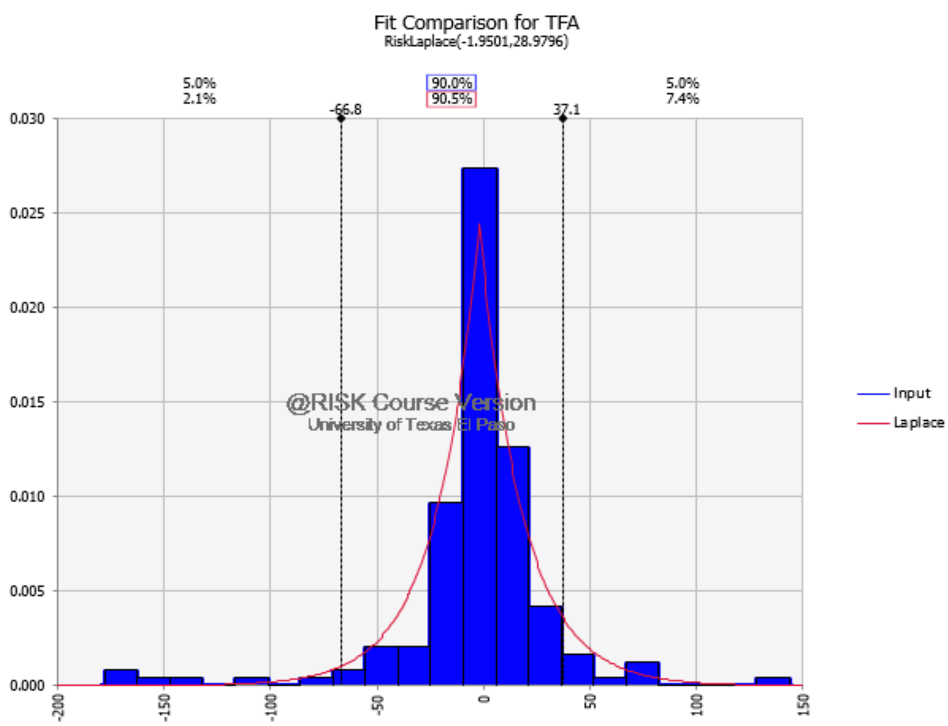


Figure 3.5: Observed and fitted probability distributions of *TFA* from U.S. 101 Dataset

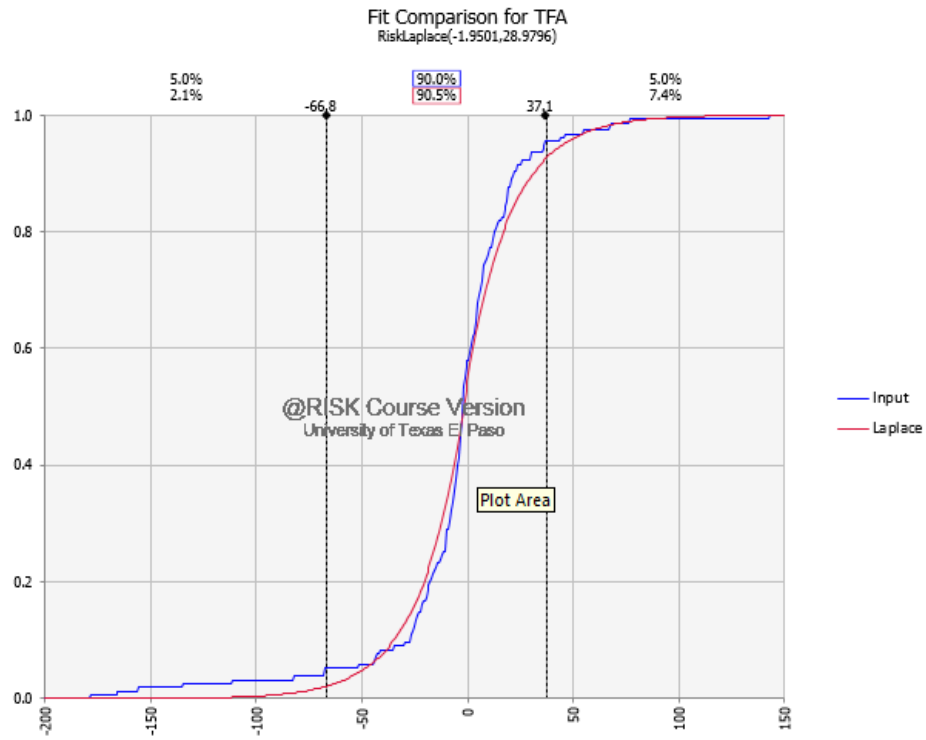


Figure 3.6: Observed and fitted cumulative ascending of *TFA* from U.S. 101 Dataset

As has been shown above, each parameter has its own distribution. Knowing the distribution of each lane changing parameter helps to find the maximum and minimum value to construct the fuzzy membership functions for each parameter.

3.6 Data Sets for Developing and Testing of Lane Changing Models

The processed data are then organized into two data sets as shown in Table 3.4. In Dataset A, all the vectors were used as the training data for the FIS. Dataset B was reserved as the test data. As has been shown in Table 3.4, the number of vehicles that have observed lane changing maneuvers is 163 for Dataset A. This corresponding number for Dataset B is 171. Furthermore, each vehicle has more than 60 vectors in different frame IDs at 0.5 second interval, that is why the number of vectors is much more than the number of subject vehicles. For example, the total number of the vehicles for Dataset A is 3,365 and these vehicles have 232,656 vectors or rows.

Table 3.4: Summary of Datasets A and B.

Dataset	A			B		
Source	I-80 Freeway April 13, 2005, 4:00-4:15 p.m.			U.S. Highway 101 June 15, 2005, 7:50-8:05 a.m.		
	Lane change (OM=1)	No lane change (OM=0)	Total	Lane change	No lane change	Total
No. of vehicles	**163**	**3,202**	**3,365**	**171**	**2,612**	**2,783**
No. of vectors	163	232,493	232,656	171	209,681	209,852

Each vector of both data sets has 18 columns which are Vehicle ID, Frame ID, Total Frames, Global Time, Local X and Y, Global X and Y, Vehicle Length, Width, Class, Velocity and Acceleration, Lane Identification, Preceding and Following Vehicle, Spacing and Headway. This information used to calculate the 10 parameters defined in Equations (2.4) to (2.12) and in Table 2.2. Column 14 was used to find out which vehicle had changed lane and to label the vectors with *OM*=1 and *OM*=0.

3.7 Summary

The NGSIM database used in this research has been explained in this chapter. After processing the downloaded data into the I-80 Dataset and US 101 Dataset, the lane changing parameters in both data sets were analyzed statistically. From the results of the correlation analysis, it was obvious that there were strong relationships between some of the parameters. Also, the best fit distribution for each parameter was determined. The lognormal distribution was the recommended for the gap parameters while the Laplace distribution was recommended for the time to collision parameters. Besides, lognormal and logistic distributions were best fit for the distance and speed of the subject vehicle, respectively. Then, the data sets were organized into the Dataset A and Dataset B. Dataset A was used to train the FIS model while Dataset B was used to test the FIS model and for comparative evaluation.

Chapter 4: Proposed Methodology

Lane changing decisions between t_3 and t_4 (checking the opportunity to make a move), on urban freeways is modelled in this chapter by means of FIS. A survey was first conducted to understand drivers' lane changing behavior and to find out the most important lane changing decision parameters. This chapter then explains the concept of fuzzy logic and describes the development of a FIS lane changing model by defining fuzzy sets, fuzzy membership functions, fuzzy rules, composition of rules and defizzificatiom. The last section of this chapter describes the training of the model with Dataset A.

4.1 Survey

To make the FIS use the input parameters as close to what drivers would use in real life, a questionnaire survey was conducted. The purpose of this survey was to select a few input parameters most frequently used by drivers in making lane change decisions.

The survey instrument consisted of multiple choice questions concerning the respondent's demographic information, his/her motivation to make a discretionary lane change, and the parameters listed in Table 2.2. For each of the parameters, the respondent was asked to select if the parameter was use all the time, most of the time, sometimes, seldom or never in making his/her lane changing decisions. Technical terms of lane change and parameters are described in simple language, English. The survey was administered to students, staff and faculty members on campus at The University of Texas at El Paso, drivers in local households and shopping malls from January to September 2014. A total of 443 useful responses were collected. The answers to the questions pertaining to the 10 parameters were analyzed and are presented in Table 4.1. The survey instrument is attached in Appendix A.

After collecting 100 responses, the results of the survey did not change significantly and they were almost as the same as the result of the Table 4.1.

Table 4.1: Results of drivers survey.

Input parameters	Reported frequency of use (% distribution)						
	All the time (a)	Most of the time (b)	Sometimes (c)	Seldom (d)	Never (e)	Total (a)+(b)+(c) +(d)+(e)	All or most of the time (a)+(b)
G_{PB}	56%	25%	13%	4%	2%	100%	**81%**
G_{FB}	21%	21%	27%	18%	13%	100%	42%
G_{PA}	61%	27%	9%	2%	1%	100%	**88%**
G_{FA}	78%	16%	6%	0%	0%	100%	**94%**
D	68%	22%	7%	1%	2%	100%	**90%**
T_{PB}	7%	15%	29%	22%	27%	100%	22%
T_{FB}	17%	24%	31%	11%	17%	100%	41%
T_{PA}	21%	28%	21%	11%	19%	100%	49%
T_{FA}	23%	28%	23%	12%	14%	100%	51%
V	40%	32%	18%	7%	3%	100%	72%

Table 4.1 shows the percentage distribution of responses for each of the parameters. The last (rightmost) column lists the percentage of the respondents who answered that they used each parameter all the time or most of the time. From the tabulated results, it is obvious that gaps and distance are used more frequently than times to collision. This may be because it is easier for drivers to judge and estimate physical distance than time to collision. Of the 10 parameters surveyed, G_{FA} is used all or most of the time by 94% of the respondents, followed by at D with

90%, G_{PA} at 88% and G_{PB} at 81%. These four parameters were therefore selected as the inputs to the FIS.

4.2 Fuzzy Logic

Fuzzy logic was introduced by Zadeh as a mathematical method to represent the imprecision in everyday life [Zadeh 1965, 1994]. Since then, fuzzy logic has emerged as a powerful method for solving a wide variety of problems relating to estimation, control, pattern recognition and decision making based on imprecise information. Fuzzy logic relies on several important concepts, of which fuzzy set, fuzzy membership and fuzzy rule are important for this research.

One way of dealing with the real world phenomena is qualitative and non-numerical in nature. In decision-making processes as in advanced precision manufacturing metrology, masses of numerical data are converted into some qualitative form and thus are dealt with only in aggregation, e.g., visual perception. This form of aggregation gives rise to a set of linguistic labels and is sometimes referred to as information granules. This aggregation of information makes the partition of space more manageable for further processing. All cognitive and inferential processing is then carried out at the level of the granules. This process of aggregation or granulation implies that we deal with the relationships of functions between linguistic labels rather than with numerical quantities. To cope with this style of cognition, a suitable modelling technique is developed using the theory of fuzzy sets, since this theory deals with granularity typical of our perception.

Fuzzy logic is introduced to describe situations in which there is imprecision due to vagueness rather than randomness in everyday life. Furthermore, in our daily life, common terms are always vague e.g., tall man, good weather, intelligent animal. In other words, this research is implemented with fuzzy logic because fuzzy logic is dealing with human reasoning and uncertainties. The term uncertainty here refer to vagueness, not randomness. These fuzzy linguistic terms can be regarded as sets of singletons, the grades of which are ranging from 0 to 1. Therefore, these fuzzy linguistic terms are called fuzzy sets.

