Modeling Driver Behavior at Signalized Intersections: Decision Dynamics, Human Learning, and Safety Measures of Real-time Control Systems

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Dissertation submitted to the faculty of the Virginia Polytechnic Institute and State University in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

In

Civil Engineering

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December 4, 2014

Blacksburg, Virginia

Keywords: *signalized intersections; dilemma zone; driver behavior; human learning; agent-based modelling; surrogate safety measure*

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ABSTRACT

Traffic conflicts associated to signalized intersections are one of the major contributing factors to crash occurrences. Driver behavior plays an important role in the safety concerns related to signalized intersections. In this research effort, dynamics of driver behavior in relation to the traffic conflicts occurring at the onset of yellow is investigated. The area ahead of intersections in which drivers encounter a dilemma to pass through or stop when the yellow light commences is called Dilemma Zone (DZ). Several DZ-protection algorithms and advance signal settings have been developed to accommodate the DZ-related safety concerns. The focus of this study is on drivers' decision dynamics, human learning, and choice behavior in DZ, and DZ-related safety measures. First, influential factors to drivers' decision in DZ were determined using a driver behavior survey. This information was applied to design an adaptive experiment in a driving simulator study. Scenarios in the experimental design are aimed at capturing drivers learning process while experiencing safe and unsafe signal settings. The result of the experiment revealed that drivers do learn from some of their experience. However, this learning process led into a higher level of risk aversion behavior. Therefore, DZ-protection algorithms, independent of their approach, should not have any concerns regarding drivers learning effect on their protection procedure. Next, the possibility of predicting drivers' decision in different time frames using different datasets was examined. The results showed a promising prediction model if the data collection period is assumed 3 seconds after yellow. The prediction model serves advance signal protection algorithms to make more intelligent decisions. In the next step, a novel Surrogate Safety Number (SSN) was introduced based on the concept of time to collision. This measure is applicable to evaluate different DZ-protection algorithms regardless of their embedded methodology, and it has the potential to be used in developing new DZ-protection algorithms. Last, an agent-based human learning model was developed integrating machine learning and human learning techniques. An abstracted model of human memory and cognitive structure was used to model agent's behavior and learning. The model was applied to DZ decision making process, and agents were trained using the driver simulator data. The human learning model resulted in lower and faster-merging errors in mimicking drivers' behavior comparing to a pure machine learning technique.

DEDICATION

I dedicate my dissertation work to my inspiring husband, Arash, who endured this long process with me, always offering support and love.

I also dedicate this work and give special thanks to my loving and patient parents, whose words of encouragement and push for tenacity ring in my ears.

Finally, I dedicate this dissertation to my exuberant and sweet little nephew, Parsa, and my always kind-hearted and encouraging sister and brother-in-law.

ACKNOWLEDGEMENT

I would like to express my special appreciation and heartfelt gratitude to my advisor and gracious mentor, Dr. Montasir Abbas. His guidance has made this effort a thoughtful and rewarding journey, and this dissertation would not have been possible without his supervision and constant help. He has helped me see what I could be, and he has given me confidence in myself. His advice on my research as well as my career has been priceless, and there are no words to show him my appreciation.

I would also like to thank my committee members, Dr. Murray-tuite, Dr. Rahmandad, and Dr. Flintsch who have been more than generous with their expertise and precious time.

ATTRIBUTION

Chapter 3, 4, 5, 6, and 7:

Montasir Abbas, PHD, Department of Civil and Environmental Engineering at Virginia Tech, is currently an Associate Professor at Virginia Tech. Dr. Abbas was a co-author on these papers and helped through the entire process.

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CHAPTER 1 INTRODUCTION

Background

According to previous research almost 45 percent of all crashes in the United States occur at intersections (Bonneson, Middleton et al. 2002, Zimmerman and Bonneson 2005, Zimmerman 2007), mainly due to the traffic conflicts related to yellow interval dilemma. Dilemma Zone (DZ) is an area ahead of intersections in which drivers are faced with a dilemma to pass through or stop at the stop bar at the onset of yellow (Gazis, Herman et al. 1960). In fact, in DZ drivers experience a state of indecision due to the need to evaluate many parameters that affects their decision to stop or go (Kikuchi, Perincherry et al. 1993). Two type of safety issues are related to DZ: (1) the inconsistency of decisions between a leading vehicle and a following vehicle resulting in a stop decision by the leading vehicle while the following vehicle decides to go, and thus the possibility of rear-end crashes, and (2) the misjudgment by drivers about the amount of time she/he needs to pass thorough before the red light comes up, and thus possibility of right-angle crashes with the side street traffic. These safety concerns have raised the DZ-related topics as a challenge to transportation researchers.

Many research efforts have been contributed to evaluating contributing factors to dilemma zone, modeling driver's behavior in dilemma zone, and introducing traffic signal algorithm to mitigate the issues related to dilemma zone. However, more research needs to be done. Regarding influential factors to dilemma zone, approaching speed and distance to intersection at the commencement of yellow indication are by far the more studied factors. Contributing factors to driver's perception of dilemma zone studied by researchers to date do not cover the wide spectrum of factors that could significantly affect driver's decision. In this study, to identify and capture all significant factors beyond existing research, a driver survey is developed and administered. The focus is mostly on determining factors from drivers' point of view since they are the main component of the decision making process in Dilemma zone. Accounting for these significant factors can contribute to more realistic dilemma zone modeling methods.

In addition to investigating influencing factors on driver's decision making, it is beneficial to study in what time duration the data should be collected to best serve the drivers' decision prediction model. In this research, accuracy of prediction models is investigated considering different time periods as well as different types of collected data. An accurate prediction model assists DZ-protection algorithms and advance signal settings in making more intelligent decisions to prevent crashes.

The state of the art so far does not include investigation of drivers' learning process (dynamic nature of drivers' decision making). Learning refers to an approximately permanent change in humans' propensity due to practice or observation (Huitt and Hummel 2006). In Dilemma zone concept, we would like to know how driving experience through various conditions at intersections (safe or unsafe) changes drivers behavior at the following intersections. The question is whether drivers learn based upon their experience, or they behave without any learning involved in their decision making process. This is an important research need to address whether driving through intersections with various DZ-protection settings could result in a learning process that can expose drivers to bigger possibility of crashes. To answer this question, a driving simulator experimental design is introduced to account for the influential factors as well as learning aspect of the drivers. The results of this effort are of relevance for better dilemma zone modeling and designing mitigation strategies.

Another shortcoming observed in the body of the literature is lacking a comprehensive safety measure to characterize the level of safety at signalized intersections and provide a comparison base for different intersections with various DZ-protection settings. In this study, a methodology is introduced that results in a new safety surrogate measure to assess the safety issues related to dilemma zone conflicts. This method utilizes real-time radar field data and integrates the concept of time to collision to produce the safety surrogate measure called Safety Surrogate Number (SSN).

In addition to the lack of our knowledge on drivers learning process as described above, the state-of-the-art DZ modeling approaches so far do not reflect the realistic human behavior, knowledge utilization, and thinking process when modeling drivers' behavior. DZ modeling could benefit from a realistic human behavior and learning model that focuses more on how human really thinks, processes the knowledge, and makes decision as oppose to previously developed models focusing mostly on the interaction of external stimuli with human reaction. In this research effort, a driver choice behavior and learning model is developed by taking into account the cognitive architecture of human memory. This model bridge the gap between machine learning and human learning by integrating the concept of human learning in a machine learning technique (reinforcement learning).

In response to the shortcomings of the literature, in this research effort, driver behavior at the onset of yellow at signalized intersections is investigated focusing on decision dynamics, influential factors, and driver's learning. Strategies that are considered in DZ-protection algorithms are discussed in relation to driver's learning, and a novel safety surrogate number is introduced to be used in comparing the efficacy of these algorithms. A DZ human learning model is developed integrating machine learning and human learning techniques which is capable of generating driver agents closer to the real human driver. The results of this study are applicable in human behavior modeling, designing DZ-related mitigation strategies, and safety evaluation of signalized intersections.

Objective and scope

The research objectives include the following:

1. Identifying significant factors beyond literature that affect drivers' decision at DZ
2. Developing an experimental design of a driving simulator study to investigate drivers' learning and influential factors on their decisions, and analyzing drivers behavior at DZ using the simulator data
3. Assessing the applicability of DZ-related data in drivers decision prediction models to use in DZ-protection algorithms, and investigating the appropriate time frame for the data collection

4. Introducing a novel safety surrogate measure related to DZ conflicts to evaluate the level of safety at a signalized intersection and compare various approaches taken by DZ-protection algorithms
5. Modeling driver choice behavior and learning in DZ utilizing cognitive architecture and integrating reinforcement learning with human learning process

Organization of the dissertation

The remainder of this dissertation is organized as follows. Chapter 2 provides a review of previous research efforts related to the focus of this dissertation. Chapter 3 describes the driver survey and analysis of the survey results. In Chapter 4, an adaptive design of the driving simulator study is described, as well as the experimental procedure, data description, statistical model, and the results. Chapter 5 presents the application of the simulator data in predicting driver' decision considering different time frames for the data collection. Chapter 6 discusses a novel surrogate safety number measure including the underlying concept, and application of this measure. Chapter 7 presents a human learning model developed by incorporating human memory structure and cognitive mechanism in a machine learning technique. Chapter 8 outlines the conclusions of this dissertation.

CHAPTER 2 LITERATURE REVIEWS

In this chapter, a general overview of the literature related to the scope of this dissertation is provided. First, a review of the Dilemma Zone previous research, contributing factors to driver behavior in DZ, and driver behavior modeling in DZ is presented. Then, traffic signal DZ related algorithms are reviewed followed by a background on safety surrogate measures. The final section reviews the human choice behavior and learning process.

Dilemma Zone

Dilemma Zone (DZ) concept was first introduced five decades ago (Crawford and Taylor 1960, Gazis, Herman et al. 1960). It is defined as an area upstream of intersections where drivers experience a dilemma to pass through the intersection or stop at the stop bar at the commencement of yellow (Gazis, Herman et al. 1960). DZ is recognized as one of the major factors contributing to the accidents at signalized intersections. Two types of accidents are attributed to DZ; first is rear-end crashes as a result of driver's decision to stop when its follower decides to go, and second is the right angle crashes due to the red light running situation and generating a conflict with the side street traffic (Pant, Cheng et al. 2001).

Earlier studies of DZ (Crawford and Taylor 1960, Gazis, Herman et al. 1960, Olson and Rothery 1961, Crawford 1962) treated it as a deterministic value (Sheffi and Mahmassani 1981). Stochastic values came to play after a while, and it was defined as the area where more than 10% and less than 90% of drivers would choose to stop (Zegeer and Deen 1978). To specify the boundaries of DZ researchers produced charts of "percent drivers stopping" versus "distance from stop bar at the onset of yellow" (e.g. (Olson and Rothery 1961, May 1968, Zegeer and Deen 1978)), which required large number of observations (Sheffi and Mahmassani 1981).

Two types of DZ have been introduced by researchers considering vehicle dynamic and driver decision (Papaioannou 2007, Koonce, Rodegerdts et al. 2008, Hurwitz 2009, Elmitiny, Yan et al. 2010, Hurwitz, Knodler et al. 2011, Hurwitz, Wang et al. 2012). In the definition of type I, DZ is where the driver can neither stop without slamming on the brakes nor clear the intersection safely before the red light is on. In Type II DZ, also referred to as option zone, DZ is where the driver is able to pass through successfully based on his decision. These two types of DZ are illustrated in Figure 1 and Figure 2. Type I DZ is eliminated by setting an appropriate yellow duration. In fact, the real challenge is in dealing with type II DZ, related to driver behavior.

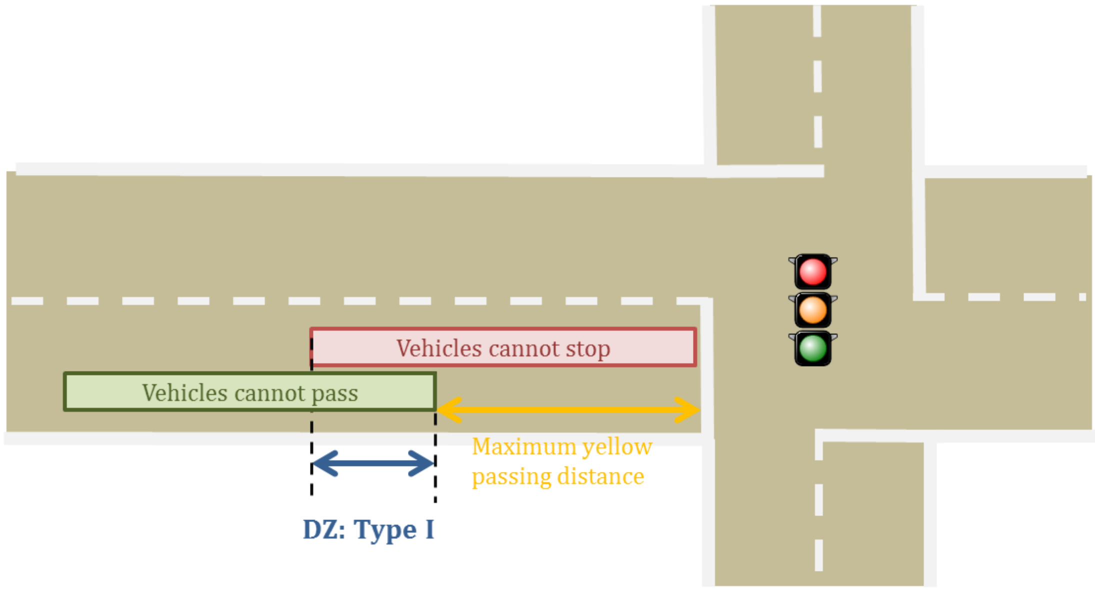


Figure 1: Type I Dilemma Zone

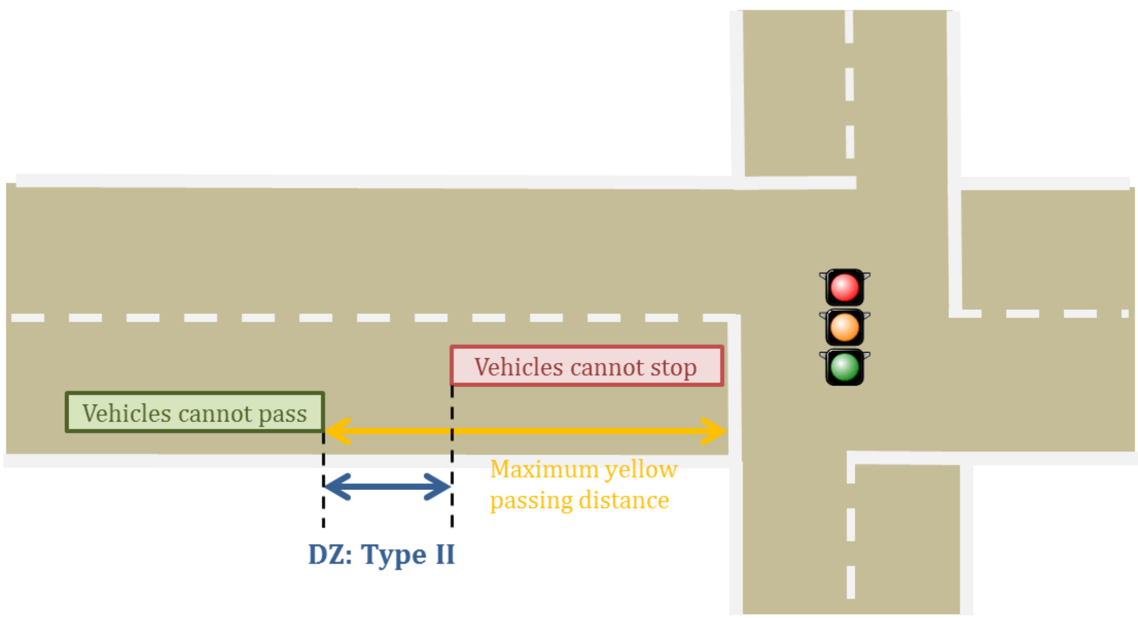


Figure 2: Type II Dilemma Zone

Contributing factors to Driver behavior in DZ

Various factors influencing DZ, driver behavior, and decision making process at the onset of yellow phase have been the subject of research in the literature (Konecni, Ebbeson et al. 1976, Wortman and Matthias 1983, Papaioannou 2007, ITE 2008, Amer, Rakha et al. 2012). These factors include driver's attributes, intersection characteristics and condition, subject vehicle characteristics, signal control settings, and traffic flow characteristics.

Drivers play an important role in safety issues related to dilemma zone since driver error is recognized as the main contributing factor in automobile crashes (Wierwille, Hanowski et al. 2002). Driver's decision making process is affected by driver's characteristics (Papaioannou 2007, Rakha, Amer et al. 2008). This influence is mostly pronounced in driver's perception reaction time (PRT) and acceleration/deceleration rate. Many research efforts have been dedicated to investigate PRT and acceleration/deceleration rate (Gazis, Herman et al. 1960, Taoka 1989, Bao and Boyle 2007, Caird, Chisholm et al. 2007, El-Shawarby, Rakha et al. 2007, El-Shawarby, Rakha et al. 2010, El-Shawarby, Rakha et al. 2011). However, the relationship between other driver-related factors such as age and gender and PRT and acceleration/deceleration rate is unclear (Amer, Rakha et al. 2012).

Some other factors related to driver include driver experience, violation record, concentration level during driving (Patten, Kircher et al. 2004, Papaioannou 2007), personality, emotional states (Van Der Horst and Wilmink 1986, Wu, Juan et al. 2009), and aggressive driving (Shinar and Compton 2004, Liu, Chang et al. 2007, Liu, Chang et al. 2011).

Intersection characteristics such as clearing width, intersection layout, number of lanes, number of arms, existence of surveillance cameras, gradient, roadway surface condition, and pavement markings are also recognized as influential factors on driver decision in DZ (Allos and Al-Hadithi 1992, Papaioannou 2007, Yan, Radwan et al. 2007, Yan, Radwan et al. 2009, El-Shawarby, Abdel-Salam et al. 2012).

Vehicle characteristics such as vehicle speed, distance to intersection, position in the traffic flow (leading or following), and vehicle type are also influential factors on driver decision in DZ (Papaioannou 2007, Kim, Zhang et al. 2008, Gates and Noyce 2010, Zhang, Wang et al. 2010, Wei, Li et al. 2011).

As expected, one of the significant influencing factors related to driver's decision in dilemma zone is signal settings. Factors such as length of yellow interval, cycle length, the ratio of the green interval to the cycle length, signal phasing sequence, control type, and existence of countdown units have been studied in this regard (Allos and Al-Hadithi 1992, Liu, Herman et al. 1996, Middleton, Research et al. 1997, Zimmerman 2003, Koll, Bader et al. 2004, Papaioannou 2007, Sharma, Bullock et al. 2007, Wu, Juan et al. 2009, Chiou and Chang 2010, Long, Han et al. 2011).

Traffic flow condition is also an important factor in DZ-related issues. Traffic characteristics include such factors as subject street volume, opposing volume, presence of side-street vehicle/pedestrian/bicycle, and capacity (Allos and Al-Hadithi 1992, Lin and Kuo 2001, Gates, Noyce et al. 2007, Liu, Chang et al. 2011).

Driver behavior modeling in DZ

Driver behavior modeling in DZ has mostly focused on the statistical methods. The prevailing modeling approach taken in the past research is to collect data and model some measure of the driver's behavior in DZ such as probability of drivers' stop/go decision based upon the existing influential factors in the collected data set (Olson and Rothery 1961, Chang, Messer et al. 1985, Allos and Al-Hadithi 1992, Caird, Chisholm et al. 2007, Gates, Noyce et al. 2007, Wu, Juan et al. 2009, Elmitiny, Yan et al. 2010, Sharma, Bullock et al. 2011).

To provide examples, some of these studies are reviewed here. One of the first modeling effort was by Olson and Rothery (Olson and Rothery 1961) who determined the probability of stopping as a function of distance to the intersection. Elmitiny et al. (2010) applied a video-based system collected data to perform a classification analysis for stop/go decision of drivers. According to their result, vehicle's distance from the intersection, operating speed, and position in the traffic flow are the most important factors. Wu et al (2009) focused on the effect of countdown units on driver decision. The result of their study revealed that when no countdown units exist at the intersection, speed is the most significant factor in driver decision. In presence of countdown units personalities and signal timing are more influential. Caird et al. (2007) modeled drivers stop or go decision as a function of time to stop bar. The result of their simulator study regarding the effect of age group showed no differences in perception reaction time.

Fewer research approaches in modeling DZ decision making process has focused on the uncertainty associated to this process, and taken the fuzzy approach. For example, Hurwitz, Wang et al. (Hurwitz, Wang et al. 2012) modeled drivers probability of stop or go applying a binary logistic regression approach. The input of their model was produced using a fuzzy subset. Kikuchi et al. (1993) developed a set of fuzzy inference rules for stopping or going through the intersection using field data. They focused on the estimation of the degree of anxiety for aggressive and conservative drivers. Another fuzzy-based study related to DZ is by Lin & Kuo (2001). They developed a procedure to estimate the change and clearance intervals of a traffic signal using a rule-based fuzzy logic system.

As discussed to this point and to the best of our knowledge most DZ studies to date are revolving around the machine learning methods such as statistical analysis. Although, some efforts such as fuzzy approach techniques have been toward taking the human learning aspect into DZ modeling, more research needs to be done. DZ modeling could benefit from considering human decision making process and cognitive architecture to provide more realistic models that conform to the characteristics of the real decision maker, human, in DZ conflicts.

Traffic signal DZ related algorithms

As mentioned earlier, traffic signal settings are one of the influencing factors in drivers' behavior at DZ. DZ-protection algorithms and advance signal settings have been developed by researchers in response to shortcomings of traditional signal settings regarding DZ related conflicts. Some examples of these advance settings and algorithms include the green extension systems (GES) (Zegeer 1977), LHOVRA (Peterson 1986), the green termination system (Kronborg 1997), the detection-control system (DC-S) (Bonneson, D.

Middleton et al. 2002), and the Platoon Identification and Accommodation System (PIA) (Chaudhary, M. Abbas et al. 2006). These systems generally work by predicting number of vehicles caught in DZ using speed estimation technologies. Using speed information, the time that vehicle will reach the stop bar is calculated, and then DZ boundaries are computed by typically subtracting 5.5 seconds and 2.0 seconds, respectively. Then, appropriate alteration in signal settings is applied to accommodate the vehicle in DZ (such as green extension). These technologies show a high potential in elevating the safety level at signalized intersections. However, a safety measure is needed to prepare a ground for comparison among them.

Safety Surrogate Measures

Traditionally, number of crashes is used to measure the level of safety at roadway facilities including signalized intersections. Crash prediction models are generally instructed by statistical methods to estimate the number of crashes. Independent variables are considered to be traffic Characteristics, geometry of the facility, and traffic control settings (Gettman, Pu et al. 2008). However, an infrequent nature of crashes and the need to evaluate safety of the traffic facility before they are built, made researchers to seek for surrogate measures. Surrogate safety measures are defined as "measures of safety not based on a series of actual crashes (Gettman, Pu et al. 2008)".

Surrogate safety measures are mostly considered in "traffic conflicts". A conflict can be defined as "An observable situation in which two or more road users approach each other in time and space to such an extent that there is a risk of collision if their movements remain unchanged (Amundsen and Hyden 1977) mentioned in (Gettman and Head 2003)." The frequency and severity of traffic conflicts affects the level of safety at a traffic facility. Time to Collision (TTC) is the primary severity conflict measure proposed by researchers (Gettman and Head 2003).

TTC has been initially suggested by Hayward (Hayward 1972) around four decades ago. It is specified as the time until collision between two vehicles if the collision situation is maintained (Hayward 1972). TTC threshold in the literature ranges from 1.5 to 5 sec, and TTC larger than 6 seconds is not considered to be dangerous (Vogel 2003). This measure has been studied for various traffic conflicts such as passing maneuvers on rural two-lane highways (Farah, Bekhor et al. 2009), rear-end vehicle crash in urban road tunnels (Meng and Qu 2012), and crossing scenarios (Berthelot, Tamke et al. 2012). TTC is extracted from different data sources such as videos (Hayward 1972, Meng and Qu 2012, Xu and Qu 2014) and vehicle trajectories (Minderhoud and Bovy 2001). It has also been studied from the drivers' point of view, meaning that how drivers perceive and estimate the TTC (Hoffmann and Mortimer 1994, Kiefer, Flannagan et al. 2006).

One of the major accident prone situations at signalized intersections is related to DZ conflicts. Investigating TTC for approaching vehicles to a signalized intersection that are exposed to traffic interval change from green to yellow provides a measure to evaluate the degree of intersection safety.

Human choice behavior and learning

Human decision making and choice behavior under uncertainty has been the subject of research over decades. One of the earliest efforts in the mid-1600s to explain the foundation of rational choice was expected-value theory indicating that the choice among options is based on maximizing the expected value. Finding a paradox in expected-value theory, Bernoulli introduced the concept of expected-utility theory which became the most affecting theory of individual choice behavior. After a while, violations of the theory's axioms were remarked by researchers which led to some modifications of the theory while keeping the core idea. One of the most significant modifications is "prospect theory" by Kahneman and Tversky (1979) indicating that "the value (a form of utility) of each outcome is multiplied by a decision weight" (Hertwig, Barron et al. 2004).

The focus of the Prospect theory (PT) is on people's choice behavior in one-shot decision situations while having complete knowledge of the outcome probability distributions of options. Based on this theory, people approve an assured gain more than a probable gain with an equal or greater expected value. In case of losses, people prefer a probable loss than a certain loss with lower expected value. In other words, in the domain of likely gains people are "risk-averse" as oppose to the domain of likely losses in which people are more "risk-seeking". Moreover, sensitivity of people to potential losses is higher than potential gains (Ahn 2010).

Human learning is in close relationship to the choice behavior. In fact, learning is the evolving of choice behavior from a one shot event to a dynamic model which occurs due to practice, experience, and observation (Roth and Erev 1995). Human learning process could be passive or active. Passive learning refers to learning from random examples while active learning means that learner can actively query the world for information (Castro, Kalish et al. 2008). Castro, Kalish et al. (2008) conducted a comparison between active and passive learning by humans in a simple classification task. They found that human perform better when they could select their own examples to learn for low noise (probability of incorrect label) level.

Human choice behavior Models

Belief-based vs. Reinforcement Models

Looking at the previous literature, different grouping methods have been introduced for human choice behavior, mostly in the ground of playing games. For instance, one grouping strategy divides the decision making models into two groups of belief-based models and choice reinforcement models (Camerer and Hua Ho 1999). Based on this definition, in belief-based models, players form some belief about other players play in the future by tracking the history of them. In contrast, in choice reinforcement model, strategies are reinforced by their previous payoffs, and they are chosen based on their stock of reinforcement.

Camerer and Hua Ho (1999) combined belief-based and choice reinforcement models into a general "experience-weighted attraction (EWA)" learning model. The improvement that they considered over choice reinforcement model is that not only the chosen strategy is reinforced but also other strategies are reinforced by a multiple δ of their payoffs. This is because people do not just learn from the experiments that are reinforcing. EWA model includes two variables of number of observation-equivalents' of past experience and strategy attraction. For both of these variables a prior value is assumed which are resulted from a transferred learning of different games or introspection.

Exploratory vs. Exploitative Decisions

Decisions are also categorized as exploratory or exploitative. It refers to the difference in decision making when subject rely on the accumulated experience to choose the option that led to the most payoff in the past (exploitative), and when decision maker risks to select less familiar option which might result in a higher payoff (exploratory). Explore/exploit related models have been the subject of interest for researchers. Daw, O'Doherty et al. (2006) investigated the explore/exploit dilemma by looking at the pattern of behavior and brain activity in 14 healthy subjects performing "four-armed bandit" task. Three Reinforcement Learning (RL) strategies for exploration -based on how exploratory actions are directed- were studied by fitting them to subjects' behavioral choices. Parameters of the models were estimated by maximizing the cumulative likelihood of the subjects' choices. In one of the recent efforts, Lee, Zhang et al. (2011) introduced a new psychological model based on switching between latent exploration and exploitation states. They compared the proposed model to existing explore/exploit RL models such as ε-greedy and Win-stay lose-shift.

Choice from Description vs. Experiment (Experience-based vs. Prediction-based Mode)

In another categorical approach, human choice decision could be from description or from experiment. Decision from description refers to a situation that the decider has a description of possible choice outcomes. On the other hand, decision from experience is made by relying on personal experience rather than knowledge of the outcome probabilities. In other words, human choice preference is a result of the feedback of past experiences in similar situations (the "experience-based" mode) or the prediction about future impact of choice outcomes (the "prediction-based" mode). Most of the research regarding human decision making is concerned with decision from description, and only a few studies exist on decision from experience (Hertwig, Barron et al. 2004). Hertwig, Barron et al. (2004) found that in decision from experience people underweight the rare events as opposed to decision from description in which rare events are overweighted. Ahn (2010) proposed a new model called "affective-cognitive (AC) decision model." It extends Prospect Theory (PT)-based subjective value functions and integrates "experience-based" mode and “prediction-based" mode in human decision making and learning process (Ahn 2010).

Although human learning and choice behavior have a long history in several science areas, transportation-related research lacks the investigation of these important topics. Incorporating human learning into the widely-used machine learning techniques will improve the modeling approaches resulting in more realistic model of driver behavior.

In conclusion, several research efforts to date have addressed DZ-related topics ranging from influential factors to driver behavior modeling and mitigation strategies. However, more research needs to be put into investigating dynamics of driver behavior, solution approaches considered in DZ-protection algorithms in relation to driver learning, and safety evaluation at signalized intersections. Specifically, literature on human learning modeling in DZ is limited. Recognizing the shortcomings of the prior DZ-related studies has motivated this dissertation research.

CHAPTER 3 DRIVER'S DILEMMA ZONE PERCEPTION: LARGE SCALE SURVEY ANALYSIS OF DRIVERS IN VIRGINIA, MARYLAND, AND PENNSYLVANIA

This chapter was jointly written by Sahar Ghanipoor Machiani and Montasir Abbas. The paper was a part of a report entitled "Modeling the Dynamics of Driver's Dilemma Zone Perception Using Machine Learning Methods for Safer Intersection Control" with report number MAUTC-2212-04. The material is reproduced with permission of MAUTC.

Abstract

At a signalized intersection, drivers encounter a dilemma to stop or go at the onset of yellow indication as they can neither cross safely nor stop comfortably. There are many factors contributing to the decision of drivers regarding how to proceed when they see the yellow light. These factors include drivers' attributes, intersection characteristics, signal control settings, vehicle characteristics, and traffic flow attributes. The purpose of this study is to identify significant factors contributing to drivers' perception of dilemma zone at the commencement of yellow, specifically from drivers' perspective. A driver survey was developed and administered in three states of Virginia, Maryland, and Pennsylvania. The responses obtained from the 1213 participants were analyzed, and a descriptive statistical analysis was carried out. Significant factor analysis of the results recognized 9 factors as the significant factors in these three states. They include speed, distance to intersection at the onset of yellow, presence of a red light camera, presence of police, whether the pavement is wet or dry, presence of a vehicle in front of the subject car, presence of a vehicle behind the subject car, how well the driver knows the intersection, and whether the traffic is bad. The results also showed that the difference between states' proportions (the percentage of responders who indicated that a given factor was influential in their decision at the onset of yellow) is significant.

Keywords: signalized intersections; dilemma zone; drivers' behaviour; driver survey

Introduction

According to the National Safety Council reports, crashes associated with signalized intersections constitutes up to 30% of all crashes (Li and Abbas 2010). Dilemma zone (DZ) is a leading cause, since a great deal of incidents occurring at intersections are resulted from issues related to dilemma zone functioning. Two types of dilemma zone related crashes are recognized at intersections: rear-end crashes (when a driver decides to stop while his/her follower decides to proceed) and right-angle crashes (when a driver violates the red light and crash with side street traffic) (Pant, Cheng et al. 2001).

This study aims at identifying significant factors that affect driver's perception of dilemma zone specifically from drivers' perspective. A literature review of influencing factors on dilemma zone is conducted to identify the existing factors. A driver survey is developed and administered to a selected representative group of drivers in Virginia, Maryland, and Pennsylvania. Several factors are defined and presented to drivers to select what they think would affect their decision at the onset of yellow. State of the art techniques in human psychology and experimental design and statistical analysis will be conducted to design the survey and interpret the results in determining significant factors.

This paper is structured as follows. Next section presents the survey design, followed by the distribution process description. Then, the result of the survey is summarized including significant factor analysis. The last section provides conclusions and future directions.

Survey design

Survey questionnaire is designed to mainly address significant factors affecting driver's decision at the onset of dilemma zone. A sample of survey questionnaire is provided on appendix A. It consists of three parts. First part of questions provides personal information on participants' age, gender, education level, race, and living location. The second part focuses on general driving questions. Participants are asked to specify their car type and how often they drive. Questions about the number of times they have been pulled over and their incident involvements are also in this part of the questionnaire. Moreover, there is a question asking participants if they consider themselves safe drivers or not. The third part mainly intends to capture information on what drivers believe influence their decision while encountering yellow light. Twenty three factors are listed for recipients to pick as influencing factors. In this part, drivers are also asked about duration of yellow light and different yellow light lengths at different intersections. At the end of the questionnaire an open answer question is designed so that responders specify their comments, experience, and suggestions.

Survey distribution

Survey questionnaire was prepared through a free online tool, Google Docs (a web-based service offered by Google to create and manage documents such as surveys). The questionnaire is accessible live on a webpage for participants to submit the answers. The survey results are also stored online and can be saved as xlsx., csv., and other formats as needed.

A pilot survey was conducted to ensure that the questions are logical and understandable, and they convey the intended concept. Twenty people participated in the pilot survey were asked to specify any vagueness or ambiguity in questions. Based on the result of the pilot survey questions were altered to deliver right messages.

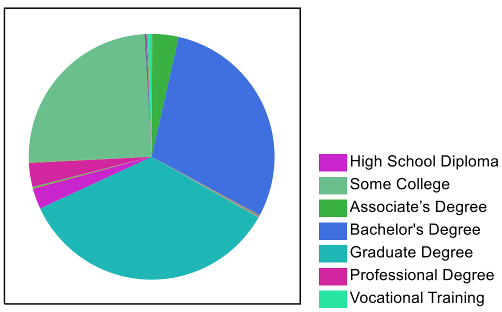
The survey was distributed at Virginia Tech, Morgan State University, and Penn State University through LISTSERVs and news webpage. Participants were asked in an email to complete the online survey which takes approximately 5 minutes. They are also informed that participation in this study is completely voluntary and their responses are anonymous and confidential. It should be noted that all participants must be at least 18 years old.

Survey results analysis

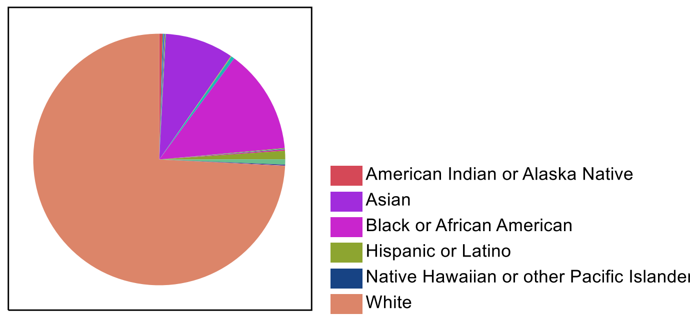
Personal Questions

Responses to the online survey was stored in excel spreadsheets. Totally 1213 people participated among which 57% were females. The Age distribution ranges from 19 to 92 years old with means and standard deviation equal to 31.59 and 12.76, respectively.

Figure 3-a and Figure 3-b depict the pie chart of the highest level of education and race distributions, respectively. As Survey was conducted at universities, it is expected that the majority of responders are graduate or undergraduate students. According to Figure 3-b, Whites are the majority racial group among the participants. The second largest ethnic group belongs to Blacks or African Americans. In both figures, some of the responses with negligible counts are excluded from the legend.



a)

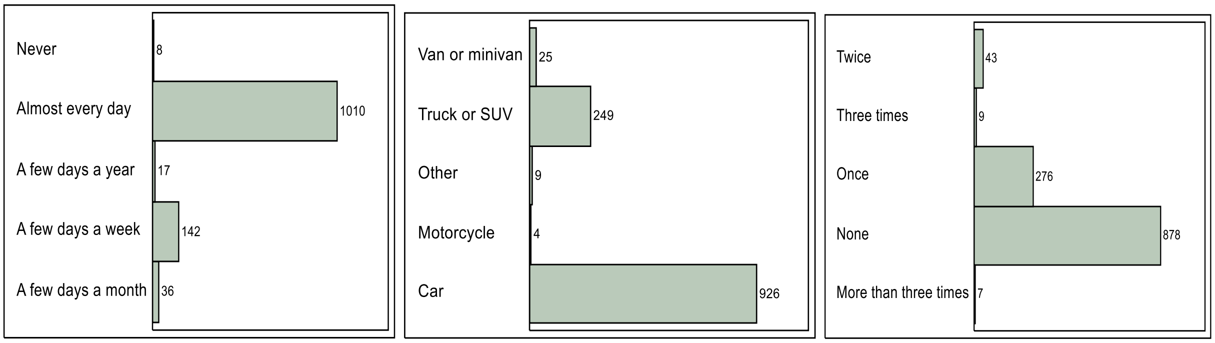


b)

Figure 3: Distribution of a) highest level of education; and b) race.

General Driving Questions

Figure 4 shows the bar charts of three questions of "how often you drive a motor vehicle?", " what kind of vehicle do you usually drive?", and "how many times have you been pulled over by the police in the past year?", respectively. Numbers shown on top of the bars indicate the count of corresponding categories. The majority of the responders drive a car almost every day, and has not been pulled over by the police.



a) b) c)

Figure 4: Distribution of a) how often participants drive; b) vehicle type; and c) being pulled over by the police.

According to the results of the next question, 22% have been involved in an accident at an intersection. Note that this does not mean they are surely at fault in the accident.

In answering the "safe driver" question, it is interesting that 94% of drivers consider themselves safe drivers, and there is a small group, 4%, who do not know if they are safe drivers or not.

Yellow Traffic Light Questions

As mentioned before, last part of the questionnaire includes questions directly related to the yellow light dilemma zone.

Figure 5-a shows how many people chose each choice in question asking "how often do they try to catch a yellow light and end up running a red light?". According to this figure the majority of drivers rarely do this, yet there is almost a large group, 30%, who sometimes try to catch the yellow light and end up running a red light. Pie charts in Figure 5-b show gender disparities in answering this question. The most apparent differences is related to the percentage of male who answered "Never" which is higher than female group, and the percentage of female who answered "Rarely" which is higher than male group. Figure 5-c summarizes the answers by states. According to this figure, Penn State drivers show riskier behavior since the "Never" portion is smaller and "Sometimes" and "Very often" portions are larger comparing to the other states.

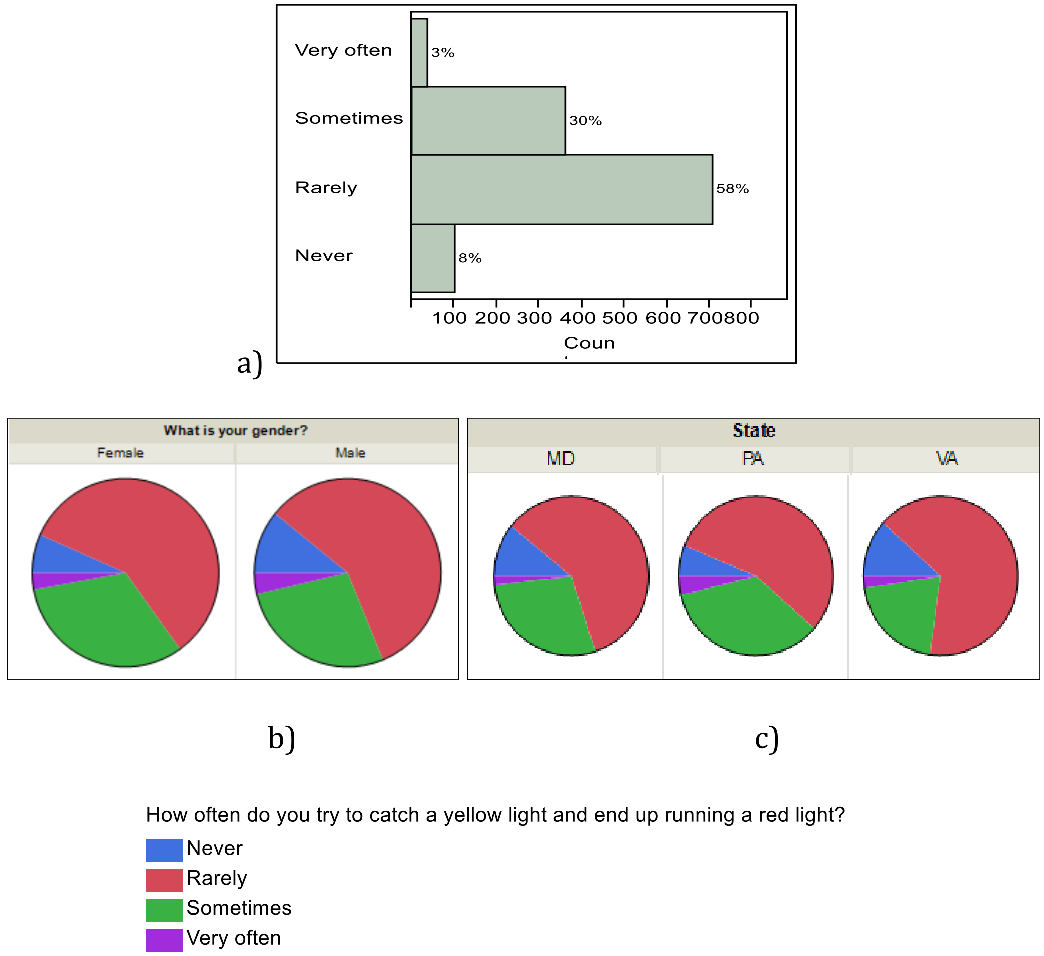


Figure 5: Yellow light catching frequency; a) bar chart; b) gender disparities; c) state disparities.

Figure 6 depicts the distribution of what responders normally do when they see a yellow light. According to this figure, most drivers decide depending on the condition they come into, and 20% of them slow down.

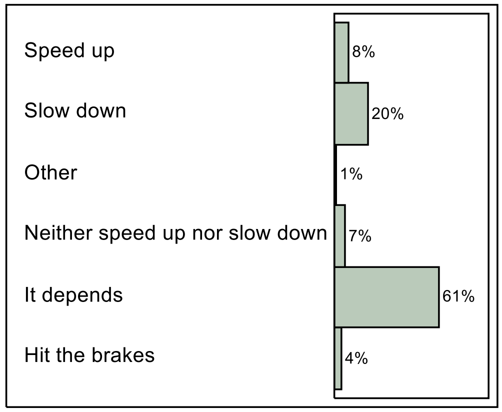


Figure 6: Distribution of responder's reaction while encountering a yellow light.

In answering the question of how long the responders think yellow light usually lasts, almost half of the participants (46%) assume that yellow light duration is 3 seconds. However, looking at the next question, the results indicate that the majority of the responders (78%) have noticed that some yellow lights are longer or shorter than others.

Result of the question regarding the influencing factor is analyzed separately in the following section of the paper entitled "Significant Factor Analysis".

In the last question, driver survey participants were asked to specify any experience or suggestion that they may have on the subject of "drivers' decision to stop or go at the onset of yellow light". The responses cover a wide spectrum of the recipients' points of view and experiences regarding this issue. General remarks are summarized below:

- Based on drivers' perception of yellow time duration and how long it has been since the light turned yellow, drivers estimate how much time they have to the end of yellow to pass through. Some drivers indicated that if they do not see the light turn from green to yellow (how attentive they are), they usually stop.
- Countdown units appear to be useful in assisting drivers with their prediction process. It has also been mentioned that pedestrian timers for the cross streets is used to anticipate whether a yellow light is likely. Although, the effectiveness of countdown units is debatable as drivers may change their behavior based on this extra information, and try to use the yellow light as much as possible to proceed through and end up running red lights more.

- Dynamic nature of drivers' decision is indicated in the responses. How well the drivers know the intersection (familiarity) (e.g. knowing that the intersection is set to have all red phase) and what they have experienced before, affect their decisions. Drivers' awareness of different timing in various states or countries and specifying that they follow cultural cues mentioned by responders, emphasizes this dynamic nature. There are interesting responses in this regard such as "If you don't know the intersection, and you see a yellow light, stop the first time and see how long the yellow is on for." and "If the light's turned red by the time I'm under it, I take note so as to improve my gauge if faced with the same yellow light again."
- Three types of flashing yellow lights are mentioned in the responses. First one is the flashing yellow light located before the intersection to warn the approaching drivers that the light is going to turn yellow. Most drivers mentioned that they slow down and get ready to stop when see it flashing. Although the majority of drivers found it helpful, some people believe it is confusing. The second flashing yellow light refers to the traffic light indicator flashing before (this one could also be flashing green instead) or after the solid yellow. Most people who mentioned this prefer flashing yellow before terminal yellow. The third type is a flashing yellow phase which is set after red in some European countries.
- Some drivers are so cautious that they pause for a little or look both ways before proceed when their light turns green due to tendency of side street drivers to run red lights.
- One critical factor for drivers to stop or go is the amount of time they should wait until the next green, especially based on degree of urgency, how much hurray the drivers are in, and value of time for them. This indicates how important it is to time the signals well especially in a string of traffic lights. Long waiting in consecutive intersections and hitting multiple red lights make the drivers impatient. Regarding this, one person stated that "If I have already stopped at a yellow light once in the last five minutes, I will be less likely to do so. Not sure why that happens, I just think it is unfair to have to stop at every consecutive light."

- Although all light being red after yellow time is considered helpful to avoid accidents, and it gives time to clear the intersection, there is this argue that it could temps drivers to catch yellow more. It is because they think they are less likely to have problems and if they end up in the intersection for additional time it is not a problem.
- Drivers try to make distance rules for themselves in order to ease the decision making process. For example, some drivers tend to pick a "point of no return" when approaching intersections. That is, if they pass a certain point and light turns yellow they decide not to stop. This point is determined based on their speed and perception of a safe stop. Apparently learnt in driver education, for some drivers this point is the start of solid white line in the middle of two lanes. Another example of rule making is a response saying that "If you're more than 2-3 car lengths away from the light, you should stop instead of try to speed through."
- It could also be helpful if there is a sign or road is somehow marked to show when it is safe to stop.
- Existence of a car behind, size and type of vehicle behind, decision made by the driver behind (being the same as the car in front or not), and how much attention the driver in back is devoting, concern many drivers about a safe stop or going through without making problems for the followers.
- Hesitation in decision of stopping or going through is as dangerous as the wrong decision. When a decision is made, some drivers believe it is better not to change your mind probably due to a small amount of time for the action.
- There are some other factors in addition to the ones in the survey that seems to be important based on the responses. They are listed below:
    - Presence of tractor trailers
    - Amount and type of cargo (heavy or fragile cargo like cake or sleeping baby)
    - If the oncoming vehicles turning left are crossing the through traffic
    - Personal knowledge of the driver on the car maintenance situation and tires (brand new or wearing)
    - Weather condition affecting visibility

    - Time of day
    - Traffic pattern
    - Type of car (e.g. SUVs are harder to brake)
    - Driving a long vehicle (e.g. bus)
    - Driving behind a large truck which blocks vision
- Yellow catching for left turn increases if there is no protected left turn phase.
- There is an interesting strategy by one person saying that "I always slow down going into an intersection when the green is "stale". He gets ready for yellow even before its arrival.
- The importance of training process and where it occurs is notable since different states have different laws on the driving manual regarding proper action while encountering yellow light. It could be helpful if this skill is tested during licensing procedure. In addition to training process, behavior at a yellow light could be country/culture related.
- Slamming on the brakes to avoid red light running causes such concerns as rear-end collision, loss of vehicle control (skidding), and ending up stopped in the middle of the intersection.
- Although the survey results show that most drivers slow down or act dependent on the situation when they see yellow, the general belief by many people is that "other drivers speed up".
- Difference in timing plan in different states and countries and the necessity of mind adjustment are mentioned in the responses. Some drivers are interested in existence of a standard timing plan which is implemented everywhere.

Significant factor analysis

The most important question in the survey is the one asking about factors which affect drivers' decision at the onset of yellow light. Contributing factors are labeled F1 to F23 based on the order shown in appendix A.

The survey results summarized in Figure 7 below shows the percentage of responders who indicated that a given factor was influential in their decision at the onset of yellow. The factors are sorted in descending order and are shown by state in a bar chart format. In every bar chart a dropping point can be recognized that indicates where there is a significant change in drivers' perception of factors being influential in their decision. These points are shown by circles in Figure 7. Factors located below the dropping points are considered significant.