4.3 Fuzzy Sets

A classical set is a collection of distinct objects. In a classical (non-fuzzy) set theory, an element either belongs to or does not belong to a set. Therefore, the membership of each element is crisp and binary. In other words, the membership of an element X is either yes (belong to the set) or no (does not belong to the set). The characteristic function $\mu_A(x)$ of a classical set, A, in the entire set, U, takes its values in $\{0, 1\}$. $\mu_A(x)$ is 1 if x is a member of A (i.e. $x \in A$) and 0 otherwise (i.e. $x \notin A$):

$$\mu_A(x) = \begin{cases} 1 & \text{if } x \in A \\ 0 & \text{if } x \notin A \end{cases} \tag{4.1}$$

A fuzzy set is defined as a set without a crisp, clearly defined boundary. It contains elements with only a partial degree of membership [Jang and Gulley 2008]. A fuzzy set permits a degree of membership for each element which ranges over the unit interval [0, 1]. The most important difference between the classical and fuzzy sets is that classical sets have two unique membership functions while the fuzzy sets may have an infinite number of membership functions. Furthermore, fuzzy sets could be considered as a generalization of classical set theory [Zadeh 1965].

A fuzzy set defines several linguistic values that are used to describe a parameter. For examples, the fuzzy set for G_{FA} may be defined as $\widetilde{G}_{FA} = \{close, medium, far\}$, the fuzzy set for D may be defined as $\widetilde{D} = \{close, medium, far\}$, and the fuzzy set for lane change decision, C, may be defined as $\widetilde{C} = \{yes, no\}$.

From the drivers survey described in Section 4.1, the four decision parameters selected were G_{FA}, D, G_{PA} and G_{PB}. The number of linguistic values in the fuzzy set for each parameter affects the number of fuzzy rules in the FIS. A useful fuzzy set would produce a meaningful expression, in terms of a single fuzzy set, of the overall performance of the model. The number of fuzzy sets which could be used for any of the input parameters in the lane changing model is restricted to drivers' perception capabilities. To keep the number of fuzzy rules to a manageable level, a decision was made to have a fuzzy set of three linguistic values for each of the input parameters, i.e., $\{close, medium, far\}$.

The FIS has only one output parameter for lane change, denoted as *C.* The fuzzy set for the output parameter is $\widetilde{C} = \{yes, no\}$. Obviously, the list of the fuzzy sets of the parameters are:

$$\widetilde{G}_{FA} = \{close, medium, far\}$$

$$\widetilde{D} = \{close, medium, far\}$$

$$\widetilde{G}_{PA} = \{close, medium, far\}$$

$$\widetilde{G}_{PB} = \{close, medium, far\}$$

$$\widetilde{C} = \{yes, no\}$$

4.4 Fuzzy Membership Functions

Fuzzy membership functions are used to map the crisp value of an input parameter into the membership value (also known as degree of membership) for each linguistic value in the fuzzy set. The membership functions may comprise different shapes. Figures 2.1 and 2.2 below are some examples of fuzzy membership functions.

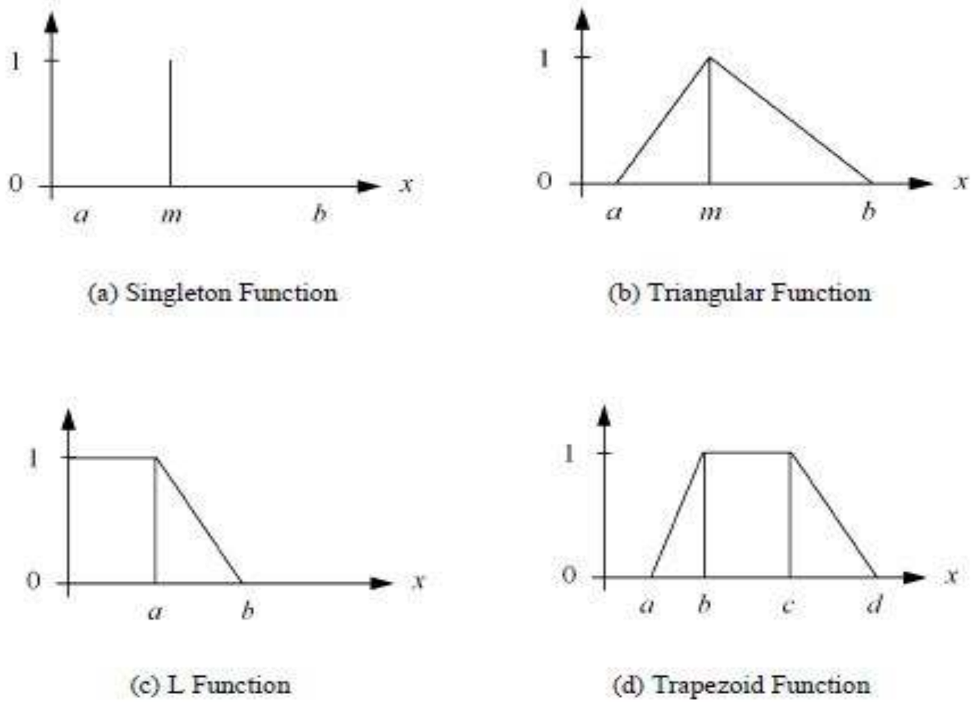


Figure 4.1: Different types of linear membership functions [from Ross [2004]].

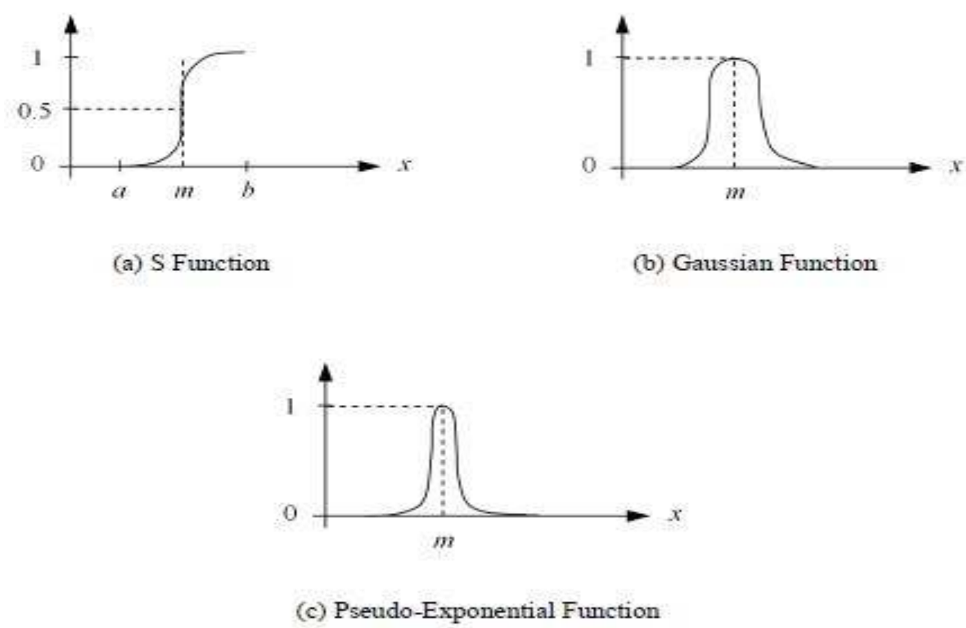


Figure 4.2: Different types of Gaussian membership functions [from Ross [2004]].

The triangular membership functions are commonly used in applications in the traffic and transportation domain. For example, triangular membership functions have been specifically used in modelling car-following and lane changing behavior of drivers [McDonald et al. 1997; Brackstone et al. 1998; Wu et al. 2000; Moridpour et al. 2009]. These triangular membership functions have also been used in long term prediction models of freeway travel times [Li 2006].

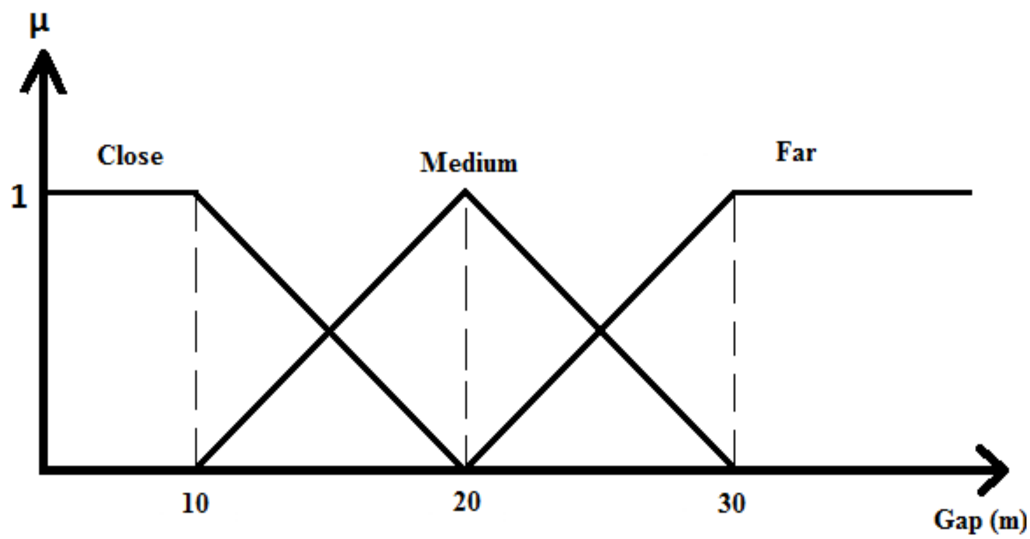
According to the Association of Car Rental Industry Systems Standards (ACRISS) car classification code [Moridpour et al. 2009]:

Table 4.2: The ACRISS car classification code

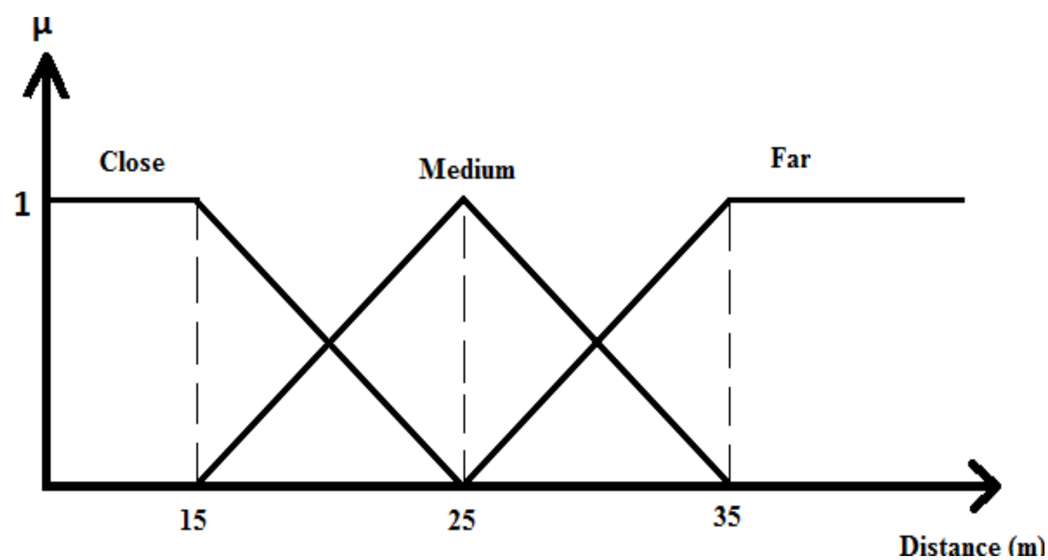
	Small	**Midsize**	**Large**
Length of Vehicle (*L*)	$L < 4.57$ (m)	$4.57 < L < 4.95$ (m)	$L > 4.95$ (m)

Therefore, 5 m is considered as the unit length of a car. According to the Texas Driver Handbook [www.dps.texas.gov], the minimum distance between two vehicles is 63 feet or almost 20 m. The above conditions, in addition to the range of parameter values obtained from the probability distributions, helped to define the membership functions.