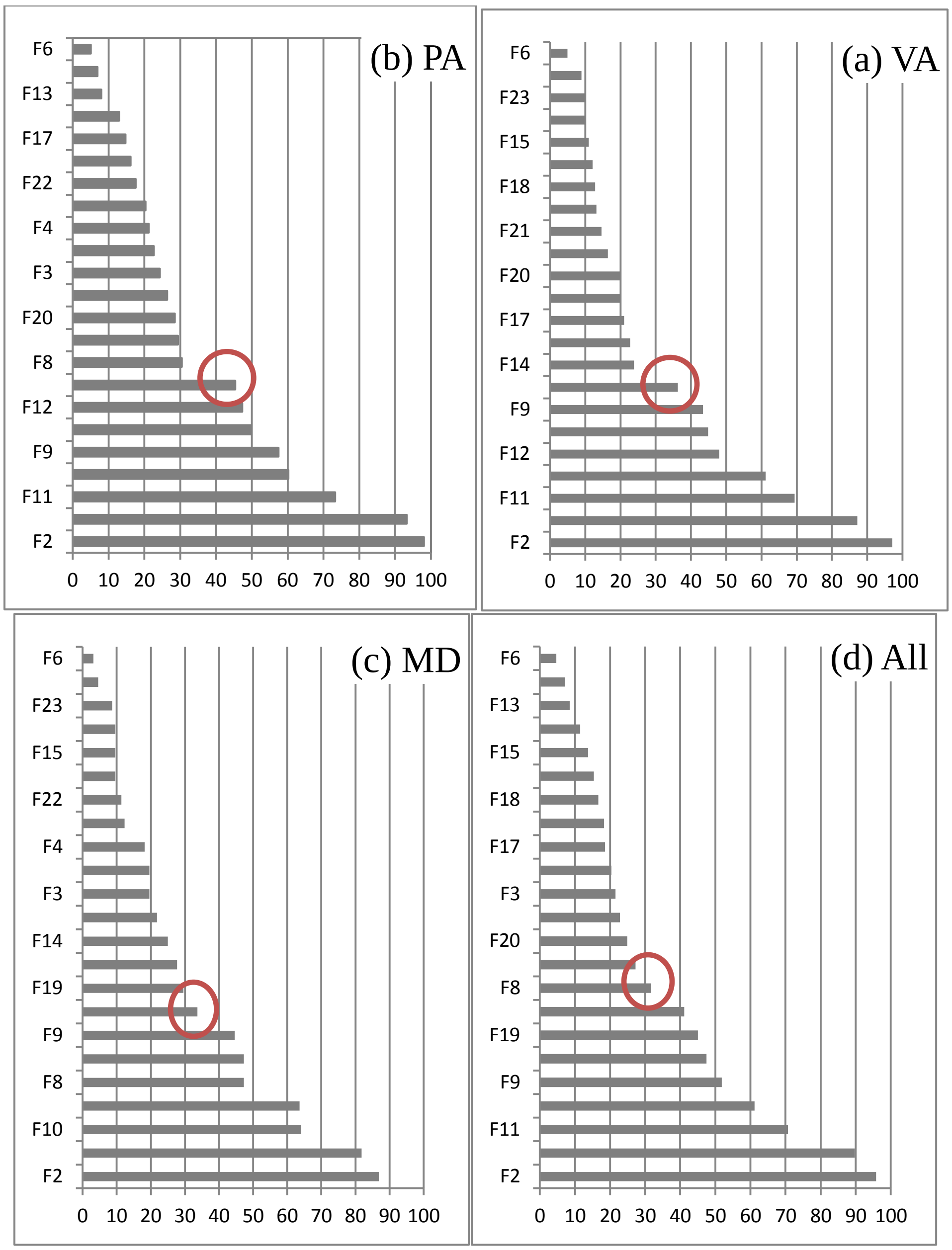


Figure 7: Bar chart of factor selection by states.

Table 1 (Part a) summarizes the result of significant factor recognition process described above. Among 9 significant factors, seven are overlapped in all states. Factor number 8 is considered significant for Maryland as opposed to factor number 19 which does not show a high selection percentage for this state as it does in other two states.

A hypothesis, two-proportion z-test, is conducted to determine whether the difference between two states' proportions is significant. If P1 and P2 are two population proportions, then the null and alternative hypotheses are as following:

H0: P1 = P2

Ha: P1 ≠ P2

Significance level of 0.05 is chosen. Pooled sample proportion is calculated as p = (p1 * n1 + p2 * n2) / (n1 + n2) where n1 and n2 are sample sizes. Standard error is also computed using the equation $SE = \sqrt{p * (1 - p) * [(1/n_1) + (1/n_2)]}$. Then, Z-score is equal to z = (p1 - p2) / SE. Corresponding p-value is compared to the significance level to reject the null hypothesis when the P-value is less than the significance level.

Table 1 (part b) summarizes the result of two-proportion z-test for significant factors among different states. P-values less than the significance level are highlighted indicating that the null hypothesis (P1 = P2) is rejected. As shown on the table only proportion of factors number 10 and 12 are not significantly different among the three states.

Table 1: Result of Two-proportion Z-test

Factor	Factor descriptions	Part a				Part b					
		Significant Factor analysis				Proportion difference significant analysis					
		States				State pairs					
						VA & PA		VA & MD		MD & PA	
		All	VA	PA	MD	z-score	p-value	z-score	p-value	z-score	p-value
F1	Your speed	x	x	x	x	-3.1	0.0019	1.663	0.0963	-5.07	0.0001
F2	Your distance to intersection	x	x	x	x	-0.85	0.3953	4.39	0.0001	-6.93	0.0001
F8	Presence of a red light camera	x			x	-2.43	0.0151	-5.76	0.0001	4.582	0.0001
F9	Presence of police	x	x	x	x	-3.99	0.0001	-0.25	0.8026	-3.36	0.0008
F10	Whether the pavement is wet or dry	x	x	x	x	0.278	0.7810	-0.66	0.5093	1.021	0.3073
F11	Presence of a vehicle in front of you	x	x	x	x	-1.24	0.2150	1.356	0.1751	-2.77	0.0056
F12	Presence of a vehicle behind you	x	x	x	x	0.202	0.8399	0.171	0.8642	-0.02	0.9840
F19	How well you know the intersection	x	x	x		-1.43	0.1527	3.498	0.0005	-5.29	0.0001
F16	Whether the traffic is bad	x	x	x	x	-2.6	0.0093	0.62	0.5353	-3.07	0.0021

Pairwise correlations were also conducted to investigate the correlation between each pair of factors for different states. The purpose of this part is to find out if any two factors are likely to be selected together by survey responders. The results show a correlation between factor number 21 (Whether the intersection is at the bottom of a hill) and 22 (Whether the intersection is at the top of a hill) in all three states. Moreover, for Maryland and Virginia, factor number 8 (Presence of a red light camera) and 9 (Presence of police) are correlated. These two later factors are recognized as significant as mentioned above. It is also notable that none of the factors located below the dropping points, shown in figure 6, are correlated with the factors above the dropping points.

Conclusions

Dilemma Zone (DZ) is an area ahead of signalized intersections in which drivers encounter a dilemma to stop or pass through the intersection at the onset of yellow indication. DZ has been a leading cause of many accidents at intersections. Therefore, factors affecting decision making process and driver behavior are crucial to be studied and taken into account in modeling and mitigation strategy development. A driver survey is designed and administered in three states of Virginia, Maryland, and Pennsylvania to identify significant factors affecting drivers' perception and decision at the onset of yellow. The results identified 9 factors to be significant in these states, namely 1) speed, 2) distance to intersection, 3) presence of a red light camera, 4) presence of police, 5) whether the pavement is wet or dry, 6) presence of a vehicle in front of the subject car, 7) presence of a vehicle behind the subject car, 8) how well the driver knows the intersection, and 9) whether the traffic is bad. The results also revealed that the difference between states' proportions (the percentage of responders who indicated that a given factor was influential in their decision at the onset of yellow) is significant. The result of this survey provides useful information on potential factors for further study and to develop proper scenarios in a driver simulator experience.

Acknowledgements

The authors thank the Mid-Atlantic Universities Transportation Center that provided funding for this study. The authors are solely responsible for the material in this paper and the views are not necessarily those of the supporting agency. The authors would like to specially thank Mr. Philip M. Garvey for his help with designing the survey questionnaire.

Appendix A: Survey Questionnaire

Driver survey

Thank you for taking the time to fill out this survey! Your responses are completely anonymous and confidential. This information will be used for research purposes only and will help us learn more about what drivers do when they get to a yellow traffic light. The survey should take you approximately 5 minutes.

PERSONAL QUESTIONS

1) In what year were you born:

2) What is your gender?

- Male
- Female

3) What is your highest education?

- Some High School
- High School Diploma
- Some College
- Associate’s Degree
- Bachelor's Degree
- Graduate Degree
- Professional Degree

- Vocational Training
- Other:………. (please specify)

4) Which of the following racial categories best describes you? You may select more than one.

- American Indian or Alaska Native
- Asian
- Black or African American
- Hispanic or Latino
- Native Hawaiian or other Pacific Islander
- White

5) Which town/city and state do you live in?

Town/City:………….. State……………

GENERAL DRIVING QUESTIONS

6) How often do you drive a motor vehicle?

- Never
- Almost every day
- A few days a week
- A few days a month
- A few days a year

7) What kind of vehicle do you usually drive?

- Car
- Van or minivan
- Motorcycle
- Truck or SUV
- Other: …………… (please specify)

8) How many times have you been pulled over by the police in the past year?

- None

- Once
- Twice
- Three times
- More than three times

9) Have you ever been in an accident at an intersection?

- Yes
- No

10) Do you consider yourself a safe driver?

- Yes
- No
- Do not know

<u>YELLOW TRAFFIC LIGHT QUESTIONS:</u>

11) How often do you try to catch a yellow light and end up running a red light?

- Very often
- Sometimes
- Rarely
- Never

12) What do you **normally** do when you see a yellow traffic light?

- Speed up
- Slow down
- Neither speed up nor slow down
- Hit the brakes
- It depends
- Other:…………..(please explain)

13) Which of the following conditions affects what you do when you see a yellow light?

Your speed	

Your distance to intersection	
Presence of passengers in the car	
Existence of yellow flashing traffic light	
Model (e.g., Toyota Camry, Ford Fusion) of the car you are driving	
Whether you are talking on the phone	
Whether it is night or day time	
Presence of a red light camera	
Presence of police	
Whether the pavement is wet or dry	
Presence of a vehicle in front of you	
Presence of a vehicle behind you	
Presence of a vehicle in the lane next to you	
Presence of a bicycle, pedestrian or vehicle in the side-street	
Whether the next traffic light is timed	
Whether the traffic is bad	
Existence of a countdown display to show the time of each traffic light color	
Whether you are tired, angry, or sad	
How well you know the intersection	
Whether it is a **safe** intersection	
Whether the intersection is at the bottom of a hill	
Whether the intersection is at the top of a hill	
Whether you've successfully beaten that red light in the past	

14) About how long you think yellow lights **usually** last?

- 1 second
- 2 seconds
- 3 seconds
- 4 seconds
- 5 seconds…
- Other: ……… …(please specify)

15) Have you noticed that some yellow lights are longer or shorter than others?

- Yes
- No
- I do not know

16) Please specify any experience or suggestion that you may have on the subject of "drivers' decision to stop or go at the onset of yellow light"

Thank you very much for your time and cooperation.

CHAPTER 4 MODELING DRIVER'S LEARNING AND DYNAMIC PERCEPTION OF DILEMMA ZONE USING AN ADAPTIVE DESIGN IN A DRIVING SIMULATOR STUDY

This chapter presents a paper that is currently under peer review. It was jointly written by Sahar Ghanipoor Machiani and Montasir Abbas. Part of this paper was published as a part of a report entitled "Modeling the Dynamics of Driver's Dilemma Zone Perception Using Machine Learning Methods for Safer Intersection Control" with report number MAUTC-2212-04. The material is reproduced with permission of MAUTC.

Abstract

Dilemma zone (DZ) is the area ahead of intersections in which drivers are confronted with the decision of either proceeding to cross or preparing to stop when they face the yellow signal indication. Many crashes at signalized intersections are attributed to DZ-related conflicts. DZ-protection algorithms have been developed in response to safety concerns related to DZ. These algorithms and advance signal settings generally provide green, yellow, or all-red extensions to protect the vehicles in DZ. The main goal of the research presented in this paper was to address the learning aspects of the driver decision-making process, and investigate the effect of learning on the different approaches taken by different DZ-protection algorithms. Besides the dynamic nature of drivers, a group of influential factors were also investigated to determine their significance in the drivers' decisions in dilemma zone. An Adaptive Randomized Incomplete Block Split-plot (ARIBS) plan was designed and implemented in a driving simulator environment. Specifications of the design and implementation stages are discussed in the paper. Data were collected from 34 drivers and statistical analysis was conducted. The results of the analysis showed that drivers learn from their experience when exposed to longer or shorter yellow durations. However, the scenario related to green extension strategies was not found to significantly affect the driver behavior. Learning associated with longer and shorter yellow duration exposures, resulted in the drivers being more cautious. In conclusion, it was found that DZ-

protection algorithms that apply green, yellow, or all-red extensions do not raise significant concerns due to drivers learning issues.

Keywords: dilemma zone; driver behaviour; driver learning; DZ-protection; crash mitigation

Introduction

Several research efforts have been dedicated to modeling drivers' decision to stop or go at the onset of the yellow indication at signalized intersections (widely known in the literature as dilemma zone). Researchers agree that drivers who are far from the signal at the onset of yellow are going to stop, while drivers who are too close to the signal are going to continue. Researchers do not necessarily agree on the definition of the "too far" and "too close" boundaries, nor on the probability of stopping in between those two boundaries. Dilemma zone (DZ) conflicts remain to be an important area of interest because of the recognition that it is a major cause of accidents at high speed signalized intersections. The issue especially arises when the driver is not able to clear the intersection before the initiation of the red light phase leading to possibility of right-angle crashes or the driver decides to stop while the following vehicle made the decision to go leading to possibility of rear-end crashes (Papaioannou 2007, Chiou and Chang 2010, Sharma, Bullock et al. 2011, Wei, Li et al. 2011, Amer, Rakha et al. 2012, Hurwitz, Wang et al. 2012, Abbas and Ghanipoor Machiani 2013, Abbas, Ghanipoor Machiani et al. 2014, Ghanipoor Machiani and Abbas 2014, Ghanipoor Machiani and Abbas 2014, Jahangiri, Rakha et al. 2015).

Drivers' decision in dilemma zone along with the signal control strategies are the two main elements that play important roles in DZ conflict analysis. These two elements have attracted significant research interests over the years, resulting in major contributions in the development of DZ-protection algorithms. DZ-protection algorithms generally target two settings in the signal control system; (1) extension of the green time, and (2) extension of the clearance (yellow and/or all-red) interval to provide the driver with extra time to clear the intersection. The challenge here is that none of these DZ-protection setups have taken the drivers learning process (dynamic nature of drivers' decision making) into account. Learning in this context refers to "an approximately permanent change in humans' propensity" due to practice or observation (Huitt and Hummel 2006). It reflects the evolving of choice behavior in decision making process from a one shot event to a dynamic model influenced by practice and observation (Roth and Erev 1995). In this paper, we attempt to answer the question of "how driving experience through various conditions at intersections (safe or unsafe) changes drivers behavior in the future." The question that we would like to answer here is that whether the drivers learn from their experience at signalized intersections with different settings, and based on the result of this learning process, which one of the DZ-protection approaches (green extension and yellow or all-red extension) is more suitable?

Background

In the earliest studies of dilemma zone (Crawford and Taylor 1960, Gazis, Herman et al. 1960, Olson and Rothery 1961, Crawford 1962), dilemma zone was mostly treated as a deterministic value (Sheffi and Mahmassani 1981). After a while, researchers started to investigate the stochastic nature of dilemma zone (Sackman, Parsonson et al. 1977, Parsonson 1978, Zegeer and Deen 1978). Stochastic dilemma zone specifies the zone where more than 10% and less than 90% of drivers would choose to stop (Zegeer and Deen 1978). This area between 10 and 90 percentile is also called "indecision zone" (Elmitiny, Yan et al. 2010). Dilemma zone has been divided into two types related to vehicle dynamic characteristics and driver's behavior. The second type which focuses on the driver decision aspect is the real DZ that has challenged the researchers for the appropriate yellow and all-red lengths (Abbas, Higgs et al. 2014).

A group of factors including drivers attributes, vehicle characteristics, intersection characteristics, traffic condition, and signal settings are attributed to dilemma zone and drivers' decision making process, and have been studied by researchers. DZ modeling techniques in the literature are generally focusing on the statistical relationship between derivers' decision with these influential factors.

Figure 8 summarizes the interaction between the factors that affect DZ conflicts. As shown in the figure, two groups of internal and external factors affect DZ location and drivers' decision in DZ. There is also an intermediate group that is under influence by the other two groups. The internal factors, drivers' characteristics and behavior, influence dilemma zone decision making by mostly influencing perception reaction time (PRT) (the time between the onset of yellow and the activation of the vehicle's brake lights) and acceleration/deceleration rate (intermediate factors shown in Figure 8). However, there is a direct relationship between drivers' attributes and DZ decisions that is occurring through the drivers learning process. The learning aspect of the drivers' hasn't been studied, and it is the focus of our research.

The external factors including vehicle, intersection, traffic characteristics, and signal settings affect DZ directly. For instance, clearing width of the intersection affects the location of DZ directly. They also affect intermediate factors resulting in an indirect effect on DZ. For example, acceptable acceleration/deceleration rate for a driver when driving an old car with unreliable brake status changes comparing to a brand new vehicle. There is a relationship between DZ and the DZ-protection algorithms signal parameters. DZ-protection algorithms change the signal settings based on the presence of vehicles in DZ and drivers' decision prediction. The focus of this study is to assess the different strategies in DZ-protection algorithms, considering the effect of learning in drivers as they experience these DZ-protection control algorithms.

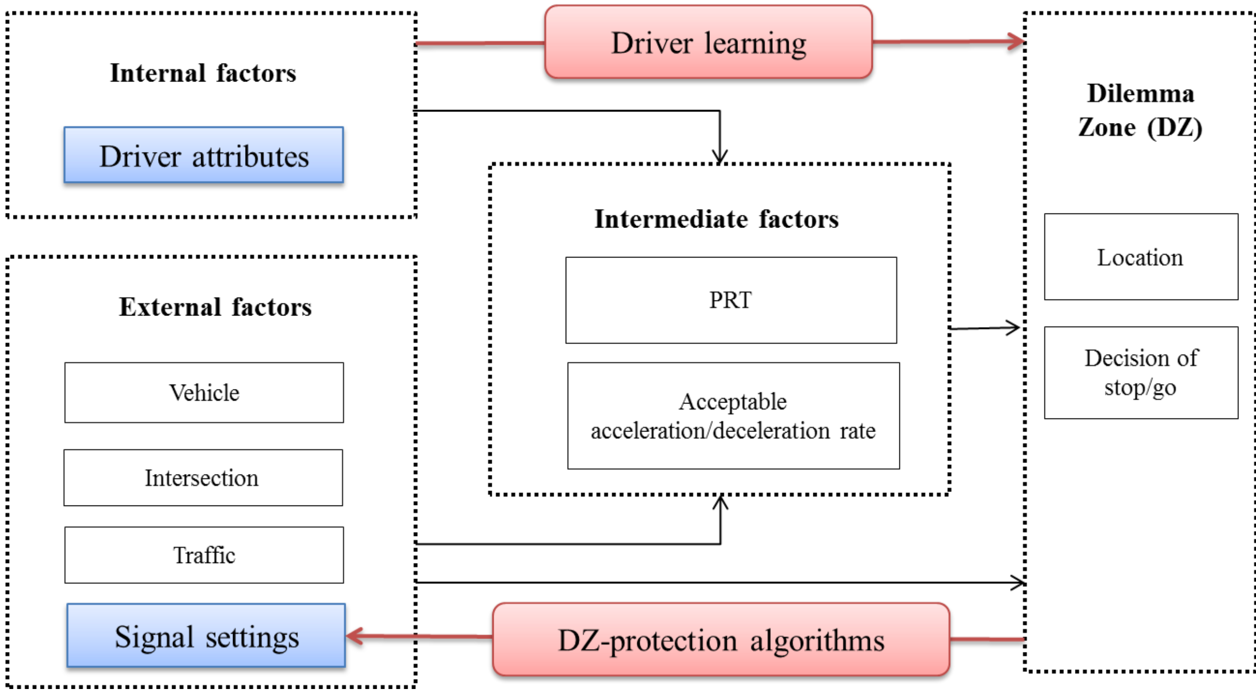


Figure 8: Dilemma zone contributing factors diagram.

Some research examples regarding DZ influential factors and DZ-protection algorithms are provided below.

Driver Influential (Internal) Factors

Drivers' age, gender, violation record, concentration level during driving (Papaioannou 2007), drivers' personality, and emotional states (Van Der Horst and Wilmink 1986) are all characteristics of drivers affecting dilemma zone decision making process. One important psychological issue in drivers related to dilemma zone improper decision is aggressive driving. Aggressive driving is correlated with gender and age in that men and older drivers are more probable to drive aggressively (Shinar and Compton 2004). Based on drivers' response to yellow indication and initial approaching speed, three categories of drivers namely "aggressive," "conservative," and "normal" are recognized in the literature (Liu, Chang et al. 2007, Papaioannou 2007). Liu et al (2011) introduced an ordered probit model, the outcome of which is one of the following responses by drivers: conservative stop, normal, and aggressive-pass. Based on their study approaching vehicle speed appears to be the best indicator to determine the aggressive level of a driver.

Signal Operation (External) Factors

Vehicle, intersection, traffic, and signal settings are included in this group. Regarding intersection characteristics many factors related to geometry of the roadway including intersection layout, clearing width, number of lanes, gradient, and number of arms as well as existence of surveillance cameras, roadway surface condition, and pavement markings have been mentioned to be affecting factors (Allos and Al-Hadithi 1992, Papaioannou 2007, Yan, Radwan et al. 2007, Yan, Radwan et al. 2009). Subject vehicle characteristics such as speed, distance to intersection, position in relation to other vehicles (leading or following), and vehicle type are also important in dilemma zone decision making process (Papaioannou 2007, Kim, Zhang et al. 2008, Zhang, Wang et al. 2010, Wei, Li et al. 2011), and have been researched (for examples see (Papaioannou 2007, Gates and Noyce 2010)). Characteristics of the traffic flow such as volume (both subject street and side-street) and presence of pedestrian or bicycle on the side-street also affect DZ related decision making (Lin and Kuo 2001, Gates, Noyce et al. 2007, Liu, Chang et al. 2011). Related to signal settings, length of yellow interval, the ratio of the green time to the cycle length, cycle length, phase sequence, control type, and existence of countdown units are influential factors on drivers decision in DZ (Liu, Herman et al. 1996, Middleton, Research et al. 1997, Zimmerman 2003, Koll, Bader et al. 2004, Papaioannou 2007, Sharma, Bullock et al. 2007, Wu, Juan et al. 2009, Chiou and Chang 2010, Long, Han et al. 2011).

Dilemma Zone Protection Systems

DZ-protection algorithms have been developed to mitigate the effects of DZ conflicts. Some examples of these advance control algorithms are D-CS (Zimmerman, Bonneson et al. 2003, Zimmerman and Bonneson 2005, Zimmerman 2007), Platoon Identification Algorithm (PIA) (Chaudhary, Abbas et al. 2006), LHOVRA (Engstrom 1994), Microprocessor Optimized Vehicle Actuation System (MOVA) (Vincent and Peirce 1988, Kronborg and Davidsson 1993), Multi-detector Green Extension System (GES) (Zegeer 1977), and Self-Organized Signal System (SOS) (Davidsson and Edholm 1997). The prevailing approach in DZ-protection algorithms and advance signal settings is to extend green, yellow or all-red to provide safer passing for drivers in DZ. However, no study to date has considered how drivers learning process affects these DZ-protection algorithms.

In this research we use an experimental design in a driving simulator environment to accomplish our research objectives. The main objective is to investigate the dynamic nature of driver's perception of dilemma zone, and whether that perception changes as a function of their driving experience through safe or unsafe intersections. This learning aspect of drivers is tested through carefully-designed adaptive driving simulator scenarios tailored to fulfill this objective. We also adopt the result of a driver survey to assess significant factors affecting driver's decision at the onset of yellow through the driving simulator study. Subject drivers drive through the designed scenarios to extract useful data from the experiment. The data is used to investigate the dynamic nature of driver's perception of dilemma zone and their learning aspect as well as the significance of contributing factors. This paper is the continuation of a previous research by authors including the pilot study (Ghanipoor Machiani and Abbas 2014). Here, we explain the design in details and present the analysis and results of the real data. The pilot study was used to verify the design of the study, and modify it for the real data collection.

This paper is organized as follows. In the next section, we discuss the methodology of the research including the adaptive scenario development, ARIBS experimental design, Implementation in the driving simulator, and experimental procedure. Next, results and discussion are provided. In this part, we describe the response variable and model effect. Then a graphical results is provided following by the statistical model and discussion of the results. The last section provides conclusions and future directions.

Methodology

Development of an Adaptive Driving Simulator Experiment

The primary goal of this study is to investigate the drivers' learning process when driving through safe and unsafe intersections. This is done by designing adaptive settings in the simulator. In fact, the driver simulator in our research acts as an intelligent agent predicting and reacting to driver's decisions, and providing responsive scenarios based on each situation. The experiment is designed in such a way that if the driver learns, the framework will capture it. A scenario would not be triggered if no learning occurred regarding that specific scenario. Figure 9 summarizes the experiment adaptation and hypotheses testing. The experiment situation and rationale behind the hypotheses are also explained. Basically, three scenarios are developed that extend green, shorten yellow, or lengthen yellow based on driver's behavior.

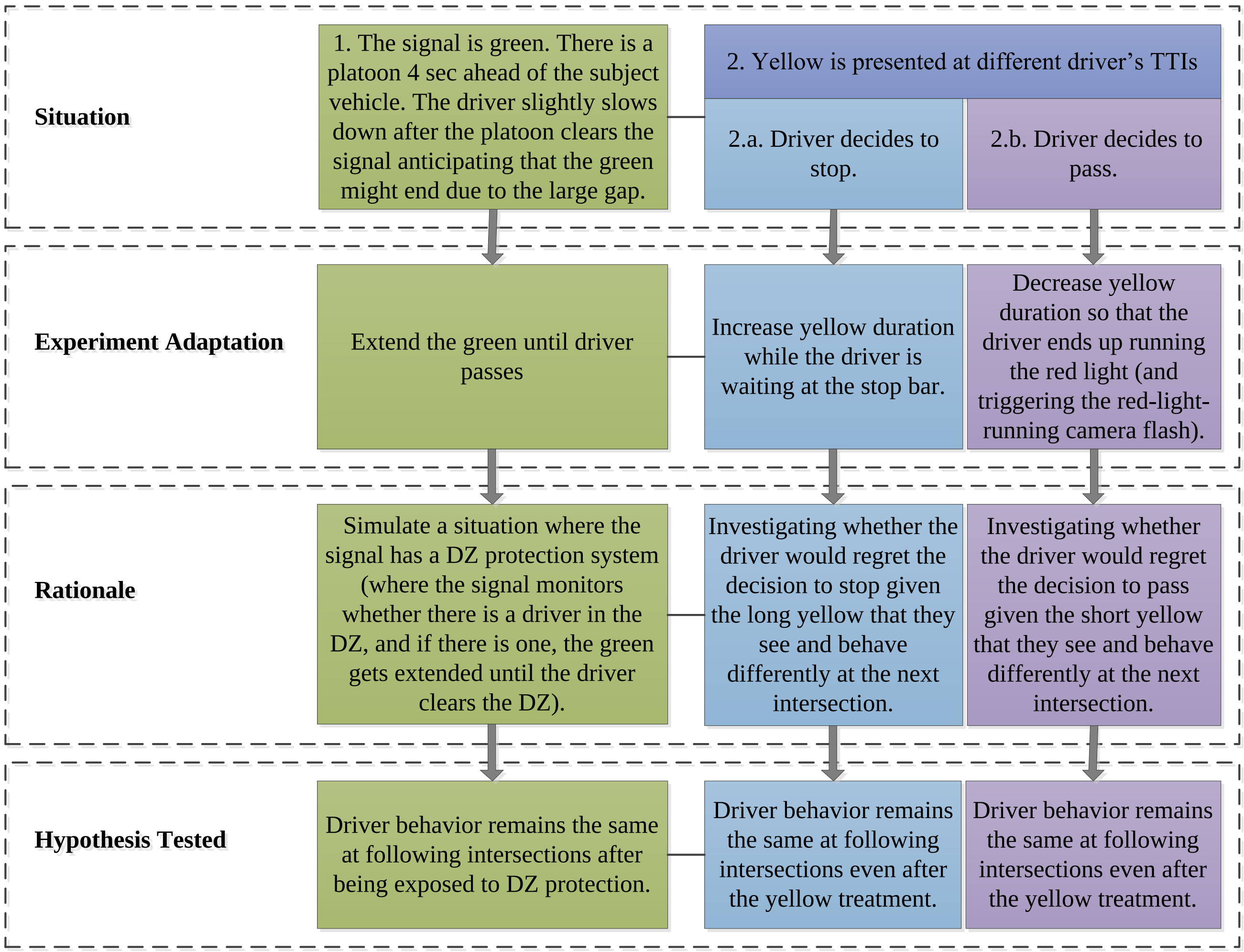


Figure 9: Experiment Adaption Situations and Rationale.

To account for the experiment adaptation, the "experiment adaptation factor" is introduced with two levels of "Do nothing" and "Do something." "Do nothing" refers to the condition that no "experiment adaptation factor" is tested on an intersection; meaning that normal yellow indication and duration is followed. In this situation, when driver slows down anticipating that the green will end due to the large gap, the signal turns yellow at 1.5 seconds ahead of the intersection as expected by the driver, and the yellow lasts for 4.5 seconds (appropriate yellow time for 55 mph speed). However, if the driver does not slow down, the yellow will be provided at 2.5, 3.5, and 4.5 seconds ahead, and lasts for 4.5

seconds. In contrast, "Do something" means one of the experiment adaptation approach explained in Figure 9 is considered depending on the situation presented by drivers' behavior. In other words, the "experiment adaptation factor" is nested within the drivers' behavior. Figure 10 illustrates the flowchart of the "experiment adaptation factor", and its nested structure. Colors in this figure are compatible to the colors in Figure 10.

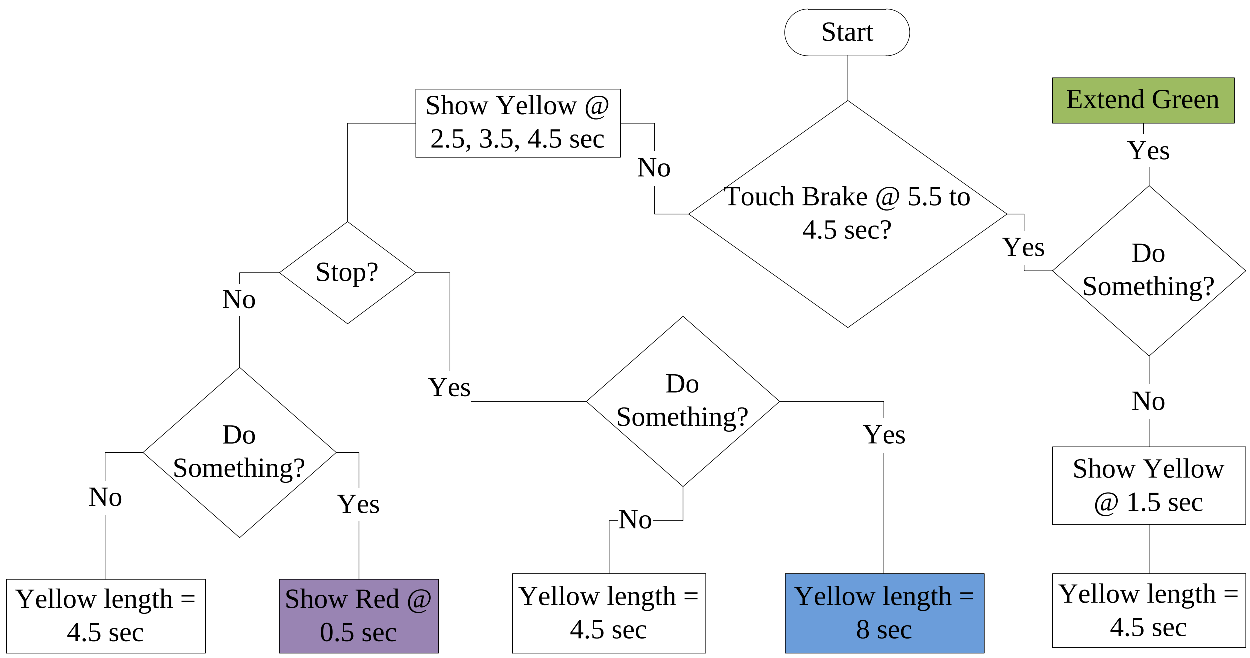


Figure 10: Flowchart of the experiment adaptation.

In addition to the learning aspect of drivers embedded in the experiment adaptation factor, some influencing factors on DZ are included in the design. These factors are extracted from the result of a survey study designed by authors, and administered in three states of Virginia, Maryland, and Pennsylvania. In response to the fact that literature to date does not cover the wide spectrum of factors, the survey was designed to include all possible contributing factors affecting driver's decision in dilemma zone. Based on the result of the survey, five significant factors were used in the scenario development of the driving simulator. These factors include (1) Time to intersection (TTI) at the onset of yellow (s) (levels: 2.5, 3.5, 4.5 sec), (2) Presence of police (levels: Yes, No), (3) Pavement condition (levels: Wet, Dry), (4) Other vehicle around (levels: No Vehicle, Back), and (5) Presence of side street queue (Levels: Yes, No).

Experimental Design: Adaptive Randomized Incomplete Block Split-plot (ARIBS)

The experimental design of this driving simulator study was considered complex for several reasons. The first reason was the high number of factors and levels. The experiment includes five two-level and a three level factors constituting 96 combinations of all factors ($2^5 \times 3^1$). Therefore to perform a full factorial design that accounts for the main effect as well as all interactions among factors, 96 runs were needed. The second complexity lies in the fact that some of the factors ("pavement condition" and "other vehicle around") are hard or meaningless to change throughout one session of driving in the simulator. For example, wet pavement condition should be consistent through a series of consecutive intersections otherwise it feels unrealistic from the driver's point of view. The third difficulty is related to the point that scenarios are tested by several drivers as opposed to one experimenter, which is the usual case in most experimental studies. Driving simulator sickness should also be taken into account as a driver could not drive in the simulator for a long time. Consequently, the number of scenarios driven by a driver is limited. Nesting structure of the experiment adaptation factor should also be added to the mentioned difficulties.

To overcome the complexity of the design discussed above we implemented the following design criteria:

A "*Fractional factorial design*" was used instead of full factorial design to overcome the high number of combinations. In fractional factorial design only a fraction of the possible combinations are actually used in the experiment. This makes some of the higher-order effects in a model non-estimable. However, since running experiments costs time and money, a trade-off between the number of runs and the resolution of the design should be considered. Especially here that the simulator experiment time was limited due to the simulator sickness. In fractional factorial design of this study, the main effects and second-order interactions are considered in determining the number of runs.

Having several drivers as opposed to one experimenter raises suspicion that drivers have significant effect on the results and significance analysis of the factors. However, we wanted to avoid having the comparison of factors distorted by the differences in drivers.

Therefore, a blocking factor was introduced into the design to block out any differences in drivers to obtain a precise comparison of the factors. A **"***randomized block design***"** was implemented in which the blocking factor (extraneous factor) was the drivers. This design assumes that factors have the same effect in every block, and the only effect of the block is to shift the mean response up or down.

"Split-plot design" was used to account for the factors that were hard to change ("pavement condition" and "other vehicle around"). Split-plot design is applied when there is a restriction in randomization process such as hard-to-change factors. In this kind of design, larger experimental units (also called whole plots) are considered to which the levels of the hard-to-change factors (whole plot factors) are assigned at random. Whole plots are then divided into smaller experimental units (also known as split plots or subplots), and other factors (split plot factors) are randomly assigned to the split plots within the whole plots. Split plot design adds to the complexity of the analysis as different levels of experimental units have different error variances. In this study, the whole plot factors were "pavement condition" and "other vehicle around," and whole plots were considered sequential intersections constituting a road corridor. Each intersection in the corridor then plays a subplot (split plot) role.

Often in experiments involving blocking factor, randomization is carried out completely in each block, but in this study it was not possible to randomize completely within each block (driver). The reason was that a complete randomization means to design specific driving simulation settings of scenarios for every driver which is not a logical/applicable approach. Therefore, instead of a complete randomization, randomization was conducted among the whole plots.

Based on the discussion above, the experimental design of this study was an Adaptive Randomized Incomplete Block Split-plot (ARIBS) design. This experimental design was implemented using custom design capability in SAS JMP Pro 10.0.0 software (2010). Considering main effect and two-way interactions of factors, the minimum number of runs was found to be 28, but this minimum was driven by the degrees of freedom required to define the model, and there were no degrees of freedom left to use for the error term. The minimum number of runs needed to also consider the error term was found to be 35.

Regarding the split plot design, the minimum number of whole plots was found to be 5, so that the design had enough whole plots to estimate the whole plot variance otherwise the whole plot effects were not testable. This leads to having 5 corridors (whole plots) including 7 (35/5) consecutive intersections (split plots). In the pilot study, the number of split plots was decided to be 10, so totally 50 runs were considered. However, the pilot run showed that having all signals turning to yellow is not a good strategy because that caused drivers to expect the signal to be yellow and get prepared, which prevent the emulation of normal reaction. To account for this in the main study, 3 out of 10 intersections in each corridor were randomly chosen to always show green signal indications. As a result, each driver (block) drove through 5 corridors (whole plots), with each corridor including 10 intersections (split plots) with 3 being always green.

Implementation of the Driving Simulator Agent

The Driving simulator used in this study was a DriveSafety DS-250 model including main software components of Vection™ (high fidelity real-time driving simulation software), HyperDrive (advanced scene and scenario authoring tool set), and Dashboard (Software that interfaces Vection and Hyperdrive). HyperDrive was used to design and implement custom driving environment models including traffic conditions, environmental states and events occurring during the simulation. Specific events and scenarios are implemented by scripting using Tool Command Language (TCL). Data collection can be activated for built-in variables as well as user defined data. The simulator is fixed-based and provides no motion cues. Participants control the accelerator, brake pedals and the steering wheel exactly how they do in an actual vehicle. The driving simulator is illustrated in Figure 11.

Figure 11: Driving simulator; DriveSafety DS-250 model.

The basis of the driving environment was constructed using drag and drop assembly of database elements called tiles. Then, static objects such as speed signs, side street traffic, and police cars are placed according to the experimental design. Pavement condition is controlled by setting weather condition throughout each scenario. Signal status changes are mostly handled using an external TCL file called “include” which is used for scripting general procedures and timer procedures using in all intersections. There is also an initialization coding environment basically for initialization set up. To specify events occurring at certain time or location to intersections time and location triggers were created and programmed appropriately. Three location trigger and one time trigger were created to program a platoon of cars ahead, and a vehicle behind the subject vehicle. In addition to these triggers, six time triggers and three location triggers were created at each intersection to implement the experimental design by specifying events occurring at certain time or location to intersections. Explanations of these triggers (shown in Figure 12) are provided below. Application of these triggers is associated with flowchart of the experiment adaptation shown in Figure 10.

1. DoSomething time trigger: Located 6 sec ahead of the intersection to specify “experiment adaptation factor”, and setting variable associated with each individual intersection.

2. TouchBrakeStart time trigger: Located 5.5 sec ahead of the intersection to start monitoring the attempt of drivers to initiate a stop. It should be noted that initiating a stop could be just by releasing the accelerator pedal which was also taken into account.
3. TouchBrakeEnd time trigger: Located 4 sec ahead of the intersection to terminate monitoring the attempt of drivers to initiate a stop.
4. YellowSignal time trigger: Located 4.5, 3.5, or 2.5 sec (depending on the scenario) ahead of the intersection to change the signal to yellow.
5. YellowSignalTouchBrake time trigger: Located 1.5 sec ahead of the intersection to change the signal to yellow associated to the scenario in which the driver initiates a stop.
6. RedLightRunner time trigger: Located 0.5 sec ahead of the intersection to change the signal to red associated to the scenario in which passing drivers are caught in red.
7. StopGoDecision location trigger: Located 17 meters ahead of the intersection to recognize the driver's decision of passing through the intersection or stopping.
8. CameraFlash location trigger: Located slightly after the middle of the intersection to present a camera flash effect as well as a sound of taking a picture to red light runners.
9. AfterIntersection location trigger: Located immediately after the intersection to terminate any virtual triggers applied in scripting time or location triggers, and change the next signal status to green.

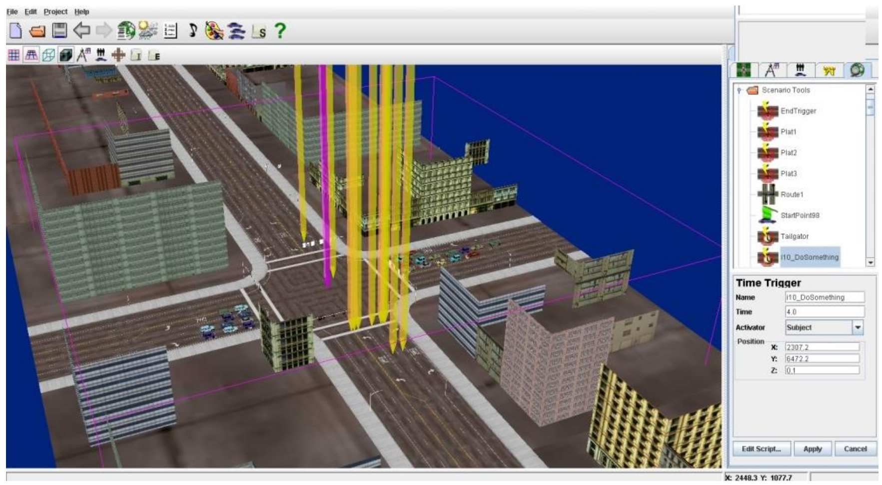


Figure 12: HyperDrive layout of triggers.

An important task in implementing the adaptive experimental design is to predict drivers' decision of stopping or going before this decision occurs. This decision prediction is used to adapt the design setting and needs to be recognized somewhere between the onset of yellow and before the RedLightRunner time trigger. The more accurate the prediction, the more relevant the adaptive design setting. However, it is not possible to predict drivers' behavior with 100% accuracy due to the changing nature of drivers' decision considering the limited time window to recognize it. For example, imagine a driver who decides to pass the intersection and changes his decision right after the RedLightRunner time trigger resulting in a hard brake and stopping a little bit after the stop bar. Many trial and error approaches were tested to come up with the best stop/go recognition process. It turned out the best approach was to use two recognition mechanisms. The first mechanism was a timer procedure starting with the yellow indication and terminating right before the minimum yellow time duration (4.5 seconds) was finished. Considering vehicle's time to intersection, this procedure calculates the amount of time the driver lost or gained after the onset of yellow respectively by decelerating or accelerating. This time lost and gain is defined compared to the condition that the driver keeps the speed. The driver is monitored after the onset of yellow. If the time-lost-gained is less than -0.2 sec, the driver is stopping. This procedure is appropriate for slower vehicles. The second mechanism was a location trigger located slightly before the stop line (17 meters upstream), and calculates time lost and gained while taking instant speed and deceleration rate into account. If the time-lost-gained is less than -0.2 sec, or both speed and deceleration are respectively less than 25 m/s and 0 m/s^2, the driver is stopping. This procedure is appropriate for faster vehicles. For each vehicle only one of these mechanisms was activated based on which mechanism triggers first.

Participants and Experiment Information

Six participants participated in the pilot study, and 36 additional drivers participated in the main study. The pilot data were used to verify the experimental design, and were excluded from the analysis. Participants were recruited by email announcement. Before beginning the experimental session, participants were asked to read and sign a consent form. They were also asked to complete a questionnaire regarding their age, gender, and driving experience. Then, they were led to sit behind the steering wheel, and drive through an adaptation drive. Participants were allowed to continue with the adaptation drive until they felt comfortable enough with driving in the simulator. The experiment lasted no more than 45 minutes. In driving simulator studies, a common issue is simulator sickness including discomfort, dizziness, or nausea. In this study, two participants withdraw from the study due to this issue.

Results and Discussion

The simulator program was configured to record data including speed, acceleration, time, and activated triggers with the precision of 60 Hz. Data manipulations and reduction was conducted using a script, and statistical analysis was performed using SAS JMP Pro 10.0.0 software. The total number of drivers that completed the experiment was 34.

Description of Variables

The response variable considered in this study was the "mean speed." This variable was calculated by averaging vehicles speed from the onset of yellow until the decision termination point (stopping point for drivers who decide to stop and right after intersection for drivers who decide to go through). The reason to choose this variable instead of the binary choice of drivers to stop or go is that "mean speed" contains information regarding drivers' decision making process beyond just stopping and going.

We wanted to know the process of stopping or going. For example, whether the driver stops by slamming on the brake hardly or smoothly reduces the speed to come to stop. Does passing through the intersection happen with the speed limit or drivers tend to accelerate when deciding to go? To reflect these differences in drivers' behavior, "mean speed" was used as the surrogate measure. To verify the compliance of "mean speed" with "stop/go" variable, a discriminant analysis was conducted. According to the results, six data points wee misclassified (%0.512) indicating that "mean speed" was an appropriate representative for "stop/go" decision.

To test for the significance of learning in drivers, based on the experiment adaptation process (explained in Figure 9) three hypotheses were introduced as follows:

- Hypothesis 1: Driver behavior does not change at the following intersections after experiencing green extension.
- Hypothesis 2: Driver behavior does not change at the following intersections after experiencing long yellow.
- Hypothesis 3: Driver behavior does not change at the following intersections after experiencing short yellow (Red Light Running).

For each hypothesis, a variable was constructed starting from zero and adding up one unit each time the driver experiences the associated treatment. In addition to these three variables associated with learning hypotheses, driver number, time to intersection (TTI) at the onset of yellow, presence of police, pavement condition, other vehicle around, and presence of side street queue are considered as model effects to determine the significance of each one of these factors. Also, a binary variable called "DoSomething" was included in the model corresponding to "Do something" and "Do nothing" levels explained before.

Graphical Analysis

Significance of the model effects were examined through the constructed model presented later in this section, but to understand the relationship between the response variable and the model effects, some examples are discussed here. Figure 13 shows the correlation between TTI and mean speed in that as TTI goes down drivers are more likely to proceed through, and mean speed increases. The points are color-coded to show blue for "Go" and red for "Stop" decisions.

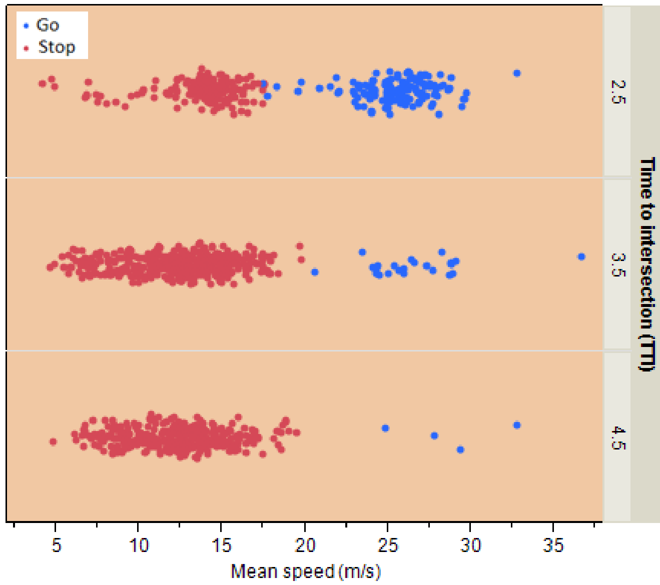


Figure 13: Mean speed versus TTI, color-coded by stop/go decision.

Figure 14 shows the correlation of learning_long yellow scenario with mean speed. According to this figure, as drivers were more exposed to the long yellow they were more likely to stop. The reason could be they lost their confidence in their own judgment and acted more cautious. However, that's a generalized result considering all drivers together. The results of individual drivers are shown in Figure 15 depicting the decision to stop and go in relation to learning_long yellow for different drivers. For examples, drivers number 11, 16, and 21 behave in line with the general result deriving from all drivers in that as the learning variable goes up on the y-axis decision to go reduces. In contrast, driver number 25 shows a reverse trend to the general result; meaning that as this driver is more exposed to long yellow, he/she tends to pass through the intersection more. Some of the drivers, like number 13, seem not to change their behavior as they experience the learning scenario.