The membership functions for $\tilde{G}_{FA}$ and $\tilde{D}$ may be defined as in Figure 4.1. According to Figure 4.1(b), for example, when D=20 m, $\mu_{\tilde{D},close}(20)$=0.5, $\mu_{\tilde{D},medium}(20)$=0.5 and $\mu_{\tilde{D},far}(20) = 0$.



(a) Gaps



(b) Distance

Figure 4.3: Fuzzy membership functions for gap and distance.

Since there are four input parameters and each of them has a fuzzy set of three linguistic values, 4x3=12 membership functions were necessary. The most popular triangular function was used for *medium*, while the trapezoidal functional form was used for *close* and *far*. The membership functions for G_{FA}, G_{PA} and G_{PB} are shown in Figure 4.3(a) while those for D are shown in Figure 4.3(b). The base and tip of the triangles and trapezoid were set at multiples of 5 m so as to approximate integer number of car length.

In the above example, a crisp value of $G_{FA}=x$ is mapped by the respective membership functions, namely $\mu_{\widetilde{G}_{FA},close}(x)$, $\mu_{\widetilde{G}_{FA},medium}(x)$ and $\mu_{\widetilde{G}_{FA},far}(x)$ into [0, 1]. Likewise, a crisp value of $D=y$ is mapped by $\mu_{\widetilde{D},close}(y)$, $\mu_{\widetilde{D},medium}(y)$ and $\mu_{\widetilde{D},far}(y)$ into their respective range of [0, 1].

4.5 Fuzzy Inference Rules

Fuzzy rules are normally expressed in the IF-THEN format. The antecedent of a rule may include more than one fuzzified parameters, combined with logical operator AND or OR. A simple example of a rule which makes use of two fuzzified parameters is

IF [($\widetilde{G}_{FA}$ is *close*) AND ($\widetilde{D}$ is *close*)] THEN ($\widetilde{C}$ is *no*)

This rule combines fuzzified inputs of G_{FA} and D to infer a fuzzified output of C. Mathematically, the membership values of the antecedent of the rule, $\mu_{\widetilde{G}_{FA},close}(x)$ and $\mu_{D,close}(x)$ are combined using the fuzzy set operator AND, which then fires the consequent of the rule to give an output value. There are several ways to mathematically calculate the fuzzified output of a rule. The two most commonly used methods are the Mamdani and Sugeno's fuzzy inference methods [Jang et al. 1997].

In Mamdani FIS [Mamdani and Assilian 1975], the consequent of a rule is characterized by fuzzy sets which are presented as follows:

$$j^{\text{th}}\text{ rule: IF } [(I_1 \text{ is } A_{1j}) \text{ AND } \ldots (I_i \text{ is } A_{ij}) \text{ AND } (I_m \text{ is } A_{mj})] \text{ THEN } (O \text{ is } B_j) \tag{4. 2}$$

where

I $= f(I_1, I_2, \ldots, I_n)$ = input parameters;

A_{ij} = fuzzy linguistic value for input I_j;

O = output; and

B_j = fuzzy subsets for output O.

The other type of FIS is Sugeno system in which the consequent of rule is the linear combination of crisp inputs [Sugeno 1985]. The important characteristic of the Sugeno system is that its output membership function is linear. A typical rule in a Sugeno fuzzy system has the following form:

$$\text{If } (Input\ 1 = x) \text{and } (Input\ 2 = y), \text{then} (Output \text{ is } z = ax + by + c) \tag{4. 3}$$

In this dissertation the Mamadani system was used because the crisp outputs will be binary, either 1 (yes, change lane) or 0 (no, do not change lane).

The application of fuzzy IF-THEN rules involves a three stage process:

1. Determine a degree of membership between 0 and 1 for all fuzzy statements in the antecedent.
2. Apply the fuzzy logic operators (e.g. AND, OR) when the antecedent comprises multiple parts. Then, determine a single degree of membership between 0 and 1 for the antecedent. This operation provides the degree of support for the rule.
3. The consequent of a fuzzy rule assigns a fuzzified value to the output.

Given that each rule in the FIS has four input parameters, each parameter has three linguistic values; the maximum number of rules was 3^4=81. Two examples of the rules are:

IF [($\widetilde{G}_{FA}$ is *close*) AND ($\widetilde{G}_{PA}$ is *close*) AND ($\widetilde{D}$ is *close*) AND ($\widetilde{G}_{PB}$ is *close*)] THEN ($\widetilde{C}$ is *no*)

IF [($\widetilde{G}_{FA}$ is *close*) AND ($\widetilde{G}_{PA}$ is *far*) AND ($\widetilde{D}$ is *far*) AND ($\widetilde{G}_{PB}$ is *close*)] THEN ($\widetilde{C}$ is *yes*)

The numerical output of each rule is assigned a binary value of {0, 1}, with C=1 for $\widetilde{C}$ =*yes* and C=0 for $\widetilde{C}$=*no*. This is equivalent to the first-order Sugeno fuzzy model [Jang et al. 2007].

It has been mentioned above that there could be up to 81 fuzzy rules. However, certain combinations of fuzzified inputs are infeasible. For example, it is impossible to have

[($\widetilde{G}_{FA}$ is *close*) AND ($\widetilde{G}_{PA}$ is *close*) AND ($\widetilde{D}$ is *far*) AND ($\widetilde{G}_{PB}$ is *close*)]

because when ($\widetilde{G}_{FA}$ is *close*) AND ($\widetilde{G}_{PA}$ is *close*), $\widetilde{D}$ cannot be *far*. This can also be inferred from the results of the correlation analysis in Section 3.4. After removing the infeasible rules, only 51 rules remained in the rule base. All the rules are listed in Appendix B.

4.6 Composition

Since there are 51 valid rules, and each rule is expected to produce a binary output of C= {0, 1}, the purpose of this composition stage is to combine the 51 binary output values into a single value.

There are two common forms of the composition operation; one is called the max–min composition and the other the max–product also referred to as max–dot composition. Each method of composition of fuzzy relations reflects a special inference and has its own significance and applications. The max–min method is most commonly used by Zadeh in his original paper on approximate reasoning using IF-THEN rules [Ross 2008]. Many have claimed, since Zadeh's introduction, that this method of composition effectively expresses the approximate and interpolative reasoning used by humans when they employ linguistic propositions for deductive reasoning.

The Mamadani fuzzy model assigns a weight to each rule, and then computes the normalized weighted average of the outputs [Jang et al. 2007]. For our FIS, all the rules are given equal weight and therefore, the composition process is equivalent to averaging the 51 binary output values to produce a single value of $C^{*} \in [0, 1]$.

Max–min:

$$\text{Max}\ \{\text{Min}\ \underbrace{\{\mu 1, \mu 2, \mu 3, \mu 4\}}_{\text{Rule 1}}, \text{Min}\ \underbrace{\{\mu 1, \mu 2, \mu 3, \mu 4\}}_{\text{Rule 2}} \ldots \text{Min}\ \underbrace{\{\mu 1, \mu 2, \mu 3, \mu 4\}}_{\text{Rule 51}}\}$$

Max–product:

$$\text{Max}\ \{\underbrace{\{\mu 1.\mu 2.\mu 3.\mu 4\}}_{\text{Rule 1}}, \underbrace{\{\mu 1.\mu 2.\mu 3.\mu 4\}}_{\text{Rule 2}} \ldots \underbrace{\{\mu 1.\mu 2.\mu 3.\mu 4\}}_{\text{Rule 51}}\}$$

4.7 Defuzzification

Defuzzification is the conversion of a fuzzy quantity to a crisp quantity, just as fuzzification is the conversion of a crisp quantity to a fuzzy quantity.

Then $C^* \in [0, 1]$ should be converted to a binary decision or recommendation of *yes* or *no* to change lane, by comparing C^* with a threshold value τ, to come out with a FIS's Recommendation *FR* which has a crisp binary value of {0, 1}:

$$FR = \begin{cases} 1 : \text{"yes, change lane"} & \text{if } C^* \geq \tau \\ 0 : \text{"no, do not change lane"} & \text{if } C^* < \tau \end{cases} \tag{4.8}$$

4.8 Fuzzy Inference System

A FIS is a collection of membership functions and fuzzy IF-THEN rules that are mainly used to model human knowledge and perception. A typical FIS comprising two inputs, four rules and one output is shown in Figure 4.4. A typical FIS comprises four stages: fuzzification, inference, composition and defuzzification [Li 2006]. The input data is usually crisp in nature. In the fuzzification stage, the crisp input is fuzzified using fuzzy sets and membership functions. The fuzzification stage involves applying membership functions associated with the input parameters to crisp magnitudes of parameters in order to determine the fuzzy inputs for the fuzzy rules. The inference is a group of logic rules which provides the relationship between the fuzzified inputs and output [Li 2006]. In the inference stage, the degree to which the antecedent of each rule has been satisfied is computed, and then applied to the consequent of fuzzy rule. In the composition stage, a single fuzzy set is assigned to each output parameter. Since a crisp output is more desired as the final output, the fuzzy set is then converted to a crisp value in the defuzzification stage [Li 2006]. The crisp output will be either 1 or 0 which represents "yes, change lane" or "no, do not change lane", respectively.

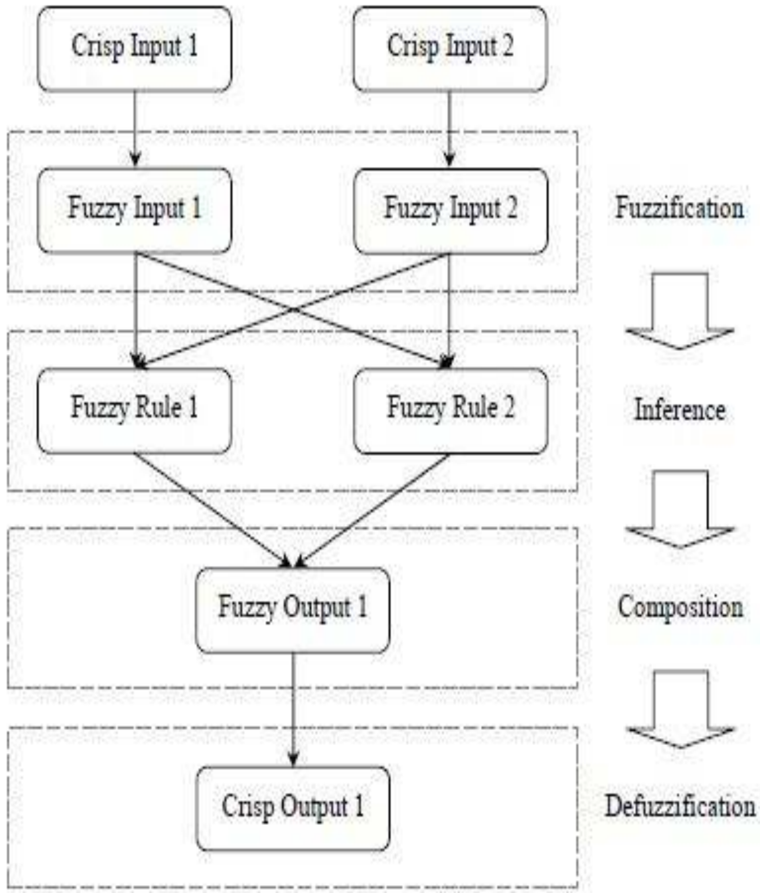


Figure 4.8: A fuzzy inference system with two inputs, four rules and one output [from Moridpour 2010].