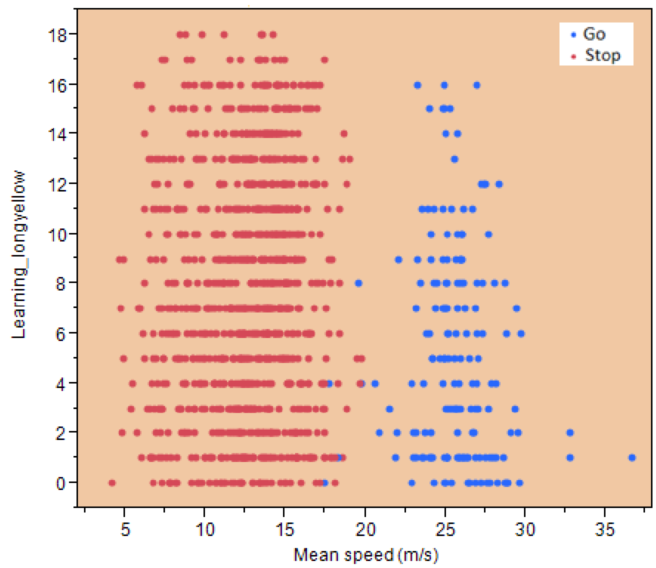


Figure 14: Mean speed versus learning_long yellow, color-coded by stop/go decision.

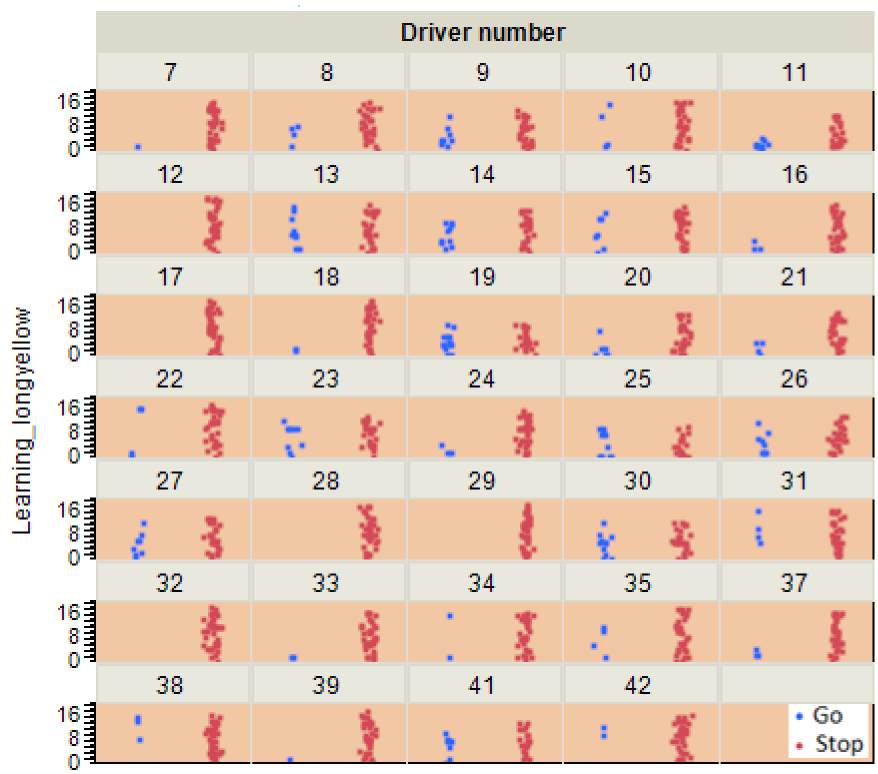


Figure 15: Learning_long yellow versus driver's decision for individual drivers.

Restricted Maximum Likelihood (REML) Model

In constructing the model, and to avoid having the comparison of factors distorted by the differences in drivers, drivers were considered as blocking factors. In line with this specification, driver characteristics such as state, age, and gender were assumed to be embedded inside each "driver number" variable.

Driver number was considered a random effect; meaning that the effects of driver was regarded as a random sample of the effects of all the drivers in the full population of drivers. Drivers were representative of a whole population of drivers and the results of the analysis can be generalizable to them. Therefore, any interaction between driver number and other variables were also random effects. To comply with the design of experiment, second order interactions between whole plot and split plot factors were considered. Learning variables were also regarded as nested in the DoSomething variable.

Restricted Maximum Likelihood (REML) was used in this study for fitting linear mixed models (containing both random and fixed effects). Summary of the fit of the model is shown in Table 2. RSquare of the model was 0.48, and Root Mean Square Error was 4.09. REML Variance Component Estimates are shown in Table 3. Random effects are listed in the first column. The second column shows the estimated variance component for the effect. The third column shows the ratio of the variance component for the effect to the variance component for the total as a percentage. The forth column indicates the ratio of the variance component for the effect to the variance component for the residual, comparing the effects' estimated variance to the model's estimated error variance. The highest variance ratio was found to belong to the interaction of the driver number and TTI variable. The forth column was calculated by dividing the values from the second column for each effect over variance component for the residual. Columns 5 and 6 provide the lower and upper 95% confidence limit for the variance component, respectively. The last column shows the standard error for the variance component estimate. The highest error is related to driver number effect.

The fixed effect tests are summarized in Table 4. The fixed effects are listed in the first column. The second column shows the degrees of freedom associated with the effect. The last two columns show the computed F ratio and the p-value for the effect test. Based on the p-values, Pavement condition, TTI, Presence of police*TTI, Presence of side street queue*TTI, Learning_RLR, and Learning_long yellow have significant effects on the response variable at the p=0.05 rate.

Table 2: Summary of the fit.

RSquare	0.484222
RSquare Adj	0.474355
Root Mean Square Error	4.085649
Mean of Response	14.49467
Observations	1173

Table 3: REML Variance component estimates.

Random Effect	Var. Component	percentage of Total	Var. Ratio	95% Lower	95% Upper	Std. Error
Driver number	1.8815599	8.266	0.1127187	-0.100032	3.8631519	1.0110349
Driver number*Presence of police	0.5740331	2.522	0.0343886	-0.187628	1.3356943	0.3886098
Driver number*Presence of side street queue	0.3455783	1.518	0.0207026	-0.323358	1.0145146	0.3413003
Driver number*Pavement condition	0.3858903	1.695	0.0231175	-0.303887	1.0756675	0.3519337
Driver number*Time to intersection (TTI)	2.5379663	11.150	0.152042	0.9137814	4.1621512	0.828681
Driver number*Other vehicle around	0.3442381	1.512	0.0206223	-0.359872	1.0483484	0.3592466
Residual	16.69253	73.336		15.293043	18.294335	0.762682
Total	22.761796	100.000		20.234509	25.796632	1.4088532

Table 4: Fixed effect tests.

Source	DF	F Ratio	p-value
Presence of police	1	2.1964	0.1460
Presence of side street queue	1	3.6999	0.0581
Pavement condition	1	14.0955	0.0005*
Time to intersection (TTI)	1	62.1816	<.0001*
Other vehicle around	1	3.8203	0.0579
Presence of police*Presence of side street queue	1	0.0222	0.8815
Presence of police*Pavement condition	1	1.1171	0.2908
Presence of police*Time to intersection (TTI)	1	5.3229	0.0213*
Presence of police*Other vehicle around	1	1.8053	0.1794
Presence of side street queue*Pavement condition	1	2.4756	0.1160
Presence of side street queue*Time to intersection (TTI)	1	21.7667	<.0001*
Presence of side street queue*Other vehicle around	1	0.5183	0.4717
Pavement condition*Time to intersection (TTI)	1	3.6258	0.0572
Pavement condition*Other vehicle around	1	0.0560	0.8131
Time to intersection (TTI)*Other vehicle around	1	0.2728	0.6016
Learning_green extension [DoSomething]	2	0.1858	0.8305
Learning_RLR [DoSomething]	2	4.9088	0.0078*
Learning_long yellow [DoSomething]	2	3.1594	0.0431*
DoSomething	1	0.0366	0.8484

Discussion

Based on the result of the learning factors, drivers' behaviors significantly change after being exposed to short yellow durations (red light running) and long yellow scenarios, but not for the green extension scenario. The feedback from the participants revealed that drivers usually do not notice the passing platoon in front of them and its relationship to the green extension treatment at the intersections. This is in line with the results concluded here (green extension scenario turned out insignificant in drivers' decision). For the other two learning scenarios (RLR and long yellow), looking closer to the changes in driver behavior (for example see Figure 14 for the long yellow scenario) reveals that drivers act more cautiously after being exposed to these learning scenarios, and tend to stop more. The reason for this could be drivers losing their confidence in their own judgment regarding stopping at the stop bar without wasting time behind the signal or passing through before the red light starts. This leads to two main conclusions that "drivers learn from their experience," and "they are more risk-averse when the likelihood of predicting the correct outcome of their actions decreases." This finding implies that in designing mitigation strategies, for the DZ-protection algorithms that focus on green extension there is no need to consider any learning effect (no learning is involved). In DZ-protection algorithms that focus on yellow or all-red extension, drivers learning will result in more stopping actions by drivers after they learn. Intension to stop more doesn't have a negative effect on the safety of the intersection. Therefore, no safety concerns should be considered in DZ-protection algorithms in regard to drivers learning process.

Conclusion and Future Research

Dilemma zones are of vital importance since they can lead to many accidents at signalized intersections. When the signal turns yellow, drivers approaching the intersection find themselves in a dilemma of deciding whether to stop or proceed through. In this research effort, we focus on investigating the learning aspect of drivers in DZ in addition to other influential and related factors. We investigated how drivers' behaviors change as a result of positive and negative experience gained from driving through safe and unsafe intersections. The effect of drivers' learning process on DZ-protection algorithms was one of the main motivations of this study. DZ-protection algorithms and strategies include extending green, yellow, or all-red indications to provide drivers with a safer operation when they are in DZ. Here, we examine how the drivers learning relates to these strategies, and what safety concerns needs to be taken to account considering drivers learning. This goal has been accomplished by introducing an Adaptive Randomized Incomplete Block Split-plot (ARIBS) design in a driving simulator study. The design was implemented in the driving simulator environment using built-in libraries as well as scripting language. The data were collected from 34 volunteered participants. The result showed that Pavement condition, TTI, and the interaction of TTI with Presence of police and Presence of side street queue significantly affect drivers' decision. Regarding learning hypotheses, the results revealed that drivers learn from what they experience; more specifically, 2 out of 3 learning hypotheses (long yellow and short yellow (Red Light Running)) turned out to have significant effects on drivers' decision in DZ. This significant effect is coupled with a higher intention of drivers to stop at the onset of yellow as they learn. In another word, drivers were found to be more risk-averse when the likelihood of predicting the correct outcome of their actions decreases. According to the results, there is no safety concerns in any of the approaches by DZ-protection algorithms whether they use green extension which is involved with no learning, or whether they use yellow or all-red extension which results in more stopping decision after the learning occurs.

The modeling approach in this study was statistical analysis that was concerned with the population of the drivers. It is beneficial to look at individual drivers using agent-based modeling techniques to explore the drivers' behavior further. This will be included in future research efforts. Driver's behavior will be individually modeled using machine learning and human learning modeling techniques. Moreover, a real time field-data assessment of DZ-protection algorithms will be conducted to quantify the changes in drivers' behavior when exposed to these protection strategies.

Acknowledgements

The authors wish to thank the Mid-Atlantic Universities Transportation Center and the Virginia Center for Transportation Innovation and Research (VCTIR) for sponsoring this study. The authors are solely responsible for the material contained in the paper and the views are not necessarily those of the supporting agencies.

CHAPTER 5 ASSESSMENT OF DRIVER STOPPING PREDICTION MODELS BEFORE AND AFTER THE ONSET OF YELLOW USING TWO DRIVING SIMULATOR DATASETS

This chapter presents a paper that is currently under peer review. It was jointly written by Sahar Ghanipoor Machiani and Montasir Abbas.

Abstract

Accurate modeling of driver decisions in Dilemma Zones (DZ), where drivers face a dilemma whether to stop or go at the onset of yellow, can increase safety at signalized intersections. DZ-protection algorithms could apply accurate models to make safer control decisions. This study utilized data obtained from two different driving simulator studies (VT-SCORES and NADS datasets) to investigate the possibility of developing accurate drivers' decision prediction/classification models in DZ. Canonical Discriminant Analysis was used to construct the prediction models, and two time frames were considered to conform to the logic behind two DZ-protection systems in signal controllers. The first time frame was during green immediately before the onset of yellow, and the second time frame was the first 3 seconds after the onset of yellow. Signal protection algorithms could use the results of the prediction model during green time to decide the best time for ending the green, and could use the results of the prediction model during the first 3 seconds of yellow to extend the clearance interval. It was found that the discriminant model using data collected during the first 3 seconds of yellow was the most accurate (with 99.7% accuracy). It was also found that data collection should be focused on variables that are related to speed, acceleration, time, and distance to intersection as opposed to secondary variables (such as pavement conditions) since these variables do not significantly change the accuracy of the prediction models. The results reveal the promising possibility of incorporating the developed models in traffic signal controllers to improve DZ-protection strategies.

Keywords: dilemma zone; drivers' decisions; driving simulator; discriminant analysis; crash mitigation;

Introduction

The yellow signal indication at signalized intersections alerts drivers of impending loss of right-of-way, at which point in time drivers must decide whether to stop or proceed through (Chang, Messer et al. 1985). The area upstream of the signal in which drivers must make this decision is called the Dilemma Zone (DZ) (Gazis, Herman et al. 1960). Driver behavior is an important element in the dynamics of traffic signal change interval conflicts that brings up major safety concerns; in cases where the driver misjudges the amount of time he/she needs to pass through when deciding to go, right-angle crashes (red-light running incidents) is likely. Rear-end crashes are also possible if the driver overreacts and decides to stop while the driver in the back decides to go (Abbas and Ghanipoor Machiani 2013). Therefore, DZ conflicts are considered to be a significant contributing factor to signalized intersection crashes. Several protection strategies and advanced signal settings have been researched to address these issues resulting in several DZ-protection algorithms (Abbas, Ghanipoor Machiani et al. 2014). These algorithms could benefit from the prediction of drivers decision to make proper adjustments to the signal settings.

The question raised here is: is it possible to predict drivers' decision and utilize that prediction in DZ-protection algorithms? What type of data needs to be collected to predict drivers' decision accurately, and what time period is appropriate to collect the data for an accurate prediction model? In this research, we attempt to bridge a significant gap in the literature of traffic signal and control by investigating and providing guidance on integrating drivers' decision in DZ into the selection of more appropriate control strategies and crash mitigation algorithms for the traffic scenario in question. The purpose is to investigate whether it is possible to determine what the driver's decision would be within the dilemma zone right before the yellow indication (during green) or in a short period of time after the yellow indication. The DZ protection algorithms can benefit from the prediction of driver's decision before the yellow indication (during green) in providing more intelligent phase control decisions. Also, driver's decision determination shortly after yellow could be used to consider an all-red extension strategy to protect red light runners (drivers who decided to go) from causing right-angle crashes. Canonical Discriminant

Analysis techniques are used in this paper to predict driver decisions using two different datasets for comparison.

The two data sources used in this study are: (1) VT-SCORES (at Virginia Tech) driving simulator study, that has been designed and administered by the authors, and (2) the U. Iowa National Advanced Driving Simulator (NADS) driving simulator study. This paper expands a study that was performed by authors that was based on a pilot study for the VT-SCORES dataset (Ghanipoor Machiani and Abbas 2014). Here we discuss the results of the full-version study conducted by 36 participants in a driving simulator environment at VT-SCORES. The analysis is also performed on the NADS dataset to compare the results from the two different datasets.

Our manuscript starts with a background review of dilemma zone definition and DZ-protection algorithms. In the following section, the methodology is described including a description of the two datasets, the discriminant analysis technique, and scenario development. Next, the results of the scenarios are provided followed by summary and discussion. Finally, conclusions and future directions are provided.

Background

Figure 16 illustrates the dynamic beginning and end of DZ for individual vehicles in a conceptual scenario. The x-axis and y-axis show the time and distance, respectively. The oblique lines present vehicle trajectories. The DZ of each vehicle is shown in the figure with the thicker lines. The points on the figure represent the following:

- Points B: predicted arrival time of vehicle 1 to the stop bar
- Points F: predicted arrival time of vehicle 2 to the stop bar
- Points C: beginning of DZ for vehicle 1
- Points G: beginning of DZ for vehicle 2
- Points D: end of DZ for vehicle 1

- Points H: end of DZ for vehicle 2

Vehicle 1 and 2 are approaching the intersection when the signal turns yellow. At the onset of yellow, vehicle 1 is about 1 second away from the stop bar, and has already passed its DZ, so it continues through the intersection without stopping. However, vehicle 2 is inside the DZ at the onset of yellow, so it is caught in the DZ. The intersection of the line drawn from the start of yellow (parallel to the y-axis) and each vehicle trajectory determines the vehicles situation with regard to the DZ. If the drawn line from the start of yellow passes through the thick part of the trajectory line, then the vehicle is in its DZ at the onset of yellow. If the line doesn't intersect the thick part while the thick part is on the left side of the line, then vehicle has already exited the DZ and will continue to pass through the intersection when yellow is presented. Finally, if the thick part is located on the right side of the line then the vehicle hasn't entered the DZ yet and it will stop at the onset of yellow.

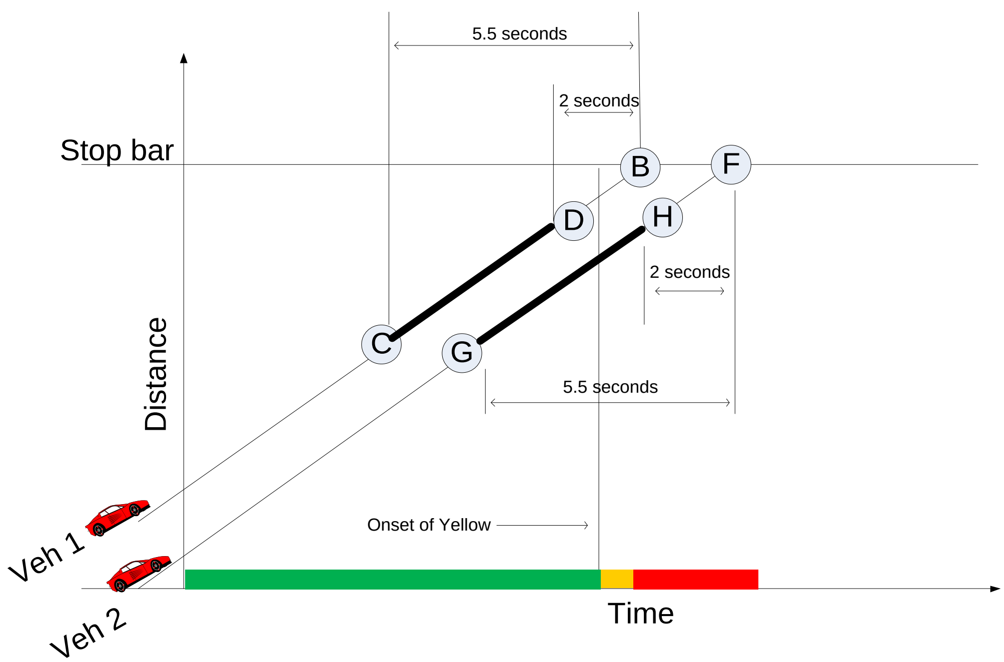


Figure 16: Illustration of the dynamic beginning and end of DZ for individual vehicles (Ghanipoor Machiani and Abbas 2014).

Two types of DZ are defined by previous research; Type I is related to vehicle dynamic characteristics, and occurs when the driver is neither able to stop safely nor clear the intersection before the beginning of a conflicting phase. Type II is related to driver's behavior, and occurs as a result of different driver decisions to proceed through or stop. Although, this type of DZ has been named differently by researchers, in fact, it is the real DZ that is challenging to overcome by providing suitable yellow and all-red durations (Abbas, Higgs et al. 2014).

In order to address type II DZ, and to increase the safety of signalized intersections, mitigation strategies and dilemma zone protection settings are introduced. Advanced options of modern Traffic Signal Controllers (2008, 2009), Advanced control algorithms for dynamic dilemma zone protection such as the D-CS (Zimmerman, Bonneson et al. 2003, Zimmerman and Bonneson 2005, Zimmerman 2007), Platoon Identification Algorithm (PIA)(Chaudhary, Abbas et al. 2006), the green extension systems (GES) (Zegeer 1977), LHOVRA (Engstrom 1994), MOVA (Vincent and Peirce 1988, Kronborg and Davidsson 1993) , and SOS (Davidsson and Edholm 1997) are some of the systems developed for this purpose. Resulting systems may differ in objectives and constraints, but they generally apply speed estimation to predict how many vehicles are in the DZ. Speed prediction is used to calculate the arrival time of the vehicle to the stop bar, which is used to back-calculate the dilemma zone boundaries by subtracting 5.5 seconds (beginning of the DZ) and 2.0 seconds (end of DZ). This information requires the controller to hold the green phase as long as there is a vehicle in DZ and force the green phase to end when the DZ is clear. These systems benefit intersection safety, and some of them have been implemented in some NEMA traffic controllers. For instance, D-CS is implemented in Naztec controllers. The difficulty of using these systems is the calibration of parameters such as stage lengths in D-CS; optimality could decrease in some traffic patterns, etc.

These DZ-protection algorithms could benefit from the prediction of drivers' stop/go decision to make more intelligent decisions in changing signal settings. The possibility of this prediction is the focus of this research. The appropriate time period and data type for a more accurate prediction model is investigated using discriminant analysis techniques.

Methodology

Dataset Descriptions

VT-SCORES dataset

The VT-SCORES dataset is obtained from a driving simulator study conducted at VT-SCORES (Signal Control & Operation Research and Education Systems Lab) located at Virginia Tech. The experimental design of the study includes five influencing factors on drivers' decision to stop or go. These factor includes Time to intersection (TTI) at the onset of yellow (s) (levels: 2.5, 3.5, and 4.5 sec), Presence of police (levels: yes and no), Presence of side street queue (levels: yes and no), Presence of other vehicle around (levels: no vehicle and vehicle in the back), and Pavement condition (levels: wet and dry). Factors such as "pavement condition" and "presence of other vehicle around" cannot be changed through one session of driving. Therefore, a split plot statistical design was used to account for this fact. Based on this type of design the two hard-to-change factors ("pavement condition" and "presence of other vehicle around") are whole plot factors, and the rest of the factors are regarded as split plot factors. Another consideration in designing the experiment was the use of fractional factorial design; meaning that instead of having all the combination of factors, only selected combinations are considered due to the limitation of the number of intersections a driver can drive in the driving simulator environment. Drivers were considered as blocking factors to control the variation pertaining to drivers' characteristics. The design was performed in SAS JMP Pro 10.0.0 software. We refer the readers to (Ghanipoor Machiani and Abbas 2014) for a detailed description of the experimental design of the study.

After the completion of the experimental design, the design scenarios were implemented in the driving simulator environment. For this study, we used DriveSafety DS-250 model of the driving simulator (see Figure 17). As shown in Figure 18, the simulator is composed of three components; namely Hyperdrive, Dashboard, and Vection. Hyperdrive is used in the creation stage to build the environment. Vection is the software to run the simulator, and Dashboard interfaces Hyperdrive and Vection. Roadway type (e.g., urban and rural) and roadway entities are implemented using built-in library elements in the authoring palette, and they are dragged and dropped into the visualization window in the Hyperdrive. More complicated settings and tasks such as traffic signal settings and monitoring process is carried out by Tool Command Language (TCL).

Figure 17: Driving simulator, DriveSafety DS-250.

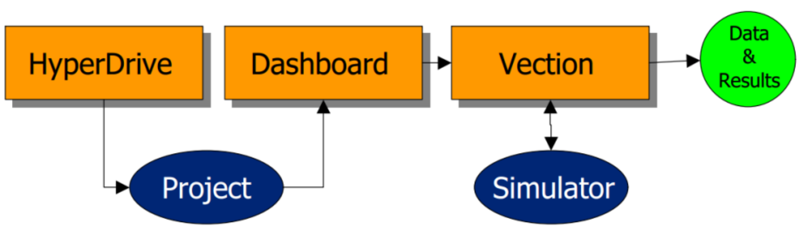


Figure 18: Driving simulator components (Melnrick 2012).

Drivers participated in this study were volunteered participants over 18 years old. They were invited to participate through an email notification and word of mouth. Totally 42 participants drove through the simulator of which the first 6 were considered for the pilot run. Experimental design was modified slightly after the pilot. Also, two participants withdraw in the middle of the run due to driving simulator sickness, and their data is excluded from the analysis. Participants were asked to fill in a questionnaire on general information (e.g., gender, age, education), and driving experience. They also drove through an adaptation drive before the real data collection started. The adaptation drive takes as much time as drivers feel comfortable enough with the simulator. Every driver drove through 5 corridors each one including 10 intersections (7 intersections turn yellow while the driver is in the DZ), and the experiment takes around 45 minutes. Data collection was carried out with the precision of 60 Hz, and the data was manipulated and reduced using a script.