4.9 Training

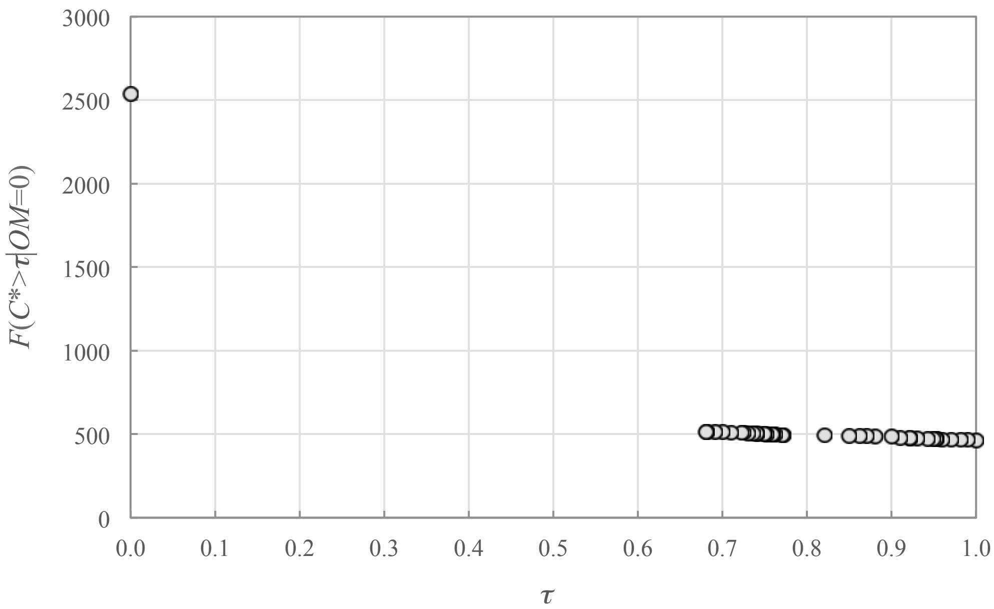
4.9.1. Max-Min Composition

The proposed FIS was implemented in MATLAB's Fuzzy Logic Designer [MathWorks 2014]. The FIS was "trained" with the training vectors in Dataset A to determine an appropriate τ value.

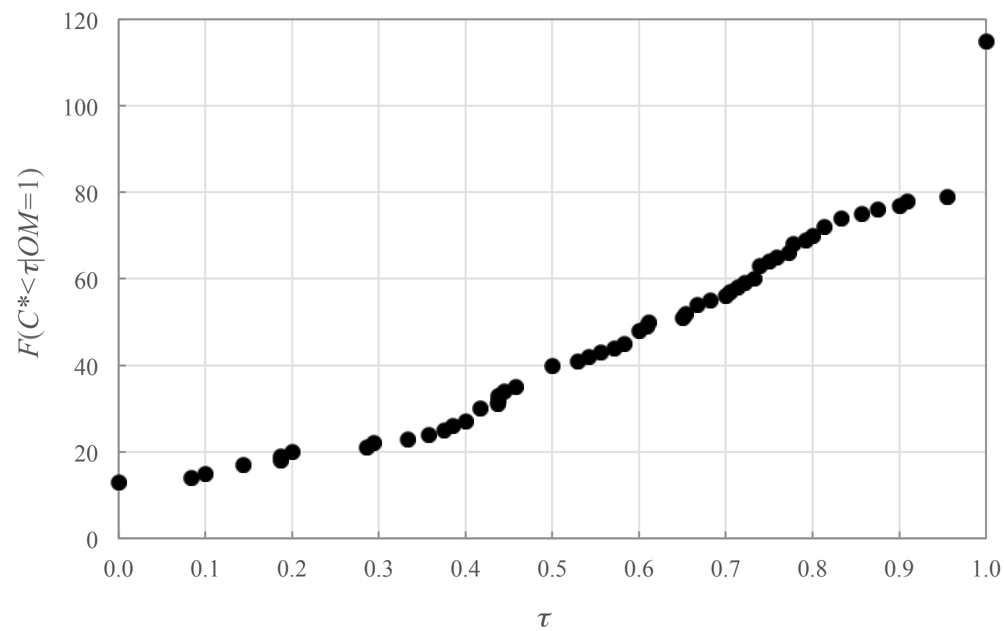
To help to select the τ value, the training vectors of Dataset A was presented to the FIS. Figure 4.5 shows the cumulative frequency distributions of C^* values derived at the various τ values. Figure 4.5(a) plots the cumulative frequency of $F(C^*>\tau|OM=0)$, while Figure 4.5(a) plots the cumulative frequency of $F(C^*<\tau|OM=1)$. $F(C^*>\tau|OM=0)$ is the number of training vectors which have no observed lane change in the NGSIM data, but the FIS (with the given τ value) recommends a lane change ($FR=1$). On the other hand, $F(C^*<\tau|OM=1)$ is the number of training vectors which have observed lane changes, but the FIS (with the given τ value) did not recommend a lane change ($FR=0$). The optimal τ value should ideally minimize the total number of errors, i.e., minimize $F(C^*>\tau|OM=0) + F(C^*<\tau|OM=1)$. An alternative is to use the objective function:

$$\text{Minimize } \omega_1 F(C^*>\tau|OM=0) + \omega_2 F(C^*<\tau|OM=1) \tag{4.9}$$

where ω_1 and ω_2 are the expected cost of committing each type of error, respectively. ω_1 is the probability of a collision (when the FIS recommends a lane change when it is not supposed to) multiplied by the cost of a collision. ω_2 is the delay cost of not changing lane in the next 0.5 second. ω_1 is expected to be very high compared to ω_2. However, from our data sets and from Figures 4.5(a) and 4.5(b), it can be observed that $F(C^*>\tau|OM=0)$ occurs much less frequently than $F(C^*<\tau|OM=1)$. In the absence of the costs of errors, it is possible to rely on $F(C^*>\tau|OM=0) + F(C^*<\tau|OM=1)$, i.e., $\omega_1=\omega_2=1$ to make a decision on the τ value. However, from Figures 4.5(a) and 4.5(b), it is clear that the minimum $F(C^*>\tau|OM=0) + F(C^*<\tau|OM=1)$ occurs when $\tau\approx 0.1$, which is in practice undesirable. Therefore, an alternate heuristic was employed to decide the τ value. First, we set $0.5 \le \tau < 1$ because higher τ value will reduce the error of $FR=1$ when in fact $OM=0$. However, increase τ beyond 0.5 will not reduce $F(C^*>\tau|OM=0)$ significantly (see Figure 4.2(a)) but instead will increase $F(C^*<\tau|OM=1)$ (see Figure 4.2(b)). It was therefore decided that $\tau=0.5$ be used for the purpose of subsequent test. If this FIS is eventually implemented in practice, the designer may select to set a different τ value.



(a) $F(C^*>\tau|OM=0)$

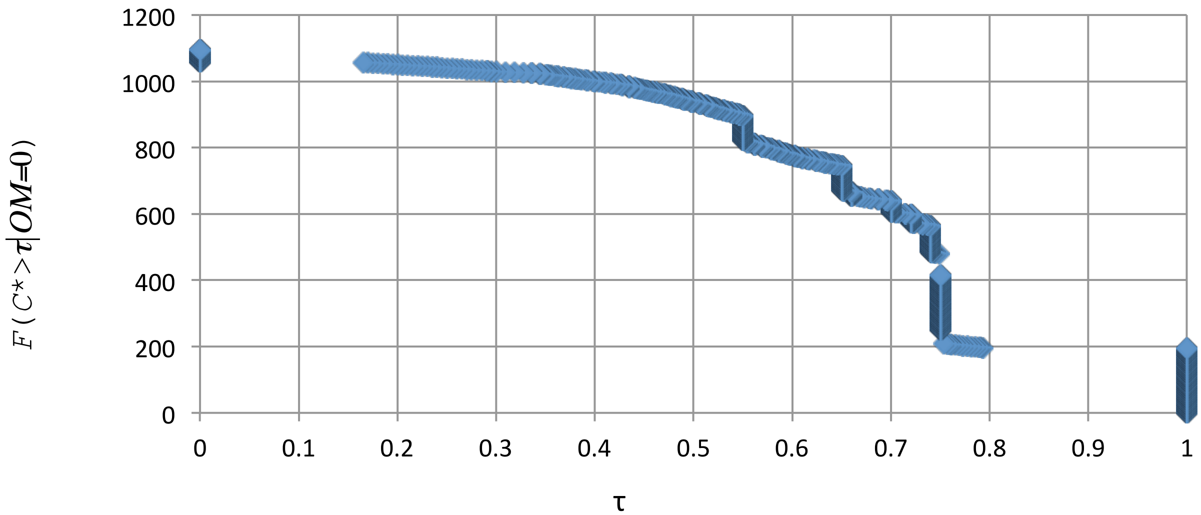


(b) $F(C^*<\tau|OM=1)$

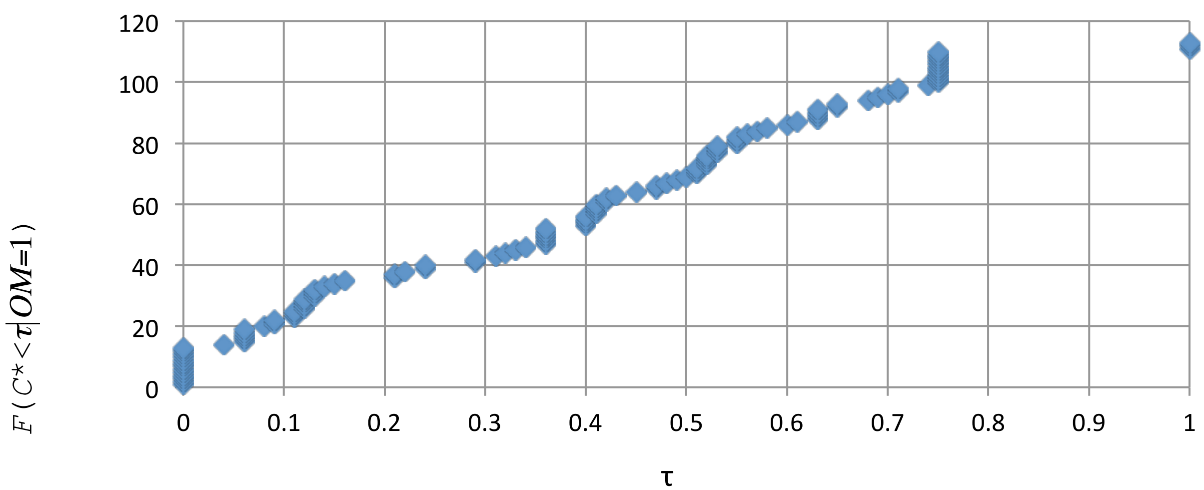
Figure 4.9: Cumulative frequency distributions of C^* from training vectors (max-min)

4.9.2. Max-Product Composition

As mentioned in the composition section, max-product is the other composition method. As can be inferred from Figure 4.10, the numerical values of max-product fuzzy outputs are smaller than max-min fuzzy outputs. In other words, the decisions based on the max-product composition are more conservative than the results of max-min composition. Based on the frequency plots in Figure 4.10, it is really impossible to immediately recognize the best τ value. As mentioned above, max-product is more conservative than max-min, therefore 0.4 is chosen for τ.



$F(C^*<\tau|OM=1)$



(b) $F(C^*<\tau|OM=1)$

Figure 4.10: Cumulative frequency distributions of C^* from training vectors (max-product)

4.10 Summary

A survey was conducted to understand drivers' lane changing behavior and to find out more important lane changing decision parameters. The result of the survey was presented in this chapter.

A FIS was used in this research to model the lane changing decisions of passenger vehicle drivers on freeways. This chapter explained the different components of the FIS such as fuzzification, fuzzy inference rules, composition and defuzzification. G_{FA}, D, G_{PA} and G_{PB} were chosen as the input parameters based on the survey results. Although 81 fuzzy inference rules were constructed, 51 of them were feasible in practice and were used in the FIS. The FIS produces a crisp out which could be either 1 or 0 which meant "yes, change lane" or "no, do not change lane", respectively. After presenting the FIS with Dataset A, it was decided that τ=0.5 for the max-min composition method and τ=0.4 for the max-product composition method.

Chapter 5: Results

The FIS model is tested in this chapter by presenting two data sets (Datasets A and B) and the results are analyzed by means of classification matrix.

In Chapter 3, the NGSIM database was processed and organized into Dataset A and Dataset B. In Chapter 4, the FIS was developed and trained to determine a τ value. In this chapter, the FIS was evaluated with the entire Dataset A, with the selected the τ value. The FIS with the selected τ value was then tested with Dataset B. The test with Dataset B serves as a transferability test, to see if the internal parameters (including the τ value) of the FIS is sensitive to different driving behavior in a different city. Furthermore, a comparison between the results of the FIS model and the TRANSMODELER's gap acceptance model is made, using Dataset B.

5.1 Dataset A

5.1.1 Max-Min Composition

The FIS, with τ=0.5, was evaluated using the entire Dataset A using max-min composition. The classification matrix used in Moridpour et al. (2012) is adopted to present the results in Table 5.1. In total, there were 232,656 vectors in the Dataset A in which 163 vectors have observed lane changes (*OM*=1). As it has been shown in the Table 5.1, the number of vectors that have changed lane (*OM*=1) and the FIS model recommended that they made lane changes is 134. However, 29 vectors had observed maneuver (*OM*=1) but the FIS model recommended no lane change (*FR=0*). On the other hand, there were 227,869 vectors with no observed maneuvers (*OM*=0) and the FIS model decided with no lane change. There were 4,624 vectors with *OM*=0 which were given wrong decisions by the FIS. From the classification matrix, it was initially concluded that the overall accuracy of the FIS recommendations was 134+227,869=228,003 out of 232,656 vectors, equivalent to 98.0%.

Table 5.1: Initial classification matrix for Dataset A (max-min)

		FIS Recommendation *FR*			
		Change lane *FR*=1	Do not change lane *FR*=0	Total	Accuracy (%)
Observed Maneuver *OM*	Change lane *OM*=1	134	29	163	82.2%
	Do not change lane *OM*=0	4,624	227,869	232,493	98.0%
	Total	4,758	227,898	232,656	

Despite this apparently high overall accuracy, there were still 4,624 instances when *FR*=1 while *OM*=0, which may potentially lead to a collision. Upon careful examination on these set of 4,624 vectors, it was found that most of them happened at a fraction to a few seconds before the instant of an observed lane change. When Dataset A was set up, for each *S*, *OM* was labeled 1 only once at t_4 while the rest of the vectors for this vehicle had *OM*=0. It was possible that the opportunity for a lane change presented itself 0.5 to a few seconds before t_4. However, due to perhaps the perception-reaction delay, or conservatively took time to double check the surrounding vehicles, the driver did not make an observable lateral move until t_4. Therefore, for the 163 subject vehicles that changed lane, those vectors before t_4 which were labeled *OM*=0 but the FIS recommended *FR*=1 were considered as correct and retagged as *FR*=0 because it is impossible to change the actual behavior by labeling *OM*=0 to *OM*=1. Table 5.2 presents the matrix after this reclassification of the FIS's outputs.

Table 5.2: Revised classification matrix for Dataset A (max-min)

		FIS Recommendation *FR*			
		Change lane *FR*=1	Do not change lane *FR*=0	Total	Accuracy (%)
Observed Maneuver *OM*	Change lane *OM*=1	134	29	163	82.2%
	Do not change lane *OM*=0	669	231,824	232,493	99.7%
	Total	803	231,853	232,656	

Comparing Table 5.1 with Table 5.2, 3,955 vectors with *OM*=0 were reclassified from *FR*=1 to *FR*=0. As has been shown in the Table 5.2, 134 out of 163 vectors with *OM*=1 decided to change the lane correctly and 134/163 is equal to 82.2%. The overall accuracy of FIS recommendations has increased to 134+231,824=231,958 out of 232,656 vectors, or 99.7%.

5.1.2 Max-product Composition

The FIS, with τ=0.4, was evaluated using the entire Dataset A using max-product composition. In total, there were 232,656 vectors in the Dataset A in which 163 vectors have observed lane changes (OM=1). As it has been shown in the Table 5.3, the number of vectors that have changed lane (OM=1) and the FIS model recommended that they made lane changes is 120. However, 43 vectors had observed maneuver (OM=1) but the FIS model recommended no lane change (FR=0). On the other hand, there were 223,193 vectors with no observed maneuvers (OM=0) and the FIS model decided with no lane change. There were 9,300 vectors with OM=0 which were given wrong decisions by the FIS. From the classification matrix, it was initially concluded that the overall accuracy of the FIS recommendations was 120+223,193=228,003 out of 232,656 vectors, equivalent to 96.0%.

Table 5.3: Initial classification matrix for Dataset A (max-product)

		FIS Recommendation *FR*			
		Change lane *FR*=1	Do not change lane *FR*=0	Total	Accuracy (%)
Observed Maneuver *OM*	Change lane *OM*=1	120	43	163	73.6%
	Do not change lane *OM*=0	9,300	223,193	232,493	96.0%
	Total	9,420	223,236	232,656	

Despite this apparently high overall accuracy, there were still 9,300 instances when *FR*=1 while *OM*=0, which may potentially lead to a collision. Upon careful examination on these set of 9,300 vectors, it was found that most of them happened at a fraction to a few seconds before the instant of an observed lane change. When Dataset A was set up, for each *S*, *OM* was labeled 1 only once at t_4 while the rest of the vectors for this vehicle had *OM*=0. It was possible that the opportunity for a lane change presented itself 0.5 to a few seconds before t_4. However, due to perhaps the perception-reaction delay, or conservatively took time to double check the surrounding vehicles, the driver did not make an observable lateral move until t_4. Therefore, for the 163 subject vehicles that changed lane, those vectors before t_4 which were labeled *OM*=0 but the FIS recommended *FR*=1 were considered as correct and retagged as *FR*=0 because it is impossible to change the actual behavior by labeling *OM*=0 to *OM*=1. Table 5.4 presents the matrix after this reclassification of the FIS's outputs.

Table 5.4: Revised classification matrix for Dataset A (max-product)

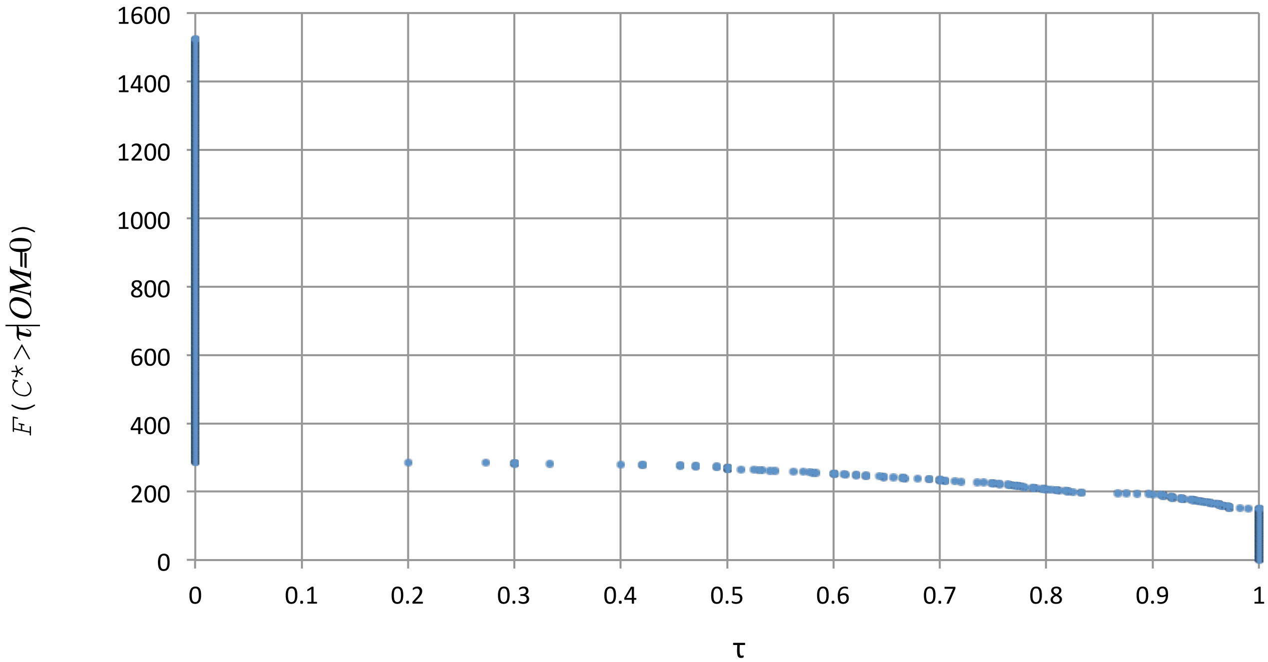
		FIS Recommendation *FR*			
		Change lane *FR*=1	Do not change lane *FR*=0	Total	Accuracy (%)
Observed Maneuver *OM*	Change lane *OM*=1	120	43	163	73.6%
	Do not change lane *OM*=0	6,510	225,983	232,493	97.2%
	Total	6,630	226,026	232,656	

5.2 Dataset B

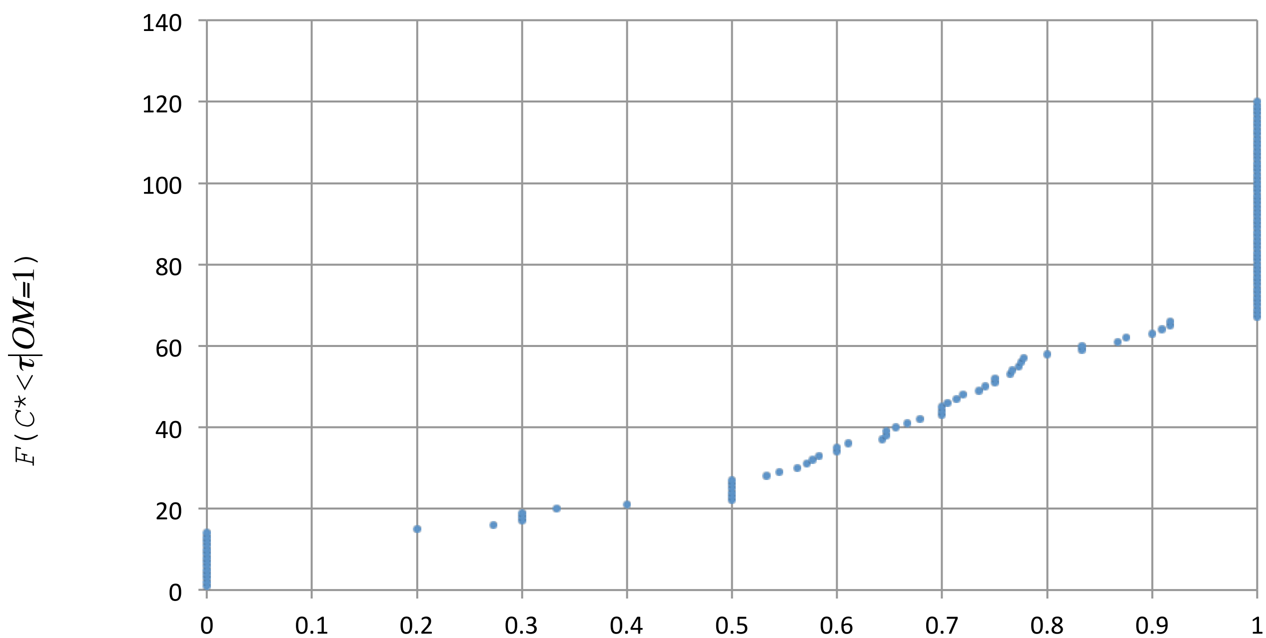
5.2.1 Max-Min Composition

The FIS was then tested with Dataset B using max-min composition. Unlike Dataset A which was collected at I-80 Freeway in Emeryville, California, Dataset B was collected at U.S. Highway 101 in Los Angeles, California. Thus, the test with Dataset B served as a validation of the trained FIS. It also tested the transferability of the FIS, developed using one city's data, to another.