NADS dataset

The second data set used in this study is from a study conducted at the U. Iowa National Advanced Driving Simulator (NADS) related to the examination of the effect of wireless telephone use on driving performance. Three age groups were considered in the study; namely young drivers (aged 18-25 years), middle (aged 30-45 years) and older (aged 50-60 years). The data was collected for participants as they drove through signalized intersections that had the setting to turn yellow when the driver was in dilemma zone (at one of two pre-determined timings (3.00 or 3.75 seconds)). The yellow duration was around 4 seconds. The drivers were involved in one of the secondary tasks of Baseline (no phone call), Outgoing call, and Incoming Call. Ambient traffic was similar for all runs, and the data was collected at 240 Hz precision. 48 participants completed the study. Each participant was associated to 18 rows of data (3 visits (3 cell phone interface)*3 secondary task (baseline (no call), outgoing, and incoming) * 2 signal changes per secondary task). In addition to these 18 rows, there were 6 rows related to familiarization runs that were excluded from the analysis.

Discriminant Analysis

A canonical discriminant analysis technique was used in this study to predict the drivers' decision to stop or go when encountering the yellow signal indication. Discriminant analysis is a classification method that uses a priori knowledge of the classification of the dependent variables in the training dataset to distinguish between the independent variables in new datasets. The result of the analysis of the training dataset is a discriminant function that maps the training dataset observations (independent variables) and associated classifications (dependent variables), and that could therefore be applied to classify future observations. The canonical part indicates the creation of new observation variables from the dataset that are used to better discriminate between the groups (utilizing principal components analysis). The discriminant function modifies the scoring coefficients for the independent variables in such a way that the measure of distance between the resulting groups is maximized. The independent variables are multiplied by coefficients and added to obtain a score. This score is compared to a threshold to determine which group a particular observation is associated with. To evaluate the utility of a discriminant model, “Percent Misclassified” is used as a measure that compares predicted group membership based on the discriminant model to the actual group membership.

The two dataset considered in this study include different variables. For the VT-SCORES dataset, the following independent variables were considered in the analysis:

- *Time to intersection (TTI)* at the onset of yellow: Participant’s time to intersection when the light turns from green to yellow.
- *MeanSpeed* (m/s): Participant’s mean speed during the time period of interest.
- *MeanAccel* (m/s^2): Participant’s mean acceleration during the time period of interest.
- *TimeLostGained* (sec): This variable is the amount of time the driver lost or gained by decelerating or accelerating comparing to a constant speed.
- *Presence of police:* Whether or not a police car is present at the intersection.
- *Presence of side street queue:* Whether or not a side street queue existed.
- *Presence of other vehicle around:* Whether or not there was a vehicle in the back.
- *Pavement condition:* whether or not the pavement was wet.

For NADS dataset, the independent variables are as following:

- *Speed_Onset of Yellow* (mph): Participant’s speed when the light turns from green to yellow.
- *Dist_Onset of Yellow* (feet): Participant’s distance from stop line when the light turns from green to yellow.

- *Accel/RelAccel/NoCahnge*: whether participants had an accelerator pedal change of greater than 10% percent. This variable has three levels of Accel (it is depressed), RelAccel (it is released), NoChange (no changes to the speed) with values 1, -1, and 0, respectively.
- *Time of Accel/RelAccel* (sec): How far during yellow participants had an accelerator pedal change of greater than 10% percent.
- *Cell Phone Interface:* Cell Phone Interface for the secondary task with three levels of Handheld, HandsFree, and HeadSet.
- *Secondary Task:* Secondary task condition including baseline (no call), outgoing call, and incoming call.

For both datasets the dependent variable is drivers' binary decision of stop or go.

Scenario Development

Three scenarios associated with different time frames and datasets were examined to predict drivers stopping decisions.

Scenario 1

Scenario 1 is related to the first 3 seconds during yellow. If the driver's decision could be predicted in this time frame, then this information is useful to increase the safety of the intersection. The reason is that, at every signal cycle, there are at least 2.5 seconds of yellow plus 0.5 seconds all red duration which adds up to 3 seconds. If in this time frame, it is predicted that the driver's decision is to pass through the intersection instead of stopping, then an all-red-extension strategy could be considered to provide the driver with a safer passing decision. The VT-SCORES dataset was used for this scenario.

Scenario 2

The time frame is exactly the same as scenario 1 (3 sec after the onset of yellow), but NADS dataset was used to predict the drivers' decision.

Scenario 3

Scenario 3 considers during green time within the DZ (between 6 sec ahead of intersection and the onset of yellow). The rationale in this scenario is that if the driver decision can be predicted in this period of time before the signal changes to yellow, a DZ-protection algorithm can decide whether to end the phase or not by taking into account the predicted safety results of that decision. This could improve the DZ-protection algorithm performance towards a more intelligent control system that targets crash reduction at signalized intersections. The VT-SCORES dataset was used for this scenario.

Results and Discussion

Scenario 1

To determine which variables to be included in the discriminant analysis, a stepwise approach was taken. Table 5 shows the F ratio and p-value of the variables indicating the significance of these variables in the model. The first four variables were chosen to be included in the model. The F ratio drops significantly after these four variables. It should be noted that the selection of the variables in different scenarios were based on their significance level as well as judgment calls to provide a common ground for comparison among scenarios.

Table 5: Significance of variables in the discriminant model for scenario1.

Variable	F Ratio	p-value
TimeLostGaind (3 sec after the onset of yellow)	173.370	0.0000000
MeanSpeed (3 sec after the onset of yellow)	246.569	0.0000000
MeanAccel (3 sec after the onset of yellow)	939.372	0.0000000
Time to intersection (TTI)	1901.03	0.0000000
Other vehicle around	0.273	0.6011854
Pavement condition	0.080	0.7776506
Presence of side street queue	1.014	0.3141747
Presence of police	0.245	0.6208850

The result for scenario 1 revealed that the discriminant function is 99.7% accurate and only 0.341% of the dataset were misclassified. The canonical plot (color-coded; “stop” is blue and “go” is red), shown in Figure 19, illustrates how well the first two canonical variables (that best separate the groups) discriminate between drivers decisions. The labeled rays on the plot show the direction of the variables in the canonical space. According to this plot, the two drivers’ decision groups are separable by the discriminant model (blue and red points located separately on the chart).

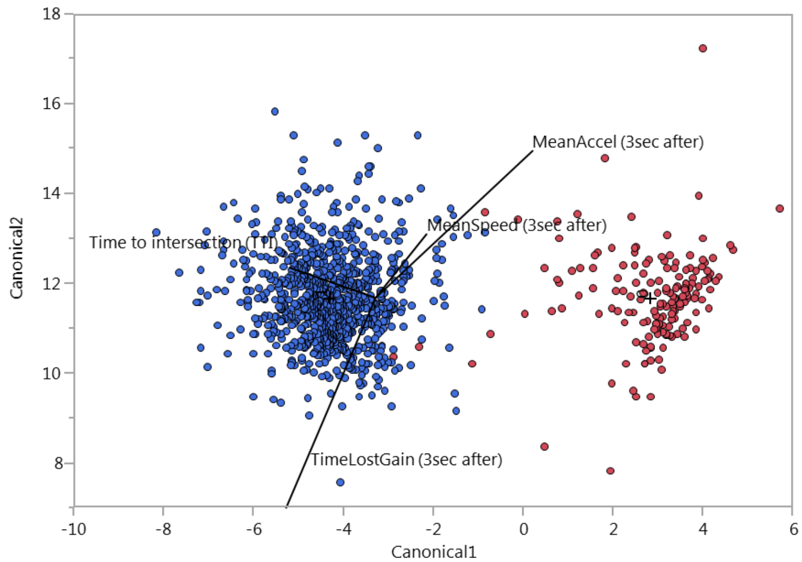


Figure 19: Canonical Plot for scenario 1.

Scenario 2

Similar to scenario 1, a stepwise discriminant model was considered. The significance of the variables are summarized in

Table 6. There is a drop after the variable "Dist_Onset of Yellow". Therefore, the first four variables were included in the model. Note that "Cell Phone Interface" and "Secondary Task" variables are nominal variables with three levels. Dummy variables needs to be constructed to include these nominal variables in the model. Dummy_HH and Dummy_HS are dummy variables for Handheld and HeadSet cell phone interface. Dummy_I and Dummy_O refer to Incoming and Outgoing calls under the "Secondary Task" variables. Note that the variable "Time of Accel/RelAccel" in the NADS dataset was below 3 seconds, so it complies with the constraint of the second scenario to predict the driver's decision within the first 3 seconds in yellow time.

Table 6: Significance of variables in the discriminant model for scenario 2.

Variables	F Ratio	p-value
Time of Accel/RelAccel	36.675	0.0000000
Accel/RelAccel/NoCahnge	36.677	0.0000000
Speed_Onset of Yellow	5.300	0.0215642
Dist_Onset of Yellow	2.333	0.1270318
Dummy_HH	0.234	0.6286570
Dummy_HS	0.389	0.5330958
Dummy_I	0.023	0.8804328
Dummy_O	0.005	0.9458041

The discriminant analysis resulted in a 33.14% misclassification of the drivers' decision; meaning that the model is 66.86% accurate. Figure 20 shows the canonical plot of the results (color-coded; "stop" is blue and "go" is red). Stop/go decisions seems to be mixed on the figure, and the accuracy of discriminant model is low.

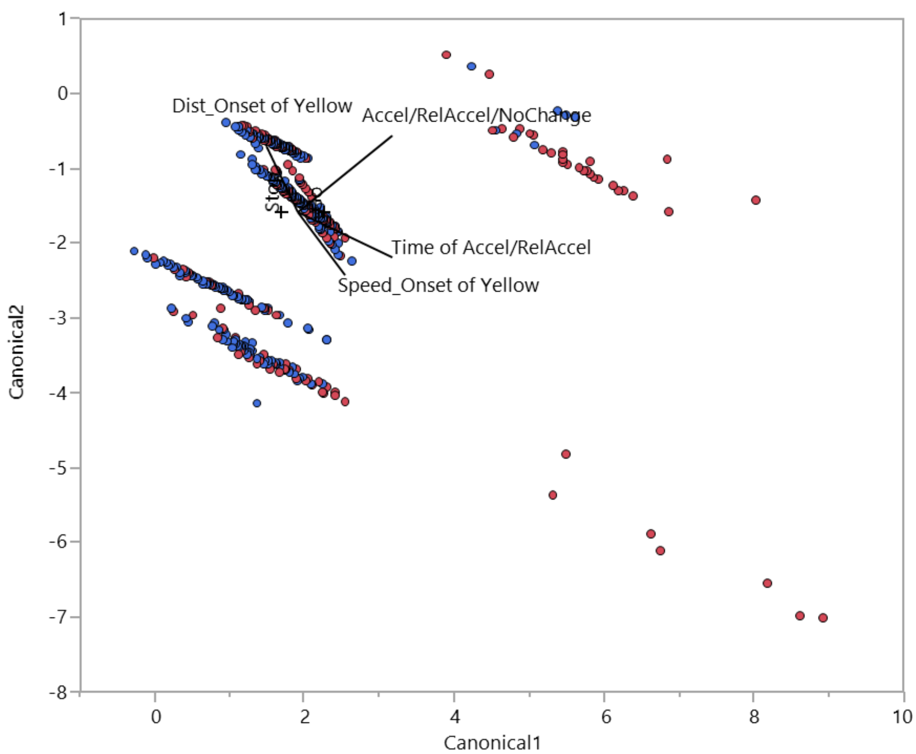


Figure 20: Canonical Plot for scenario 2.

Scenario 3

Table 7 summarizes the significance of the variables in the discriminant model for scenario 3. The two variables "MeanSpeed" and "Time to intersection (TTI)" have the lowest p-values, so they are included in the model. The next two higher ones are "TimeLostGained" and "MeanAccel." Therefore, in total, the first four variables are included in the model (similar to scenario 1).

Table 7: Significance of variables in the discriminant model for scenario 3

Variables	F Ratio	P-value
TimeLostGained (6 to TTI)	5.914	0.0151676
MeanSpeed (6 to TTI)	21.635	0.0000037
MeanAccel (6 to TTI)	7.270	0.0071120
Time to intersection (TTI)	295.542	0.0000000
Other vehicle around	4.035	0.0448001
Pavement condition	3.748	0.0531170
Presence of side street queue	3.055	0.0807504
Presence of police	3.329	0.0683281

For this scenario, the time period in which independent variables are calculated is variable based on TTI at the onset of yellow (e.g., 1.5 seconds when TTI at the onset of yellow is 4.5 (6 - 4.5 = 1.5)). The result of the analysis showed that 19.52% of data is misclassified. Therefore, the accuracy of the model is 80.48%. The canonical plot for this scenario is shown in Figure 21. As it can be seen, the two groups of drivers' decisions (colored differently, blue showing "stop" and red showing "go" decisions) are not very distinguishable in this plot.

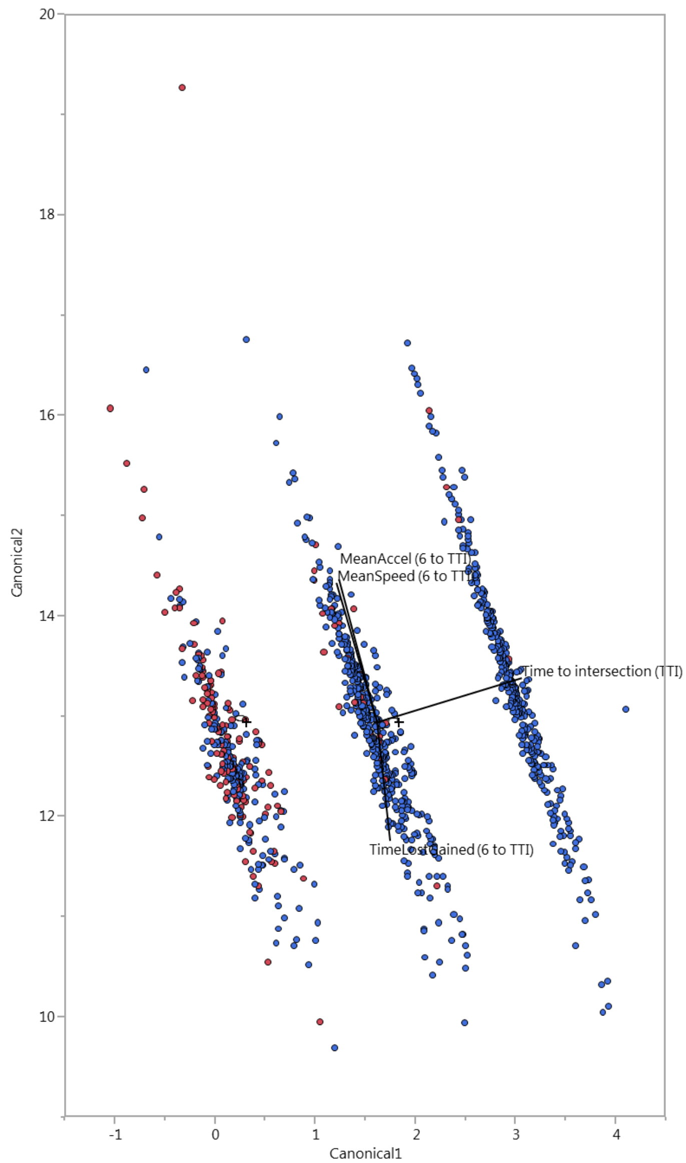


Figure 21: Canonical Plot for scenario 3.

Summary and Discussion

Table 8 summarizes the standardized scoring coefficients of the independent variables for all scenarios. The discriminant functions are calculated by multiplying these coefficients times the associated variables, which is used to classify future data points.

Table 8: Standardized scoring coefficients of the discriminant functions for Canon1.

	Scenario No.		
Variables	Scenario 1	Scenario 2	Scenario 3
TimeLostGained	-1.28153	NA	0.0876771
MeanSpeed	-1.389146	NA	-0.269642
MeanAccel	0.7545219	NA	-0.250638
TTI at the onset of yellow	2.3270189	NA	0.9610118
Speed_Onset of Yellow	NA	0.4219585	NA
Dist_Onset of Yellow	NA	-0.282016	NA
Time of Accel/RelAccel	NA	0.839324	NA
Accel/RelAccel/NoChange	NA	0.844776	NA

Table 9 summarizes the accuracy of the models for all scenarios. According to this table, comparing scenario 1 and 2 that has the same time frame, the accuracy of the model for VT-SCORES dataset is higher than NADS. This difference is attributed to the difference between the independent variables. In scenario 1, the independent variables in the VT-SCORES dataset are time to intersection at the onset of yellow, mean speed, mean acceleration, and time-lost-gained in the first 3 seconds of yellow. In scenario 2, the independent variables in the NADS dataset used for classification are speed and distance at the onset of yellow, whether or not the driver touched the acceleration pedal, and how far during yellow the driver touched the pedal. These variables all belong to instants of time starting from yellow indication until 3 seconds after. Time to intersection at the onset of yellow from VT-SCORES dataset is translatable to speed and distance at the onset of yellow in NADS dataset. However, the other variables in VT-SCORES dataset are not instant variables; they actually provide information about the continuous time of 3 second after yellow. They monitor the driver accelerating behavior through this time, and capture it in their values. This continuous monitoring nature of the variable makes the classification model more accurate.

It seems that the accuracy of the model for scenario 3 should be less than scenario 2 as the information obtained during green time (scenario 3) should be less capable of predicting the driver's decision compared to the situation where the drivers have already seen the yellow. However, as shown in the table, the accuracy of scenario 3 is even higher than scenario 2 which is due to the continuous monitoring nature of the independent variables in the VT-SCORES dataset. Therefore, to construct a discriminant model that could predict drivers' decision with a high level of accuracy, it is recommended to collect the data in a continuous manner by continuously monitoring the driver during the time period of the interest.

Table 9: Discriminant function accuracy for VT-SCORES and NADS datasets.

Scenario No.	Time frame	Dataset	Accuracy
Scenario 1	3 seconds after the onset of yellow	VT-SCORES	99.7%
Scenario 2	3 seconds after the onset of yellow	NADS	66.86%
Scenario 3	6 seconds ahead of intersection to the onset of yellow	VT-SCORES	80.48%.

The discriminant analysis performed for the two time period of interests (during green in DZ and the first 3 seconds of yellow) resulted in a model with a promising accuracy of 99.7% and 80.48%, respectively. This reveals the possibility of predicting drivers' decision in DZ when there is still time to make the appropriate changes to the signal settings. Therefore, the following conclusions are drawn based on the results of this research effort:

- An appropriate time to predict drivers' decision to stop or go at DZ is during the first 3 seconds after the onset of yellow.
- To generate an accurate prediction model, the collected data needs to have a continuous nature (accumulating variables) instead of using instantaneous data points.
- Variables that are not directly related to speed, acceleration, distance, and time don't significantly affect the accuracy of the prediction model. These type of variables (e.g., pavement condition, secondary task, etc.) are not needed for producing accurate prediction models.

The discriminant function could be integrated into the signal controller algorithm to extend the all-red interval when the driver is predicted to run the red light. This could reduce the right-angle crashes that usually happen when the driver misjudge his or her ability to pass through in the remaining yellow time and meanwhile the other driver on the side street sees the green and enter the intersection.

Conclusions

Dilemma zone is defined as the area upstream of a signalized intersection where drivers are faced with a dilemma to stop or pass at the onset of yellow. Safety concerns associated with dilemma zone related issues have made this topic an attractive ground for research, resulting in development of several mitigation strategies and DZ-protection algorithms. Everyday growing signal controller technology could benefit from prediction of drivers' decision at dilemma zone to improve phase settings toward safer intersections. This study uses discriminant analysis technique to examine the possibility of predicting drivers' decision during an appropriate time frame to use in DZ-protection algorithms. Two different driving simulator datasets were used (VT-SCORES and NADS datasets), and two time frames were considered. The first two scenarios considered in this study focused on predicting drivers' decision after the onset of yellow in a reasonable time frame (3 seconds). The third scenario focused on predicting drivers' decisions during green. The three scenarios were examined utilizing the two time frames and datasets. Scenario 1 was examined during the time frame of the first 3 seconds of yellow and using the VT-SCORES dataset, scenario 2 with the time frame of the first 3 seconds of yellow and using the NADS dataset, and scenario 3 during green immediately before yellow (starting from 6 seconds ahead of intersection) and using the VT-SCORES dataset.

The result revealed that the highest accuracy of the prediction model (99.7%) was obtained when the nature of the data is continuous (as opposed to instantaneous data points), and the data was collected during the first three seconds of yellow. Moreover, some variables such as "pavement condition" or "presence of other vehicle around" that were not directly related to speed, acceleration, distance, and time to intersection did not significantly affect the accuracy of the model, and could therefore be eliminated in the data collection process.

This study used two driving simulator datasets. As a future effort, field data will also be examined to compare findings with the results of driving simulator data. Also, incorporating the prediction model in DZ-protection algorithms will be investigated to quantify the effect of the model on intersection safety.

Acknowledgements

This study was supported in part by the Mid-Atlantic Universities Transportation Center as well as the Virginia Center for Transportation Innovation and research (VCTIR). The authors are solely responsible for the material in this paper and the views are not necessarily those of the supporting agencies.

CHAPTER 6 SAFETY SURROGATE NUMBER (SSN): A NOVEL REAL-TIME SAFETY ASSESSMENT OF DILEMMA ZONE RELATED CONFLICTS AT SIGNALIZED INTERSECTIONS

This chapter presents a paper that is currently under peer review. It was jointly written by Sahar Ghanipoor Machiani and Montasir Abbas.

Abstract

Dilemma zones (DZ) are one of the main contributing factors to crashes at intersections. DZ refers to the area ahead of an intersection in which drivers encounter a dilemma to stop or go through the intersection when the signal turns yellow. An improper decision to stop by the leading vehicle when the following driver decides to go can result in a rear-end collision, unless the driver in the back recognizes the dangerous situation, and performs a behavioral adjustment during and/or shortly after the onset of yellow. Considering the significance of DZ related crashes, a comprehensive safety measure is needed to characterize the level of safety at signalized intersections. In this study, a novel safety surrogate measure is developed utilizing real-time radar field data. This new measure, called Safety Surrogate Number (SSN), captures the degree and frequency of DZ related conflicts at each intersection approach. SSN includes detailed information regarding the possibility of the crashes as it is calculated based on the vehicles conflicts. An example illustrating the application of the new methodology at two study sites in Virginia is shown and discussed, and a comparison is provided among SSN and other DZ related safety surrogate measures suggested in the literature. The results of the study reveal the potential capability of the SSN to evaluate DZ-protection algorithms independently of their protection approach to select, and potentially even develop better new algorithms.

Keywords: signalized intersections; Safety Surrogate Number (SSN); Time to Collision (TTC); Dilemma Zone (DZ); DZ-protection algorithms

Introduction

A great number of crashes occurs at signalized intersections (Li and Abbas 2010). These crashes are highly attributed to drivers' dilemma zones at the onset of yellow interval. Dilemma zone is the area ahead of signalized intersections in which drivers encounter a dilemma to decide whether to pass the intersection or stop before the stop bar when they see the yellow light. Variation in decisions in dilemma zone might lead to drivers in front attempting to stop while divers in the back desiring to continue. Drivers in the back would usually recognize the impending rear-collision danger and adjust their decision accordingly. The faster those drivers decelerate, the sooner the dangerous situation subsides. If a driver fails to recognize the dangerous situation, or does not pay attention, a crash occurs. This "turbulence" of behavioral adjustment occurs during and/or shortly after the onset of yellow.

Drivers' decisions and interactions with each other's play an important role in traffic conflicts in DZ. Recognizing this interaction and developing a measure to quantify the dangerous interaction can help signal practitioners selecting appropriate DZ-protection strategies to reduce the possibility of the crashes. Safety surrogate measures related to DZ issues, such as the number of vehicles caught in DZ, number of yellow and red light violators, and stop line encroachment have been introduced in the literature (Gettman and Head 2003). Various DZ-protection algorithms and advance signal technologies have addressed different part of the safety concerns related to DZ conflicts. Most of these algorithms consider the number of vehicles in DZ and adjust the signal settings to clear the DZ (e.g., D-CS (Zimmerman, Bonneson et al. 2003, Zimmerman and Bonneson 2005, Zimmerman 2007), LHOVRA (Engstrom 1994), MOVA (Vincent 1988)). Some others take also into account other considerations such as the queue clearance in Platoon Identification Algorithm (PIA)(Chaudhary, Abbas et al. 2006), and continuous tracking in Wavetronix systems (2014). A real time evaluation system is needed to independently evaluate the efficacy of these algorithms, and potentially suggest which protection algorithm is more suitable. Such a system could be used to answer questions such as whether the DZ-protection algorithms that focus on red light extension or the ones that are focusing on the queue clearance are more beneficial. This real time safety evaluation system is the focus of this study.