Initially, the process of training was repeated for Dataset B to see if it would give a different τ value, that is, there is a need to retrain τ. Graphs similar to Figures 4.5(a) and 4.5(b) were plotted with Dataset B. As has been shown in Figure 5.1, both (a) and (b) figures show similar trends and it was determined that τ=0.5 was still suitable. Therefore, it can be said that the FIS trained with Dataset A is transferable to Dataset B. The evaluation result with Dataset B is presented in Table 5.3.



(a) $F(C^{*}>\tau|OM=0)$



τ

(b) $F(C^{*}<\tau|OM=1)$

Figure 5.1: Cumulative frequency distributions of C^* from Dataset B (max-min)

Table 5.5: Initial classification matrix for Dataset B (max-min)

		FIS Recommendation *FR*			
		Change lane *FR*=1	Do not change lane *FR*=0	Total	Accuracy (%)
Observed Maneuver *OM*	Change lane *OM*=1	141	30	171	82.5%
	Do not change lane *OM*=0	6,285	203,396	209,681	97.0%
	Total	6,426	203,426	209,852	

The initial classification outcomes with Dataset B resulted in an accuracy of 97%. As it has been shown in the Table 5.3, the number of vectors that have changed lane and the FIS model recommended that they have the lane changing maneuver is 141 while 30 vectors had observed maneuver (*OM*=1) but the FIS model recommended no lane changing maneuver. On the other hand, there were 203,396 vectors with no observed maneuvers (*OM*=0) and the FIS decided no lane change correctly. Also there were 6,285 with *OM*=0 but they were given wrong decisions by the FIS. In total, there were 209,852 vectors in Dataset B which 171 vectors have changed lane. From the classification matrix, it was initially concluded that the accuracy of the FIS recommendations was 97.0%.

After the FIS's recommendations of *FR*=1 were reclassified as *FR*=0, for the vectors of the subject vehicles immediately before $t_{4,}$ the revised result is presented in Table 5.4. The accuracy of FIS has improved to 99.5%.

Table 5.6: Revised classification matrix for Dataset B (max-min)

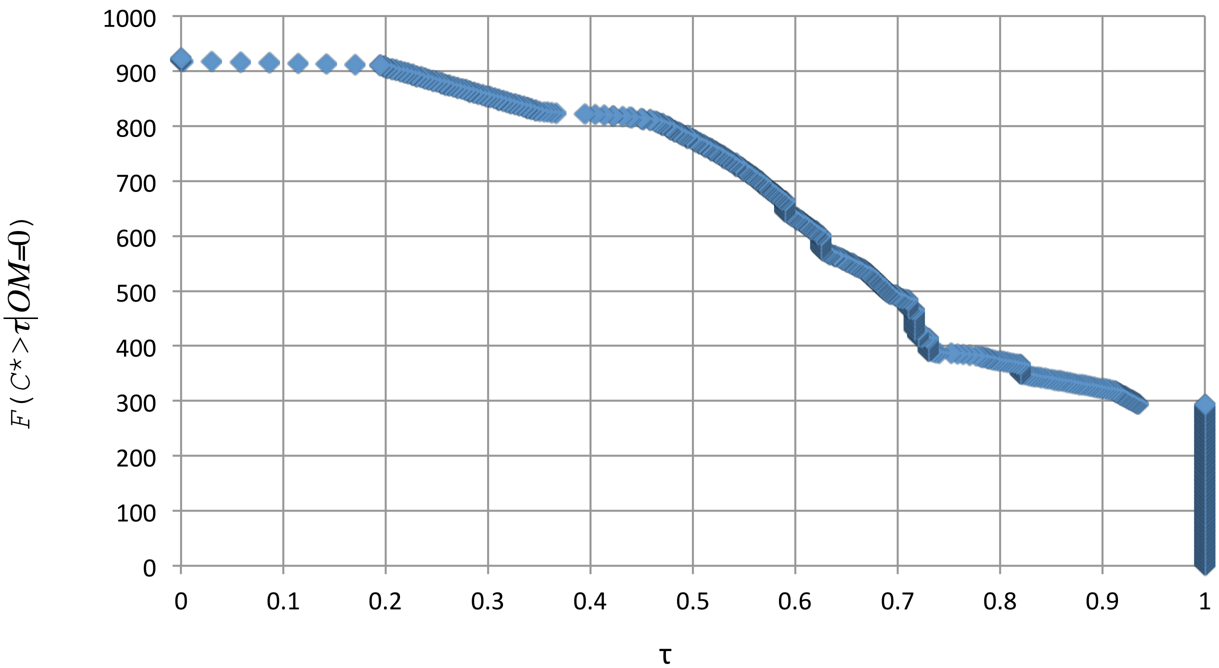
		FIS Recommendation *FR*			
		Change lane FR=1	Do not change lane FR=0	Total	Accuracy (%)
Observed Maneuver OM	Change lane OM=1	141	30	171	82.5%
	Do not change lane OM=0	1,020	208,661	209,681	99.5%
	Total	1,161	208,691	209,852	

As has been shown in the Table 5.4, the FIS recommendation is 141 out of 171 vectors with OM=1. This correct decision is equal to 82.5%.

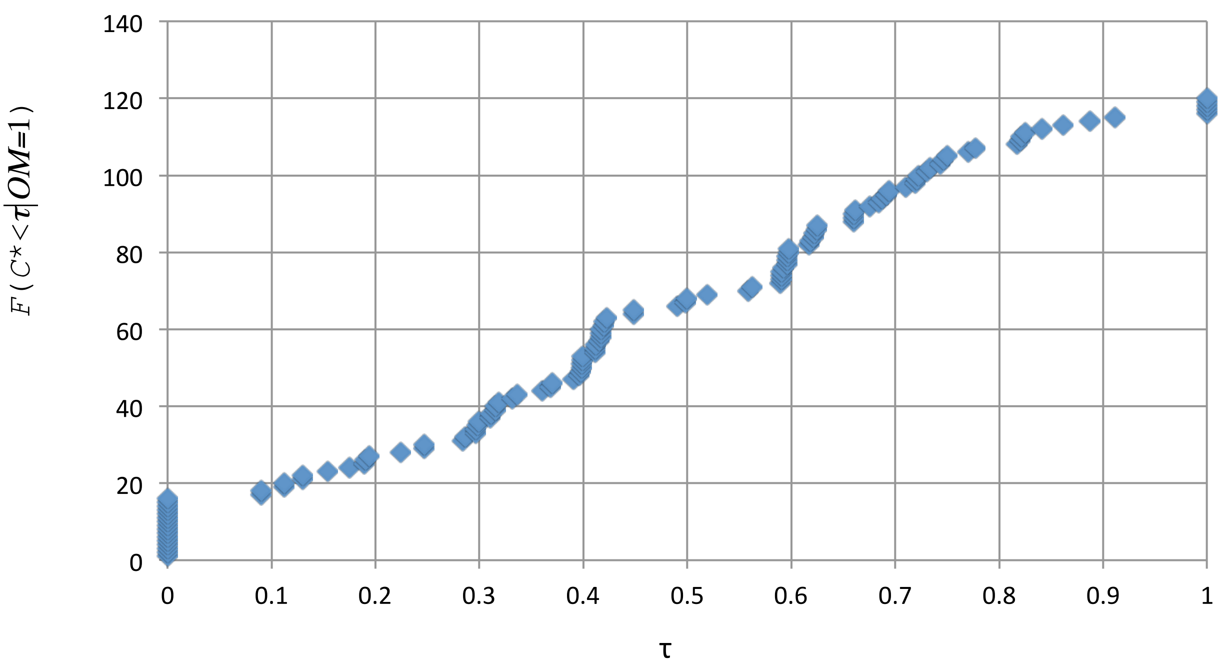
5.2.2 Max-product Composition

The FIS, with τ=0.4, was also tested with Dataset B using the max-product composition.

Initially, the process of training was repeated for Dataset B to see if it would give a different τ value. As has been shown in Figure 5.2, both (a) and (b) figures show similar trends like in Figure 4.10, and it was determined that τ=0.4 was still suitable. Therefore, it can be said that the FIS with max-product composition trained with Dataset A is transferable to Dataset B. The evaluation result with Dataset B is presented in Table 5.7.



(a) $F(C^{*}>\tau|OM=0)$



(a) $F(C^{*}<\tau|OM=1)$

Figure 5.2: Cumulative frequency distributions of *C** from Dataset B (max-product)

Table 5.7: Initial classification matrix for Dataset B (max-product)

		FIS Recommendation *FR*			
		Change lane *FR*=1	Do not change lane *FR*=0	Total	Accuracy (%)
Observed Maneuver *OM*	Change lane *OM*=1	127	44	171	74.2%
	Do not change lane *OM*=0	12,161	197,520	209,681	94.2%
	Total	12,288	197,564	209,852	

The initial classification outcomes with Dataset B resulted in an accuracy of 94.2%. As it has been shown in the Table 5.7, among the 171 vectors that have changed lane (*OM*=1) , the FIS model recommended that 127 make the lane changing maneuver (*FR*=1),while 44 vectors had observed lane changing maneuver (*OM*=1) but the FIS model recommended no lane change (*FR*=0). On the other hand, there were 197,520 vectors with no observed maneuvers (*OM*=0) and the FIS decided no lane change correctly. Also, there were 12,161 vectors with *OM*=0 but they were given wrong decisions to change lane (*FR*=1) by the FIS. From the classification matrix, it was initially concluded that the accuracy of the FIS recommendations was 94.2.0%.

After the FIS's recommendations of *FR*=1 were reclassified as *FR*=0, for the vectors of the subject vehicles immediately before $t_{4,}$ the revised result is presented in Table 5.8. The accuracy of FIS has improved to 96.1%.

Table 5.8: Revised classification matrix for Dataset B (max-product)

		FIS Recommendation *FR*			
		Change lane *FR*=1	Do not change lane *FR*=0	Total	Accuracy (%)
Observed Maneuver *OM*	Change lane *OM*=1	127	44	171	74.2%
	Do not change lane *OM*=0	8,178	201,503	209,681	96.1%
	Total	8,305	201,547	209,852	

Comparing the classification matrices of the FIS with Dataset B, between the max-min and max-product composition methods, the FIS with the max-min composition has better accuracy. Therefore this FIS was selected to compare with the TRNSMODELER's gap acceptance lane changing model in the next section.

5.3 Comparative Performance

This section compares the performance of the FIS, in terms of classification accuracy, against the performance of the gap acceptance model in TRANSMODELER. The gap acceptance model in TRANSMODELER has been described in Section 2.1. The parameter values in the gap acceptance model has been calibrated with NGSIM data [Caliper 2011], and coded into the TRANSMODELER simulation program. The details of the model calibration are not documented. The calibration process can either use the data from the I-80 Freeway in Emeryille, U.S. Highway 101 in Los Angeles, or both. In our case, we have trained the FIS, with the max-min composition, with Dataset A and tested with Dataset B both resulted in the same decision of τ=0.5 and the classification matrices (Tables 5.1 to 5.4) have the same level of accuracy. Therefore, it is expected that the gap acceptance model, whether calibrated with Dataset A, B, or both, will achieve the same level of performance. With this assumption, Equations (2.2) and (2.3) were applied directly to Dataset B. The gap acceptance model is also a binary decision model. Its recommendation is either "yes, change lane" (*GR*=1) or "no, do not change lane" (*GR*=0). Based on the classification outcomes, some vectors with *OM*=0 but the gap acceptance model's initial recommendations of *GR*=1 immediately before t_4 were reclassified as *GR*=0, in the same fashion as described in Section 5.1. The results after reclassification are reported in Table 5.5. The accuracy of the gap acceptance model for vectors which belong to *OM*=1 is only 58.5%, while that for vectors which belong to *OM*=0 is only 66.7%. Compare to the results in Table 5.4 (which has 82.5% and 99.5% respectively); the FIS has much better accuracy. This means that the FIS makes recommendations on the lane changing move much closer to what is observed in Dataset B.