We introduce and define a novel Safety Surrogate Number (SSN) measure to capture the degree and characterization of dilemma zone related conflicts. Our method is based on real-time field measurement of vehicle trajectory data (obtained, in this case, from a Wavetronix radar), and a histogram plot of time-to-collision frequencies shortly before, during, and shortly after the change intervals at signalized intersections. The SSN provides a more complete and comprehensive picture of the safety level at intersection approaches. The result of this study is of relevance to collision avoidance systems. It could be used as a performance measure to evaluate different DZ-protection algorithms and strategies.

Our manuscript is organized as follows: The subsequent section provides a background review of the related efforts. Next, the methodology is described, including the research approach and the data collection system. Then, application of the method is presented including the description of the study sites and data, followed by results and discussion. The last section draws the conclusions on the proposed approach and discusses future research efforts.

Background

Dilemma zone has been a subject of research for decades. Contributing factors to dilemma zone related issues, modeling approaches, and mitigation strategies have been widely studied. A review of these research efforts is provided in research studies such as (Papaioannou 2007, Rakha, Amer et al. 2008, Adam, Abbas et al. 2009, Sharma, Bullock et al. 2011, Abbas and Ghanipoor Machiani 2013, Abbas, Ghanipoor Machiani et al. 2014, Ghanipoor Machiani and Abbas 2014, Ghanipoor Machiani and Abbas 2014, Jahangiri, Rakha et al. 2015). In this study, we focus mostly on the background of DZ collision and safety measures in Dz.

A broad range of transportation studies has been dedicated to collision prediction and avoidance models and algorithms (for example, see (Sato and Ishii 1998, Kuchar and Yang 2000, Jansson and Gustafsson 2008)).The first safety measure that has been used to evaluate the level of safety at transportation facilities is the number and severity of crashes. However, infrequency of crash occurrences as well as the need to evaluate the safety of transportation facilities before they are built led to the consideration of surrogate measures. Surrogate safety measures are “measures of safety not based on a series of actual crashes (Gettman, Pu et al. 2008) .” Many surrogate measures have been introduced by researchers, such as Vehicle delay, Queue lengths, Percentage of left turns, Deceleration distribution, etc. (Gettman and Head 2003). One of the recent efforts related to surrogate measures is the development of the Surrogate Safety Assessment Model (SSAM) software tool. SSAM uses specific format of the vehicle trajectory data obtained from simulation software to evaluate simulated traffic conflicts. Some of the simulation software packages are able to produce this specific format (Gettman, Pu et al. 2008).

Surrogate safety measure is a main concept in relation to traffic conflict analysis. A conflict is defined as a situation in which there is a risk of collision between two or more road users if they don’t change their trajectory. The traffic conflicts technique is a field observation method to determine conflicts by considering shifty maneuvers such as slamming on the brake (Gettman and Head 2003). Time to Collision (TTC) is the primary severity conflict measure proposed by researchers, and is defined as the expected time for two vehicles to collide if they maintain their speeds and directions (Gettman and Head 2003).

TTC is widely used as a safety indicator to measure crash risk, evaluate roadway safety, and test the importance of contributing factors to crashes (Kiefer, Flannagan et al. 2006, Meng and Weng 2011). TTC has been suggested as a scale of danger more than four decades ago by Hayward (Hayward 1972). Hayward defined TTC as the time measured until collision between two vehicles if the collision situation and speed difference are maintained (Hayward 1972). This measure is calculated using different sources of data including videos and trajectories. For examples, Hayward (1972) used traffic sensing and surveillance system of the federal highway administration to calculate this measure from the captured videos at an urban intersection (Hayward 1972). Xu and Qu (2014) also applied Beijing expressway video data to investigate the effect of road environments, traffic conditions, and vehicle types on TTC. The result showed that TTC means and vehicle types are not correlated. On the other hand, it was found that traffic conditions and road environments influence TTC significantly (Xu and Qu 2014). Minderhoud and Bovy (2001) used vehicle trajectory on a specific road segment for a certain time period to introduce safety measures based on the TTC. These safety indicators, named Time Exposed, Time-to-collision, and Time Integrated Time-to-collision, are applicable to intelligent driver support systems (Minderhoud and Bovy 2001).

The concept of TTC has been applied to different crash situations and maneuvers, such as passing maneuvers on rural two-lane highways (Farah, Bekhor et al. 2009) and rear-end vehicle crash in urban road tunnels (Meng and Qu 2012). Farah et al. (2009) used an interactive driving simulator to develop a model to predict the risk in passing maneuvers on rural two-lane highways. The measure of risk in their study was TTC. Meng and Qu (2012) proposed a model to estimate the rear-end vehicle crash frequency in road tunnels based on the TTC distributions. TTC was analyzed using data from the traffic videos of two road tunnels in Singapore. Inverse Gaussian distribution was concluded as the best model to relate TTC and its contributing factors. Berthelot et al. (2012) also developed a real-time algorithm to compute the probability distribution of TTC applicable to the design of cars and advanced driver assistance system. They investigated the accuracy of their approach by simulating several crossing scenarios.

Kiefer et al.(2006) investigated TTC from drivers' point of view (TTC judgment). In this test track research, participants were asked to indicate the time to collision to a lead vehicle by pressing a button. The results showed that when driver's speed decreased or relative speed increased the ratio of perceived TTC to actual TTC increased. Hoffmann and Mortimer (1994) also examined drivers' estimation of the time to collision in a laboratory simulation. The results showed that drivers underestimated the time to collision when the value of TTC was low (Hoffmann and Mortimer 1994).

Some research efforts have been spent toward comparing TTC with other safety measures, such as the inverse time to collision (Balas and Balas 2006) and headway (Vogel 2003). Vogel (Vogel 2003) indicated that suggested TTC threshold in the literature ranges from 1.5 to 5 seconds, and TTC larger than 6 seconds was not considered to be dangerous (Vogel 2003).

Although TTC has been widely researched as evidenced by the aforementioned studies, to the best of our knowledge, this measure has not been directly used in DZ related studies. DZ conflicts are one of the main contributing factors to the number of crashes and safety related concerns at signalized intersections. Surrogate measures such as Stop-bar encroachments , Red- and yellow-light violations by phase, and Number of vehicles caught in dilemma zones have been considered in this regard, although no quantitative assessment has been done to relate these measures to the number of crashes (Gettman and Head 2003). In this research, we take advantage of the TTC concept to develop a novel safety surrogate measure that we call the safety surrogate number (SSN) of the DZ related conflicts at signalized intersections. This new measure provides useful information regarding the level of safety at signalized intersections and can provide insightful perspective on evaluating the efficacy of DZ-protection algorithms.

Methodology

Research Approach and Rationale

The basic idea behind our approach relies on the TTC concept. Utilizing real-time vehicle trajectory data, we measure and plot the TTC for every two consecutive vehicles on a time space diagram. If there are more than two vehicles, every pair is analyzed separately. Figure 22 illustrates an instance of the produced time-space diagram for two vehicles (A and B, where vehicle A is following vehicle B). At every point in time, the TTC can be calculated based on the speed of each vehicle. In this figure, the slope of each line corresponds to the speed of the vehicle. For example, in the figure, the slope of the curves at point c shown by the red color represents the speed of two vehicles at this point in time. The time between the intersecting point of these two slopes and point c is the TTC from point c (shown as TTC_c in the figure). Similarly, the TTC can be calculated for every other point in time. In the figure, two other TTC values are illustrated at points d and f, and are named TTC_d and TTC_f, respectively. At point c, vehicle A has started to decelerate to avoid the collision, so as time passes the TTC value increased from point c to point f. At point e, as the two slopes become almost parallel, the TTC value approaches infinity. If the front vehicle continues through the intersection, while the back vehicle comes to stop, the value of TTC could even change to a negative value. In other words, as positive values of TTC go down, vehicles are considered to be more exposed to dangerous situations. Small positive value of TTC shows that collision is imminent. Negative TTC means that the two subject vehicles are getting far from a possible collision.

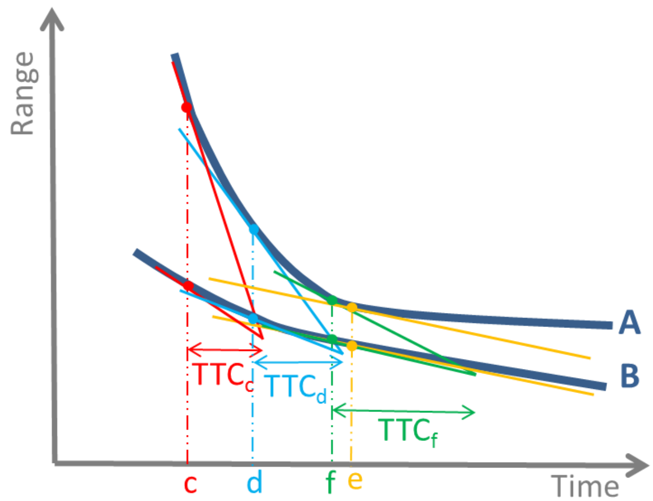


Figure 22: TTC values plotted on a time-space diagram.

It should be noted that, instead of using the slope of the continuous time-space diagram to calculate the TTC, we use the speed data collected discretely over time. In cases where speed data is not available for the leading vehicle at the same point of time, an interpolation method is applied to estimate the speed at that exact time. Using speed data is more realistic and accurate than calculating the slope of a fitted curve to the data points in a discrete time-space diagram. To illustrate this concept, consider Figure 23 shown below. In this figure, an imminent collision situation and a safety conflict between vehicle A and B is illustrated. Vehicle trajectory field data are shown as dots on the time-space diagrams. The color of each dot indicates the measured speed as shown on the color map to the right of the chart. The x-axis represents time in seconds overlaid by the signal indication colors (green, yellow, and red). The y-axis shows the range (distance) in feet assuming zero for stop bar at the intersection. Vehicle A is following vehicle B as they are approaching the intersection. The parts of the vehicles' trajectories that show the discussed behavioral changes are shown by the surrounding dotted polygons in the figure. During yellow, as vehicle B decides to stop, vehicle A needs to change its passing decision to avoid collision.

As vehicle A starts to decelerate, it increases its distance to the leading vehicle, and the TTC value changes to a greater positive values. Therefore, monitoring changes in the value of TTC for approaching vehicles as well as the frequency of each TTC value would provide a characteristic assessment of the safety level at the intersection.

Based on the literature, TTC values that are greater than 6 seconds are considered safe (Vogel 2003). In this research, a number is generated to sequentially show the histogram frequency of TTC less than 1 sec, between 1 and 2 sec, between 2 and 3 sec, between 3 and 4 sec, between 4 and 5 sec, and between 5 and 6 sec. This number is called the Safety Surrogate Number (SSN), and represents the safety level of an intersection approach.

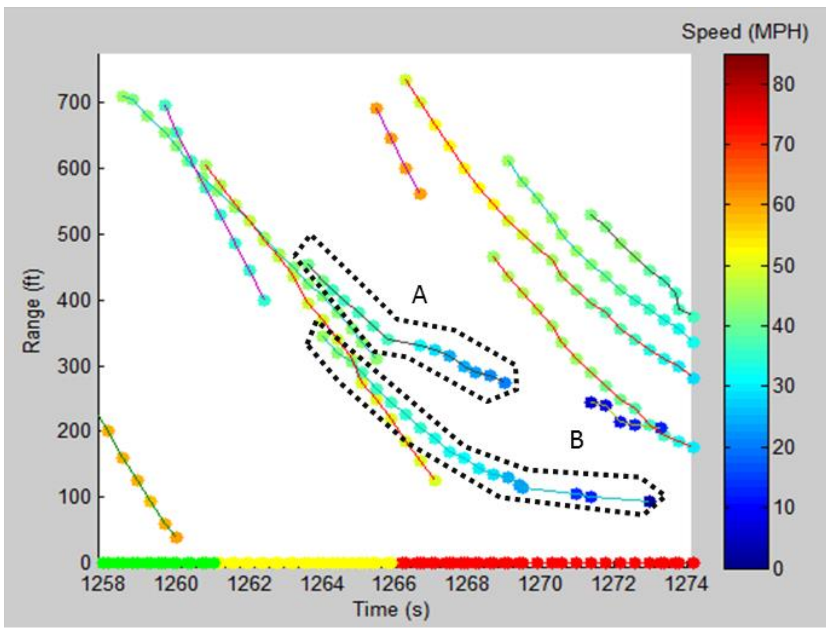
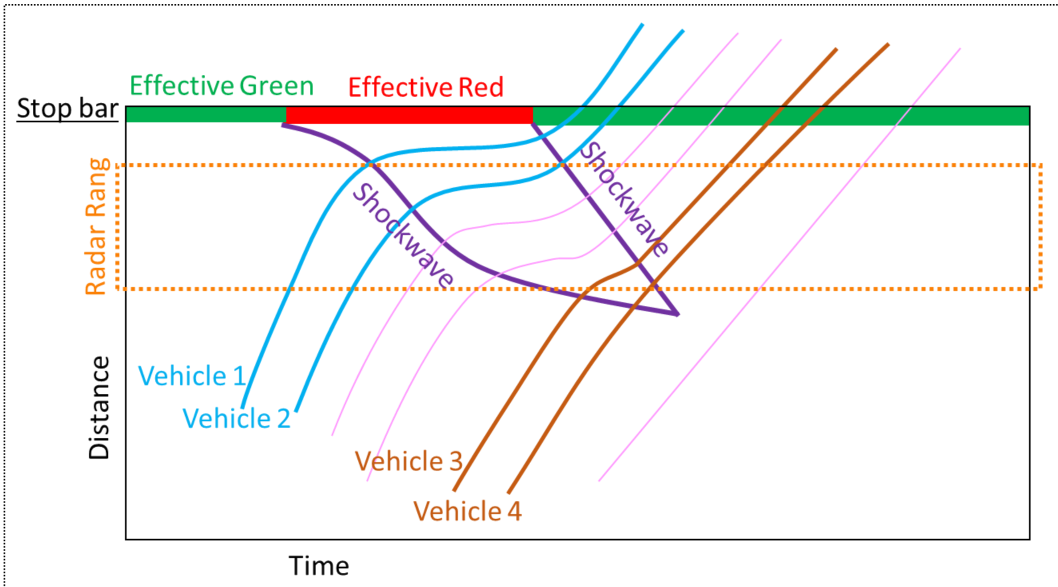


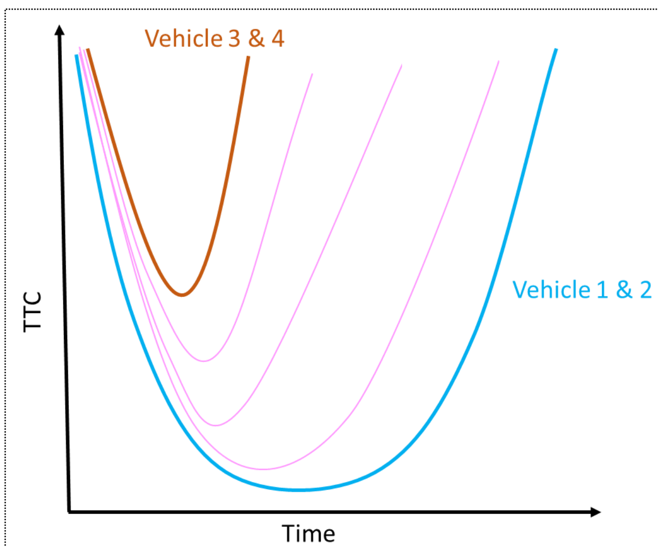
Figure 23: Time-space diagram color coded by speed for approaching vehicles.

The concept behind the SSN is related to the behavior of traffic passing through the red and green shockwaves at the intersection. Figure 24 illustrates this relationship. The stop bar location is at the top of the Figure 24-a, color coded based on the signal indication. The x-axis and y-axis represent time and distance, respectively. The start and end of red phase form the two shockwaves shown by the purple color on the figure. Consider a case where the traffic is approaching the signal. Vehicle 2 is following vehicle 1, and they are going to face the red interval. Vehicle 1 hits the brake to reduce the speed. At this moment, the TTC for these two vehicles drops to a very low value. This is shown in Figure 24-b where the blue line (representing vehicles 1 and 2) has the negative steep slope. The value of the TTC stays low until vehicle 2 also starts to slow down. Afterward, the TTC increases as the vehicles reach the same speed and pass through the intersection. Consider the same situation for Vehicle 3 and 4, with a lag in time when they hit the shockwaves at the far end of it. Vehicle 3 reduces its speed to accommodate the shockwave, so TTC for these two vehicles drops a little as shown in Figure 24-b on the brown graph. These two vehicles recover to large TTC values faster than vehicles 1 and 2.

Therefore, as the duration of the red light gets shorter, the vehicles mostly meet the far end of the shockwave resulting in larger values of TTC and shorter recovery time, whereas larger red durations result in smaller TTC values and slower recovery time. This is an important point to be taken into account in DZ-protection algorithms that change the effective red light duration. This effect of red light extension could be inherently captured and evaluated through the SSN measure. The previous measures such as the number of vehicles caught in DZ do not capture such information.



a.



b.

Figure 24: TTC concept in relation to shockwave

VT-SCORES Real-Time Intersection Data Collection System

The data used in this study is collected through the second-generation of the intersection safety data collection and evaluation system which has been developed by Virginia Tech Signal Control & Operations Research and Education System (VT-SCORES) lab. The system, illustrated in Figure 25, uses the Wavetronix system integrated with the signal phase, detector, and video data. It includes a hardened field computer, two advanced Bus Interface Unit (BIU), a Sierra wireless modem, two Wavetronix click 304 units, and up to four camera streams. The computer collects and stores data through the data stream between the controller and other cabinet components using the two BIUs (Terminal and Facilities (TF1) BIU including signal phase status and detector BIU including detectors status). The Sierra wireless modem provides the wireless communication and data transfer to the lab. The two Wavetronix click 304 are applied for collecting the radar data for every approach of the intersection through the Wavetronix system. The Wavetronix system (shown in Figure 26) continuously monitors approaching vehicles, and collects data using radar technology. It is capable of keeping track of up to 25 vehicles per approach, simultaneously.

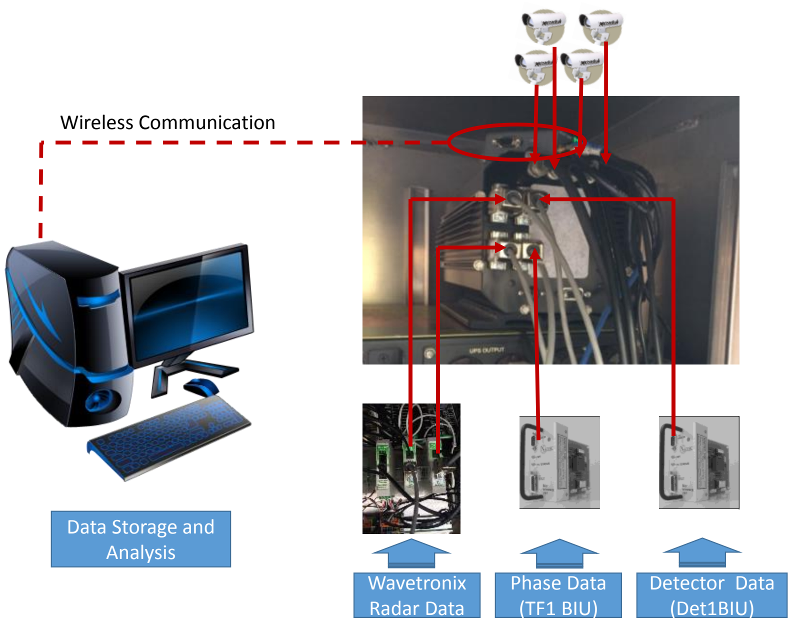


Figure 25: VT-SCORES safety data collection and evaluation system (Abbas, Higgs et al. 2014).

Figure 26: Wavetronix setup (2014).

Application of the Methodology

Study Sites

The data collection system was installed at two T-intersections in Virginia, both featuring TS-2 cabinets (shown in Figure 27). The first intersection (US220 site), shown in Figure 28-a, is located at US 220 and US 87. The video detection system is Autoscope at this site. The second site (US460 site), shown in Figure 28-b, is located at US 460 and Southgate, and the video detection systems is PEEK. The AADT for US460 site and US220 site is 32,000 and 16,000, respectively. The speed limit for both sites is 55 mph.

Figure 27: Installed system at a TS-2 cabinet.

a. b.

Figure 28: Study sites; a. US220 site, b. US460 site

Data Description

The data collection process has started in May 2014, for a continuous 24/7 data collection period. For every hour, the raw data includes a csv format file and some short avi (video) format files that captures red light runners. The csv file contains vehicle tracks, speed, and range data that are obtained from the radar system. It also stores phase information and detector counts located at the intersections. The reduction and manipulation of the data is performed using a MATLAB script. Figure 29 shows an example of the processed data for a day. The x-axis shows the time slots for 24 hours with the naming schema of Site-Date-Time. The y-axis illustrates the number of vehicles for every cycle color coded based on the number of vehicles caught in DZ during each cycle.

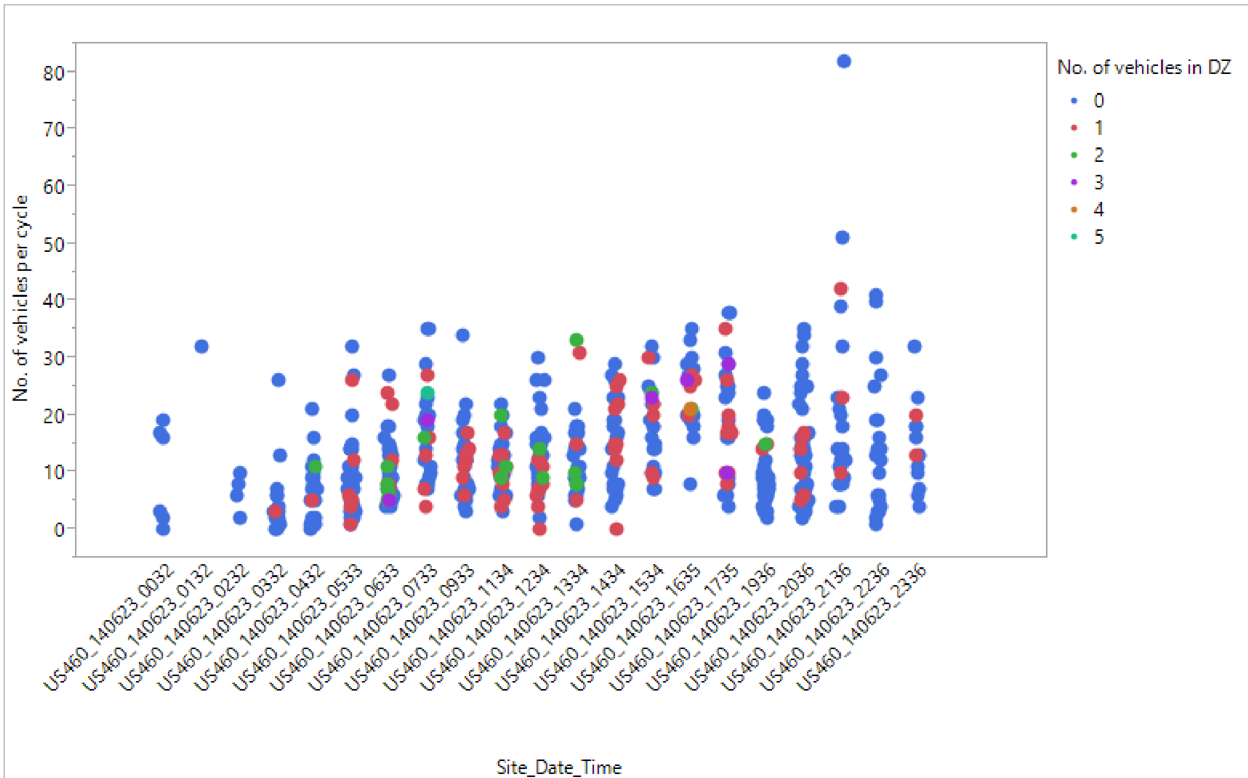


Figure 29: An example of collected data; number of vehicles per cycle color coded by the number of vehicles caught in DZ for 24 hours

A data analysis tool was developed to generate integrated data plots as well as for analyzing the data for TTC calculations. An example of the time-space diagram extracted from the data is shown in Figure 30. Vehicle trajectories are shown in as dots colored based on the speed of the vehicle (shown on the color map to the right). The color on the x-axis indicates the signal indication (green, yellow, and red).