Table 5.9: Revised classification matrix for Dataset B, from the gap acceptance model.

		Gap Acceptance Model Recommendation *GR*			
		Change lane *GR*=1	Do not change lane *GR*=0	Total	Accuracy (%)
Observed Maneuver *OM*	Changed lane *OM*=1	100	71	171	58.5%
	Did not change lane *OM*=0	69,810	139,871	209,681	66.7%
	Total	69,910	139,942	209,852	

5.4 Summary

Datasets A and B are presented to the FIS model to train and test the model, respectively. The initial lane changing decision accuracies for Datasets A and B were 98% and 97%, respectively, which were the minimum accuracies that could be achieved. Then after retagging *FR*=0 to *FR*=1 before t_4, the classification matrices showed that higher accuracies of 99.7% and 99.5% were obtained for the Datasets A and B, respectively. These percentages represent the maximum accuracy that could be achieved. At the end, the gap acceptance model in TRANSMODELER, when tested with Dataset B, resulted in 66.7% maximum overall accuracy. The FIS outperformed the existing TRANSMODELER's gap acceptance model.

Chapter 6: Conclusions, Potential Applications, Contributions, Limitations and Future Studies

6.1 Conclusions on Research Performed

This research has defined 10 parameters that describe vehicle interactions during a lane change, analyzed the probability distributions of these parameters, correlation behavior of the parameters, using actual vehicle trajectory data extracted from the NGSIM database. It is found that, overall,

- The parameters related to gap (in distance unit) and distance can be described by the Log-normal distribution.
- The parameters related to time of collision (in time unit) can be described by the Laplace distribution.
- The parameter related to speed can be described by the Logistic distribution.

The distributions fitted to the NGSIM data collected at the I-80 Freeway in Emeryville, California, and the U.S. Highway 101 were compared. Although the same distribution was fitted to the same lane changing parameter, the fitted distribution parameter values were different for the two sites. This indicates that the driving behaviors are different at the two data collection sites. Besides the maximum, minimum and the mean of each parameter in descriptive analysis were used in defining fuzzy membership functions.

From the correlation analysis, it appears that many parameters are highly correlated. Therefore it is highly possible to use fewer parameters to quantify a lane changing event.

This research has developed a FIS to recommend to the driver if an opportunity has opened up for him/her to perform a discretionary lane changing move to the adjacent target lane. G_{FA}, D, G_{PA} and G_{PB} were chosen as the input parameters based on the survey results. Although 81 fuzzy inference rules were initially constructed, only 51 of them are feasible in practice and were used in the FIS. The FIS has only one crisp output which could be either 1 or 0 which meant "yes, change lane" or "no, do not change lane", respectively. The accuracy of the FIS's lane changing recommendations ranges from 98.0% to 99.7% for Dataset A (collected at I-80 Freeway in Emeryville, California, in which part of the data was used in training), and 96.7% to 99.5% for Dataset B (collected at U.S. Highway 101 in Los Angeles, California). The FIS model has achieved very encouraging results in the independent validation and transferability test using Dataset B. At the end, the comparative performance made to compare the FIS and the gap acceptance model in TRANSMODELER with Dataset B yielded 66.7% maximum overall accuracy for the TRANSMODELER. Thus, the FIS outperformed the existing TRANSMODELER's gap acceptance model.

6.2 Potential Applications

The FIS takes four inputs parameters most frequently used by drivers in making lane changing decisions. These parameters may be estimated by sensors instrumented in the subject vehicle, avoiding the necessity of vehicle-to-vehicle communications. The FIS can be programmed as part of a microscopic traffic simulation tool, or a lane change assist system. It is envisioned that the lane change assist system will function as follows: (i) the driver of the subject vehicle indicates his/her desire to change lane and have selected the target lane by turning on the vehicle's turn indicator (turn signal); (ii) the sensors in the subject vehicle estimate the distances and relative speeds between itself and the surrounding vehicles, and compute the crisp values of the input parameters; (iii) the input parameters are fed into the FIS, and the FIS recommends a decision; (iv) the recommendation is communicated to the driver by voice, audio signal and/or visual indicator on the instrument penal. The U.S. Federal Highway Administration has estimated that between 8.4% and 13.7% of vehicle-to-vehicle collisions on highways occurred during merging or changing lanes [FHWA 1996]. The occurrence of collisions during lane changes may be reduced with the implementation of lane change assist systems embedded with this FIS. This is the potential application of this research.

6.3 Contributions

This research has demonstrated the potential of FIS in modeling discretionary lane changing decisions on freeways. The FIS outperformed the existing TRANSMODELER's gap acceptance model (which is developed for discretionary lane change, and calibrated with the same NGSIM database). The FIS has better accuracies than this competitor in making "yes, change lane" and "no, do not change lane" recommendations.

In this research, the lane changing behavior of a driver has been characterized as a sequence of four steps which are motivation to change lane, selection of the target lane, checking the opportunity to move and a lateral move. As mentioned before, the FIS to be developed in this research replicates the driver's decision at the beginning of the third step; that is, checking for opportunity in the target lane for actual lateral movement of the vehicle. The model answers the question "Is it the time to start moving into the target lane?"

This research has provided an improved model of lane change which is explained below:

1. The survey has showed which lane changing parameters are more important than the others (which are used by drivers in making decisions) which should be the inputs to the FIS.
2. Fuzzy sets and membership functions of the parameters has been decided based on the ACRISS table and the Texas Drive Handbook.

6.4 Limitations

The major limitations of this research are:

- The subject vehicles are cars. The probability distributions of the parameters for other types of vehicles are likely to be different. However, sample sizes for other types of vehicles are much smaller and therefore they were not studied in this dissertation.
- The FIS model was developed and tested with NGSIM data which is from moderate to heavy volume (1200 to 1600 vphpl, and 15 to 30 mph).
- For each lane changing event, the parameter values were taken at the time when the subject vehicle has 0.2 m/s lateral velocity. Obviously this is in the middle of lane change execution. The driver of the subject vehicle usually makes his/her decision to change lane a fraction of a second to a few second ago. However, it is impossible to tell when he/she makes this decision and measure the decision parameters at this point in time.
- A successful lane changing event may be preceded by several unused (or unsafe) lane change opportunities. This is synonymous to the gap acceptance scenario where there are more rejected gaps than accepted gaps. The distributions of the same parameters without an observed lane change are yet to be studied. However, the unused opportunities may not be easily observable.
- For the distinctions between mandatory and discretionary lane changes, and between different road types, integrating the FIS with the vehicle's map matching/navigation system will be necessary

6.5 Future Studies

Although promising, there exist several limitations in the FIS which should be addressed in future research:

- The FIS developed so far is for passenger cars as the subject vehicles. Similar model, with different fuzzy membership functions and τ values may be developed for trucks, for mandatory lane change, and for arterial roads.
- Although the current version of FIS has very high accuracy, the model may further be improved by adjusting the bases and tips of the triangular and trapezoidal fuzzy membership functions, and/or by assigning different weights to the fuzzy rules.
- A more objective way could be developed to determine the τ value. One possibility is to estimate and include the w_1 and w_2 values in the objective function.
- Due to budget constraint, the drivers' survey was conducted only in El Paso, Texas. The results of the survey may be biased towards the local behavior. In future, the survey should be expanded to cover other cities, especially the cities where the vehicle trajectory data was collected and used to calibrate and test the FIS.
- The FIS model was developed and tested with NGSIM data which is from moderate to heavy volume (1200 to 1600 vphpl, and 15 to 30 mph). The performance of the FIS in low volume, high speed traffic should be tested when data is available.

The real test of the FIS is user acceptance of its recommendations, and the resulting safe maneuver during actual freeway driving. Therefore, conducting laboratory test (using a driving simulator) and field test (with an instrumented vehicle) with a sample of drivers should be two of the major tasks in future research.

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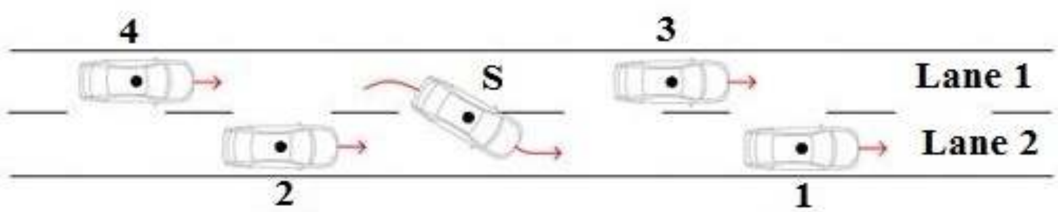
Appendix A

Transportation Survey on Lane Changing

UTEP is conducting research into how drivers change lane on highways and freeways. We want to understand how drivers make decisions on when to change lanes. Your answers will help us to understand lane changing motivation and behavior.

This survey has 3 parts and a total of 16 questions.

Suppose you are driving on a long stretch of a 2-lane highway with no entrance and exit. The following figure illustrates a lane changing scenario and you are the subject vehicle (vehicle **S**). You can be surrounded by up to 4 vehicles (vehicles **1** to **4**).



Part 1 – Motivation

1 - When you want to change the lane from lane **1** to lane **2**, what are usually your main reasons for changing lane? (You may select more than 1 choice)

- ☐ Vehicle **4** is too fast
- ☐ Vehicle **3** is too slow
- ☐ Vehicle **1** is too fast
- ☐ Vehicle **2** is too slow
- ☐ Vehicle **2** is too far
- ☐ Vehicle **4** is too near
- ☐ To reach a higher speed
- ☐ Others (please specify): ______________________________

Part 2 – Safety Checks (Please circle 1 answer per question)

2 - When you want to move from lane **1** to lane **2**, how often do you check the *distance* between your vehicle (**S**) and vehicle **1**?

- **a-** All the time
- **b-** Most of the time
- **c-** Sometimes
- **d-** Seldom
- **e-** Never

3 - When you want to move from lane **1** to lane **2**, how often do you check the *distance* between your vehicle (**S**) and vehicle **2**?

- **a-** All the time
- **b-** Most of the time
- **c-** Sometimes
- **d-** Seldom
- **e-** Never

4 - When you want to move from lane **1** to lane **2**, how often do you check the *distance* between your vehicle (**S**) and vehicle **3**?

- **a-** All the time
- **b-** Most of the time
- **c-** Sometimes
- **d-** Seldom
- **e-** Never

5 - When you want to move from lane **1** to lane **2**, how often do you check the *distance* between your vehicle (**S**) and vehicle **4**?

- **a-** All the time
- **b-** Most of the time
- **c-** Sometimes
- **d-** Seldom
- **e-** Never

6 - When you want to move from lane **1** to lane **2**, how often do you check the *distance* between vehicle **1** and vehicle **2**?

- **a-** All the time
- **b-** Most of the time
- **c-** Sometimes
- **d-** Seldom

- **e-** Never

7 - When you want to move from lane **1** to lane **2**, how often do you check the *speed* of your vehicle (**S**)?

- **a-** All the time
- **b-** Most of the time
- **c-** Sometimes
- **d-** Seldom
- **e-** Never

It is written in the Texas Driver's Handbook that

> **"A good driver always keeps a safe distance from the car in front of him/her. A good rule is to stay at least 2 to 4 seconds behind the vehicle ahead of you."**

Other states also have similar guideline.

8 - How often do you check this *time* (**2** to **4** seconds) between your vehicle (**S**) and vehicle **3** before lane changing?

- **a-** All the time
- **b-** Most of the time
- **c-** Sometimes
- **d-** Seldom
- **e-** Never

9 - How often do you check this *time* (**2** to **4** seconds) between your vehicle (**S**) and vehicle **4** before lane changing?

- **a-** All the time
- **b-** Most of the time
- **c-** Sometimes
- **d-** Seldom
- **e-** Never

10 - How often do you check this *time* (**2** to **4** seconds) between your vehicle (**S**) and vehicle **1** after lane changing?

- **a-** All the time
- **b-** Most of the time
- **c-** Sometimes
- **d-** Seldom
- **e-** Never

11 - How often do you check this *time* (**2** to **4** seconds) between your vehicle (**S**) and vehicle **2** after lane changing?

- **a-** All the time
- **b-** Most of the time
- **c-** Sometimes
- **d-** Seldom
- **e-** Never

Part 3 – About yourself

12 - Please tell us your age: ______ years

13 - Please circle your gender: Male / Female

14 - Year when you first received your driving license (e.g. 2012): ________

15 - What type of vehicle do you drive most often? (Please circle only 1 answer)

- **a-** Sedan
- **b-** SUV
- **c-** Van
- **d-** Pickup Truck
- **e-** Other (please specify):___________________

16 - How often do you drive on highway or freeway? (Please circle only 1 answer)

- **a-** Everyday
- **b-** Almost every day (4-6 times a week)
- **c-** Sometimes (1-3 times a week)
- **d-** Seldom (less than once a week)
- **e-** Never

End of survey. Thank you!

Appendix B

Fuzzy inference rules

1- If GFA is **close** and GPA is **close** and D is **close** and GPB is **close** Then **No Lane Change**.
2- If GFA is **close** and GPA is **medium** and D is **close** and GPB is **close** Then **Lane Change**.
3- If GFA is **close** and GPA is **far** and D is **close** and GPB is **close** Then **Lane Change**. (impossible)
4- If GFA is **close** and GPA is **close** and D is **medium** and GPB is **close** Then **Lane Change**.
5- If GFA is **close** and GPA is **close** and D is **far** and GPB is **close** Then **Lane Change**.
6- If GFA is **close** and GPA is **close** and D is **close** and GPB is **medium** Then **No Lane Change**.
7- If GFA is **close** and GPA is **close** and D is **close** and GPB is **far** Then **No Lane Change**.
8- If GFA is **close** and GPA is **medium** and D is **medium** and GPB is **medium** Then **Lane Change**.
9- If GFA is **close** and GPA is **far** and D is **far** and GPB is **far** Then **Lane Change**.
10- If GFA is **close** and GPA is **close** and D is **far** and GPB is **far** Then **Lane Change**. (impossible)
11- If GFA is **close** and GPA is **close** and D is **medium** and GPB is **medium** Then **No Lane Change**.
12- If GFA is **close** and GPA is **close** and D is **medium** and GPB is **far** Then **Lane Change**.
13- If GFA is **close** and GPA is **close** and D is **far** and GPB is **medium** Then **Lane Change**.
14- If GFA is **close** and GPA is **medium** and D is **close** and GPB is **medium** Then **No Lane Change**.
15- If GFA is **close** and GPA is **far** and D is **close** and GPB is **far** Then **No Lane Change**. (impossible)
16- If GFA is **close** and GPA is **medium** and D is **far** and GPB is **close** Then **No Lane Change**.
17- If GFA is **close** and GPA is **medium** and D is **far** and GPB is **medium** Then **Lane Change**.
18- If GFA is **close** and GPA is **medium** and D is **far** and GPB is **far** Then **Lane Change**.
19- If GFA is **close** and GPA is **medium** and D is **medium** and GPB is **close** Then **No Lane Change**.
20- If GFA is **close** and GPA is **far** and D is **far** and GPB is **close** Then **Lane Change**.
21- If GFA is **close** and GPA is **medium** and D is **medium** and GPB is **far** Then **No Lane Change**.
22- If GFA is **close** and GPA is **far** and D is **medium** and GPB is **close** Then **Lane Change**. (impossible)

23- If GFA is **close** and GPA is **far** and D is **medium** and GPB is **medium** Then **Lane Change**. (impossible)
24- If GFA is **close** and GPA is **medium** and D is **close** and GPB is **far** Then **No Lane Change**.
25- If GFA is **close** and GPA is **medium** and D is **medium** and GPB is **far** Then **Lane Change**.
26- If GFA is **close** and GPA is **far** and D is **close** and GPB is **medium** Then **No Lane Change**. (impossible)
27- If GFA is **close** and GPA is **far** and D is **far** and GPB is **medium** Then **Lane Change**.
28- If GFA is **close** and GPA is **far** and D is **medium** and GPB is **far** Then **Lane Change**.
29- If GFA is **medium** and GPA is **medium** and D is **medium** and GPB is **medium** Then **Lane Change**.
30- If GFA is **medium** and GPA is **far** and D is **medium** and GPB is **medium** Then **Lane Change**. (impossible)
31- If GFA is **medium** and GPA is **close** and D is **medium** and GPB is **medium** Then **Lane Change**.
32- If GFA is **medium** and GPA is **medium** and D is **far** and GPB is **medium** Then **Lane Change**.
33- If GFA is **medium** and GPA is **medium** and D is **close** and GPB is **medium** Then **Lane Change**. (impossible)
34- If GFA is **medium** and GPA is **medium** and D is **medium** and GPB is **far** Then **Lane Change**.
35- If GFA is **medium** and GPA is **medium** and D is **medium** and GPB is **close** Then **Lane Change**.
36- If GFA is **medium** and GPA is **far** and D is **far** and GPB is **far** Then **Lane Change**.
37- If GFA is **medium** and GPA is **medium** and D is **far** and GPB is **far** Then **Lane Change**.
38- If GFA is **medium** and GPA is **medium** and D is **close** and GPB is **close** Then **No Lane Change**. (impossible)
39- If GFA is **medium** and GPA is **close** and D is **medium** and GPB is **close** Then **Lane Change**.
40- If GFA is **medium** and GPA is **far** and D is **medium** and GPB is **far** Then **Lane Change**. (impossible)
41- If GFA is **medium** and GPA is **close** and D is **close** and GPB is **medium** Then **No Lane Change**. (impossible)
42- If GFA is **medium** and GPA is **far** and D is **far** and GPB is **medium** Then **Lane Change**.
43- If GFA is **medium** and GPA is **medium** and D is **far** and GPB is **close** Then **Lane Change**.
44- If GFA is **medium** and GPA is **close** and D is **far** and GPB is **close** Then **No Lane Change**.
45- If GFA is **medium** and GPA is **close** and D is **far** and GPB is **medium** Then **Lane Change**.

46- If GFA is **medium** and GPA is **close** and D is **medium** and GPB is **far** Then **Lane Change**.
47- If GFA is **medium** and GPA is **close** and D is **far** and GPB is **far** Then **No Lane Change**. (impossible)
48- If GFA is **medium** and GPA is **far** and D is **medium** and GPB is **close** Then **Lane Change**. (impossible)
49- If GFA is **medium** and GPA is **medium** and D is **close** and GPB is **far** Then **No Lane Change**. (impossible)
50- If GFA is **medium** and GPA is **close** and D is **close** and GPB is **far** Then **No Lane Change**.
51- If GFA is **medium** and GPA is **far** and D is **close** and GPB is **close** Then **No Lane Change**. (impossible)
52- If GFA is **medium** and GPA is **far** and D is **close** and GPB is **far** Then **No Lane Change**. (impossible)
53- If GFA is **medium** and GPA is **far** and D is **far** and GPB is **close** Then **Lane Change**.
54- If GFA is **medium** and GPA is **far** and D is **close** and GPB is **medium** Then **No Lane Change**. (impossible)
55- If GFA is **medium** and GPA is **close** and D is **close** and GPB is **close** Then **No Lane Change**.
56- If GFA is **far** and GPA is **far** and D is **far** and GPB is **far** Then **Lane Change**.
57- If GFA is **far** and GPA is **medium** and D is **medium** and GPB is **medium** Then **Lane Change**.
58- If GFA is **far** and GPA is **close** and D is **far** and GPB is **far** Then **Lane Change**.
59- If GFA is **far** and GPA is **medium** and D is **far** and GPB is **far** Then **Lane Change**.
60- If GFA is **far** and GPA is **far** and D is **close** and GPB is **far** Then **Lane Change**. (impossible)
61- If GFA is **far** and GPA is **far** and D is **medium** and GPB is **far** Then **Lane Change**.
62- If GFA is **far** and GPA is **far** and D is **far** and GPB is **close** Then **Lane Change**.
63- If GFA is **far** and GPA is **far** and D is **far** and GPB is **medium** Then **Lane Change**.
64- If GFA is **far** and GPA is **far** and D is **close** and GPB is **close** Then **No Lane Change**. (impossible)
65- If GFA is **far** and GPA is **far** and D is **medium** and GPB is **medium** Then **Lane Change**.
66- If GFA is **far** and GPA is **close** and D is **far** and GPB is **close** Then **Lane Change**.
67- If GFA is **far** and GPA is **medium** and D is **far** and GPB is **medium** Then **Lane Change**.
68- If GFA is **far** and GPA is **close** and D is **close** and GPB is **far** Then **No Lane Change**. (impossible)
69- If GFA is **far** and GPA is **medium** and D is **medium** and GPB is **far** Then **Lane Change**. (impossible)
70- If GFA is **far** and GPA is **medium** and D is **far** and GPB is **close** Then **Lane Change**.
71- If GFA is **far** and GPA is **medium** and D is **medium** and GPB is **close** Then **Lane Change**. (impossible)

72- If GFA is **far** and GPA is **medium** and D is **close** and GPB is **medium** Then **No Lane Change**. (impossible)
73- If GFA is **far** and GPA is **close** and D is **medium** and GPB is **close** Then **Lane Change**.
74- If GFA is **far** and GPA is **close** and D is **close** and GPB is **medium** Then **NO Lane Change**. (impossible)
75- If GFA is **far** and GPA is **close** and D is **medium** and GPB is **medium** Then **Lane Change**.
76- If GFA is **far** and GPA is **far** and D is **medium** and GPB is **close** Then **Lane Change**. (impossible)
77- If GFA is **far** and GPA is **far** and D is **close** and GPB is **medium** Then **Lane Change**. (impossible)
78- If GFA is **far** and GPA is **medium** and D is **close** and GPB is **close** Then **No Lane Change**. (impossible)
79- If GFA is **far** and GPA is **medium** and D is **close** and GPB is **far** Then **No Lane Change**. (impossible)
80- If GFA is **far** and GPA is **close** and D is **medium** and GPB is **far** Then **Lane Change**. (impossible)
81- If GFA is **far** and GPA is **close** and D is **close** and GPB is **close** Then **No Lane Change**. (impossible)

Vita

Esmaeil Balal was born in Isfahan, Iran in 1985. He received his BSc Degree in Civil Engineering from Shahid chamran University of Ahvaz in 2007. His approach through his bachelor's degree was based on learning from anyone who was more knowledgeable, whether a professor, a technician, an assistant, or even a student. This approach helped him a lot in achieving valuable experiences. He became more confident about my choice, civil engineering, when he started to get some fundamental courses. After his first two years in the university and passing various courses, he found himself more interested in the field of Road and Transportation Engineering by getting high score in related courses and their projects. Consequently, He was able to choose his field of choice by being in the top of 2 % of more than 25,000 participants taking the national M.Sc. program entrance exam for transportation engineering. He chose to pursue my studies in the area of Transportation Engineering in one of the most prestigious university of technology in Iran, K. N. TOOSI University of technology, which is the oldest university in Iran (1928). Since being admitted as a PhD student at The University of Texas at El Paso in fall 2013, he has started working as a Doctoral Research Assistant at the Border Intermodal Gateway (BIG) Transportation Lab, which is also part of Center for Transportation Infrastructure Systems (CTIS) with Dr. Kelvin Cheu.

He has participated in different conference presentations such as: TXITE Spring Meeting, College Station, Texas, March 2015; TXITE Spring Meeting, Galveston, Texas, March 2016; TXITE Fall Meeting, Fort Worth, Texas, September 2016; TRB 95th Annual Meeting, Washington D.C, January 2016. In addition, he is a member of Texas Institute of Transportation Engineers (TXITE).

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This thesis/dissertation was typed by Esmaeil Balal.