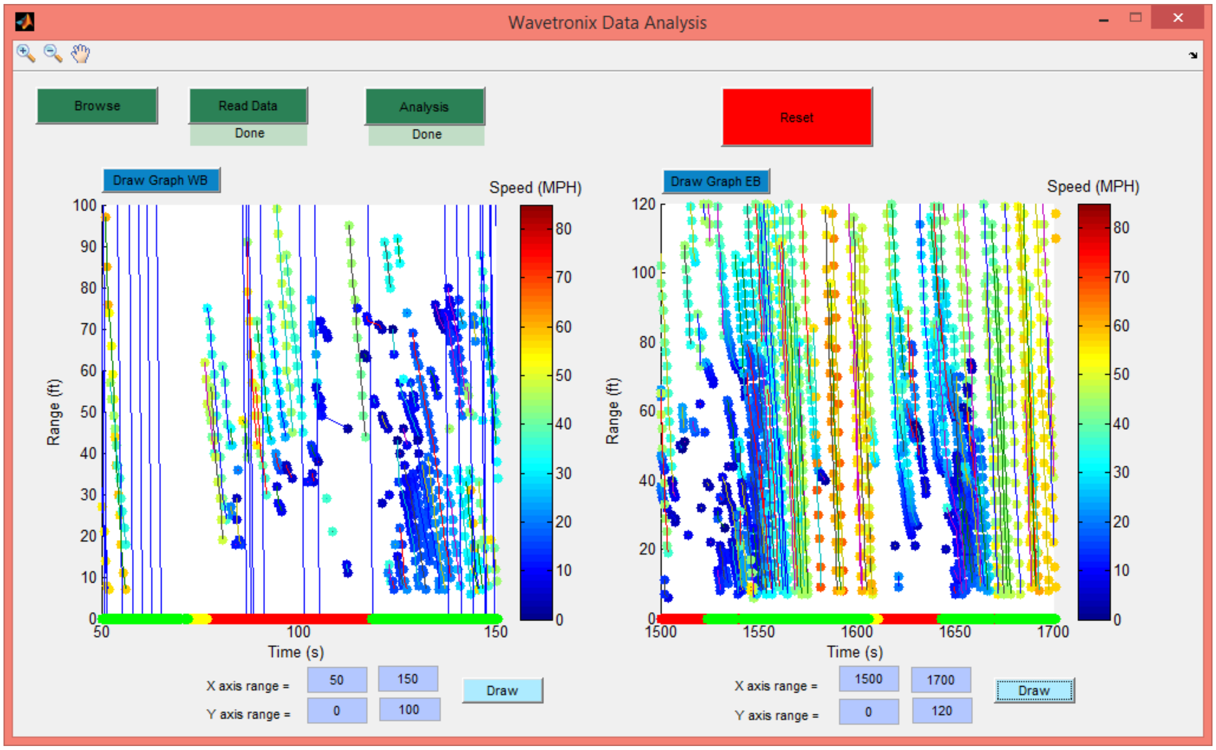


Figure 30: An example of the interactive time-space plots.

Results and Discussion

The time evolution of TTC is extracted from the time-space diagram of the vehicles as well as speed data. We only include unsafe positive TTC values less than 6 seconds. The time window that was assumed to investigate every pair of vehicles interaction and calculate the TTC is 8 sec of green plus yellow duration plus 3 sec of red. We included 8 sec of green duration to the analysis period to account for the effects of flashing yellow beacons located around 800 feet ahead of the signal to warn the drivers about the impending onset of yellow. Figure 31 illustrates an example of the calculated TTC for a pair of vehicles approaching to the intersection when the signal turns yellow. As it can be seen, the TTC value reduces down to less than 1 sec as the following vehicle gets close to the leading vehicle while having a high speed difference. Then, the TTC value starts to go up as the following vehicle recognizes the dangerous situation and decelerates.

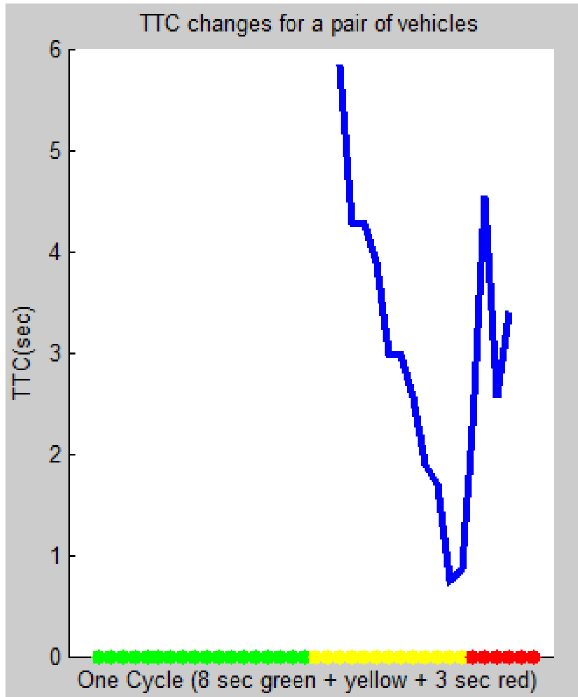


Figure 31: TTC changes for a pair of vehicles.

The first SSN calculation that is carried out is related to the relationship between the length of the red light duration and TTC. As discussed in the methodology part, based on the relationship between the shockwave and speed modification of the approaching drivers, as the length of the red light gets longer the TTC values drops more and take more time to recover to the higher values. We examine this for two sets of consequitive cycles of an hour; first one with the mean red light duration of 50 seconds and the second one with the mean red light duration of the 100 seconds (see Figure 32). The SSN results are shown in Figure 33. As expected, the SSN values are higher for the cycles that have longer red light durations. This is an important point to be taken into account in the DZ-protection algorithms that extend the red duration. Most of these algorithms base their calculations on the number of vehicles caught in DZ, which does not give such information as the SSN regarding the relationship between the red light duration and TTC variation (in addition to other factors).

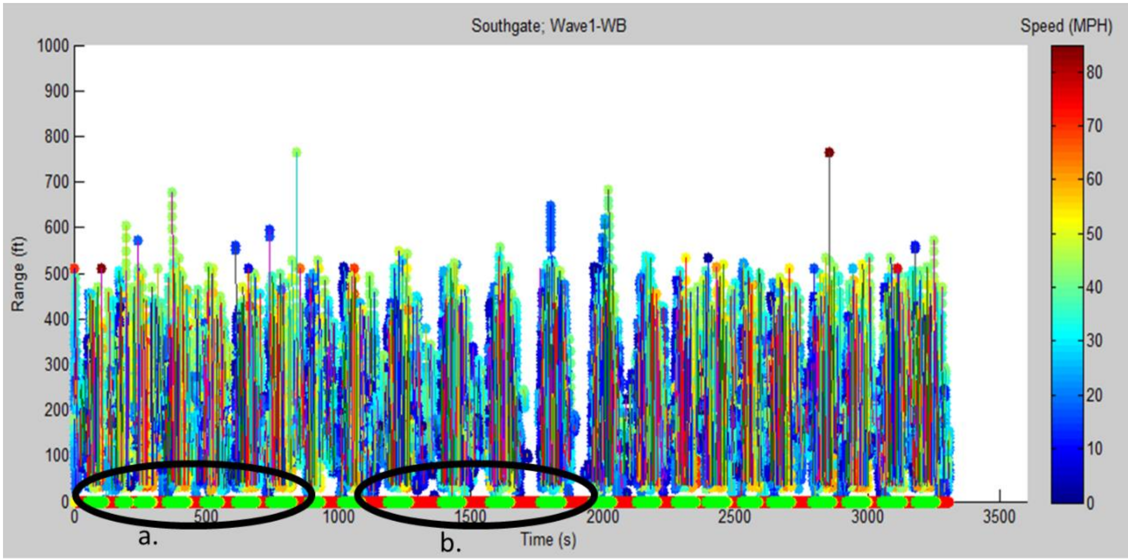
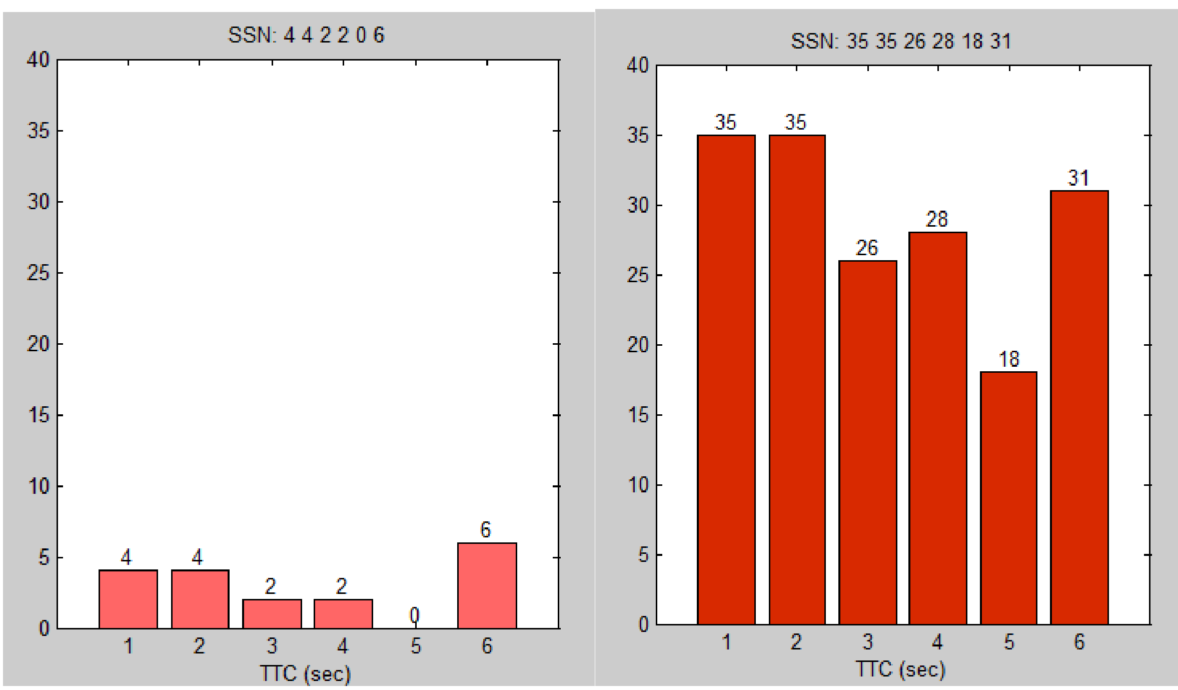


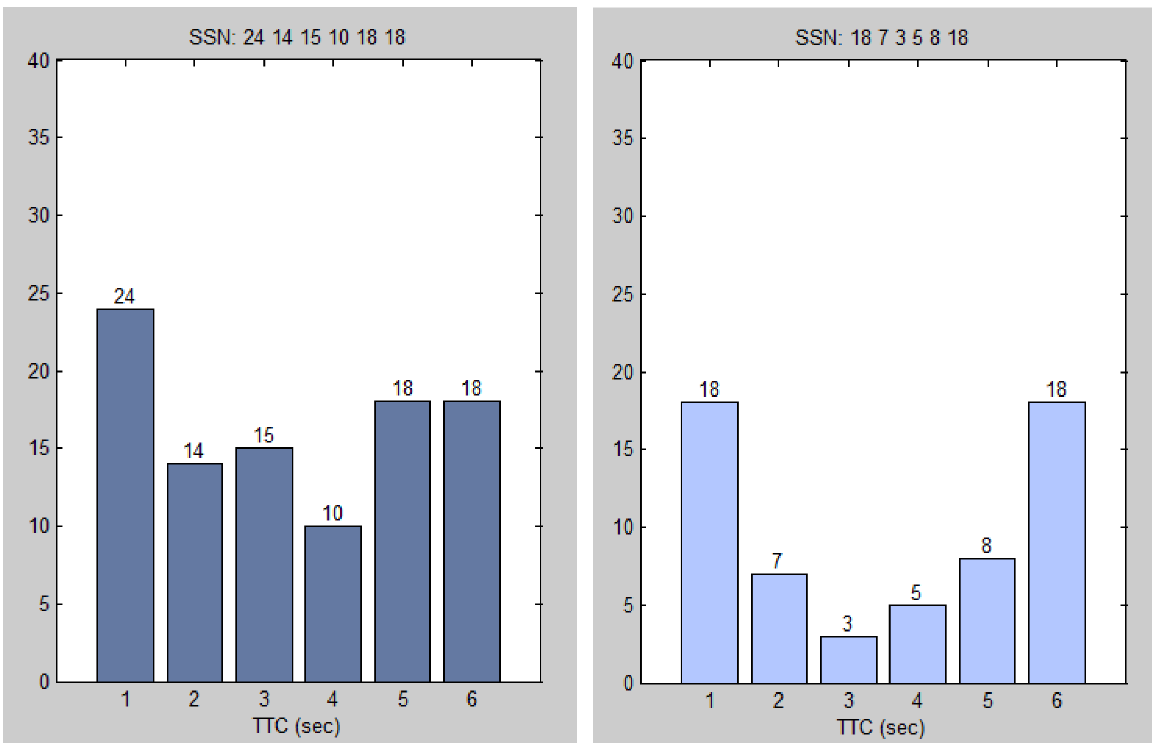
Figure 32: Cycle selection in comparing SSN for different red light durations; a: shorter red, b: longer red



a. b.

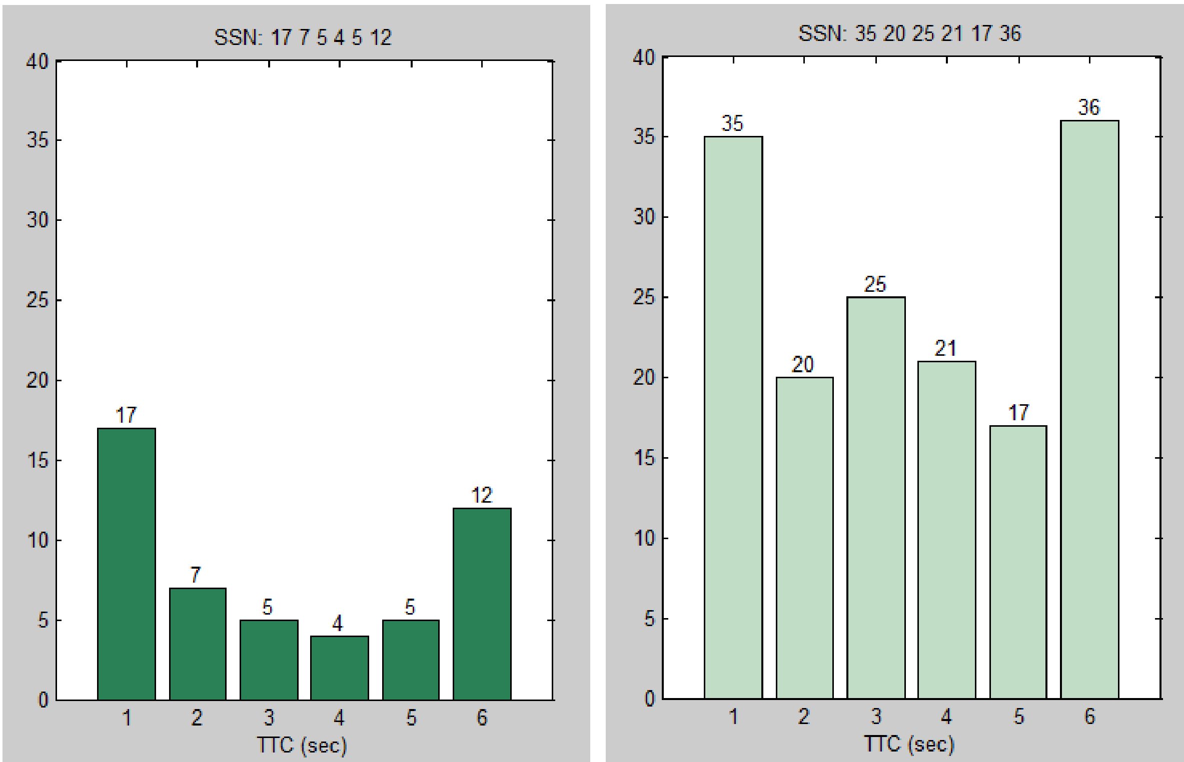
Figure 33: SSN for different red light durations; a: shorter red light, b: longer red light duration

In the second part of the analysis, one hour of the data for both study sites are investigated. Figure 34 and Figure 35 show the frequency of TTC dropping under 6 seconds during an hour of data collection for the two sites at the same date and time of the day (for every approach). The SSN is presented in six sequencing number to easily represent the safety level of an intersection. For example, the SSN for US220 site Southbound is 24 14 15 10 18 18; meaning that in one hour, 24 TTC values were under 1 sec, 14 values were between 1 and 2 sec, and so on (so it is a numerical representation of the shown histogram). According to the figures for US220 site, the southbound direction has a higher SSN, and for the US460, the eastbound direction has the higher SSN comparing to the other approach.



a. b.

Figure 34: Safety Surrogate Number (SSN) for US220 site; a. Southbound, b. Northbound.



a. b.

Figure 35: Safety Surrogate Number (SSN) for US460 site; a. Westbound, b. Eastbound.

A comparison is carried out among the results of the SSN and three widely-used safety measures, namely number of vehicles caught in DZ, number of yellow light runners (YLR), and number of red light runners (RLR). The number of vehicles caught in DZ and the SSN share some similarity with regard to the type of accident that they are targeting to evaluate. Both of these measures are focused on rear-end crashes at the intersection. However, SSN is a more detailed and accurate measure as it is directly related to crash probabilities. Consider a situation that number of vehicles caught in DZ measure has the value of 1. However, if this vehicle is the only vehicle at the intersection, or other vehicles are far enough to avoid any traffic conflicts, no rear-end crash prone situation exists. On the other hand, the SSN reports values when there is definitely a conflicting pair of vehicles. This detailed information embedded in SSN is also pronounced when queues are present at the intersection. In such cases, the number of vehicles caught in DZ does not relate to the existing queue whereas the SSN takes it into account. The yellow light runners seems to be effective for evaluating right-angle crashes with the side street traffic as opposed to the number of vehicles caught in DZ and SSN that target the rear-end crashes.

Table 10 summarizes these measures. The number of red light runners for both site is 0, and does not include any detailed safety message. Looking at the values in the table, no relationship is observed between these measures. As opposed to SSN, the number of vehicles caught in DZ are very close for the two approaches of each site.

Table 10: Safety surrogate measures for the two study sites on both approaches.

Site	Direction	Number of DZ caught vehicles	Yellow light runners (YLR)	Red light runners (RLR)	Safety surrogate number (SSN)
US220	**Southbound**	8	3	0	24 14 15 10 18 18
US220	**Northbound**	10	11	0	18 07 03 05 08 18
US460	**Westbound**	15	36	0	17 07 05 04 05 12
US460	**Eastbound**	13	91	0	35 20 25 21 17 36

The SSN could play an important role in evaluating the level of safety at intersections. A high value of this measure is a red flag for practitioners for further investigation of the safety problems that cause the high SSN values. These investigations could range from the signal phasing and control settings to the safety issues with the geometry of the intersection. It could also be used in connected vehicles applications to send appropriate speed adjustment messages to the vehicles approaching an intersection to smooth out the shockwave. Using this new measure of safety paves the road for new DZ-protection algorithms such as queuing-model-based DZ protection algorithms since the SSN presents a higher level of information regarding the existing queues.

Conclusions

Introducing proper safety measures has been the subject of research efforts for decades. Application of safety measures is essential in the determination of the level of safety at roadways and for planning suitable crash mitigation strategies. A comprehensive measure of safety that could be calculated from the collected road data is in high demand for safety evaluation purposes.

The focus of this study was on the traffic safety at signalized intersections, and especially for the evaluation of the dilemma zone related conflicts. In this paper, we present a novel methodology that is capable of characterizing the safety level at each approach of a signalized intersection. Moreover, a new safety surrogate measure is developed and is called the Safety Surrogate Number (SSN). Time-space diagrams and speed data are used to produce a SSN for every approach at signalized intersections. The discussion is backed up by examples of the application of the methodology for two test sites in Virginia. A comparison was also carried out among this new safety measure and previous measures suggested in the literature, such as the number of vehicles caught in DZ, number of yellow light runners, and number of red light runners. The result of comparison between the two sites shows that there was no high correlation between the SSN and other safety surrogate measures. According to our analysis, the SSN sheds more lights on the different approaches taken by DZ-protection algorithms. For example, changes in signal timing safety concerns is observable through the use of SSN whereas the widely-used "number of vehicles caught in DZ" measure does not encompasses such information.

This research laid the groundwork for several subsequent contributions. In the future, the developed SSN will be evaluated for a longer data collection period to determine the critical hours more prone to accidents. Intersection traffic and signal characteristics will be assessed to determine the positive and negative factors that affect the SSN distribution so that better crash mitigation strategies and algorithms could be determined. Also, a new dilemma zone protection system is going to be installed at the subject intersections. The developed safety surrogate measure will be applied to quantify the benefits of the new system.

Acknowledgements

The research undertaken in this paper was sponsored by Virginia Center for Transportation Innovation and Research (VCTIR). The authors are solely responsible for the material in this paper and the views are not necessarily those of the supporting agency. The authors would like to thank Ms. Cathy McGhee, Mr. Ben Cottrell, and the oversight research panel for their support. We would like to especially thank Mr. Joe Smith and his

team for their dedication and great assistance and support during the field installation process.

CHAPTER 7 MODELING HUMAN LEARNING AND COGNITION STRUCTURE: APPLICATION TO DRIVER BEHAVIOR IN DILEMMA ZONE

The material in this chapter will be submitted for peer review in the near future. It was jointly written by Sahar Ghanipoor Machiani and Montasir Abbas.

Abstract

In transportation studies, modeling human learning and decision making process plays a key role on developing realistic safety countermeasures and appropriate mitigation strategies. In this study, a human learning model is introduced that is able to capture the process of learning and cognitive structure of human memory. The relationship between long term and short term memories -base on Unified theories of cognition (UTCs)- is incorporated to a reinforcement learning technique to construct the human learning model. The model is then applied to a Dilemma Zone (DZ) data collected in a simulator study. Dilemma Zone is an area of the roadway approaching a signalized intersection in which drivers encounter difficulty deciding to stop or proceed at the onset of yellow. Driver choice behavior and learning process in DZ is modeled taking into account drivers experience at the previous intersections, and is compared to a pure machine learning model. The results of the model revealed lower and faster-merging errors in training an agent when human learning is considered. The DZ human learning model presented here could be used to evaluate DZ-mitigation algorithms by considering their effects on driver agents. The proposed approach takes a step toward more realistic human behavior modeling, and thus could benefit agent based modeling techniques.

Introduction

Dilemma Zone is an area ahead of intersection in which drivers encounter a dilemma to pass through the intersection or stop at the stop bar at the onset of yellow indication. The overall safety of signalized intersections and likelihood of crashes is highly related to the dilemma zone conflicts. An improper decision by the driver could lead to rear-end or right-angle crashes, and thus jeopardizing intersection safety. One of the main components contributing to DZ related issues is driver behavior, including driver perception, reaction, and decision making. Therefore, the learning process that occurs in relation to the decision making is also important. The question raised here is how the experience of passing through intersections with various DZ-protection algorithms and signal settings change the behavioral tendency to stop or go at the onset of yellow—how this human learning process comes to play when modeling driver behavior in DZ.

Complexity of the human learning process and choice behavior is attested by the existence of various descriptions and theories regarding this topic. Human choice behavior studies have a long history going back to the mid-1600s when the expected-value theory was introduced (Hertwig, Barron et al. 2004). Learning refers to a behavioral alteration in humans' propensity due to practice, experience, and observation (Huitt and Hummel 2006). The relationship between learning process and human choice behavior is that learning reflects the evolving of choice behavior from a one shot event to a dynamic model influenced by practice, experience, and observation (Roth and Erev 1995). The subject of human learning is applicable to many areas of study including human behavior modeling in transportation research. The majority of focus in behavior modeling techniques has been toward machine learning applications. In this study we bridge the gap between machine learning and human learning. Reinforcement learning as a closer machine learning method to human learning is reconstructed and altered in an analogy with the structure of human cognition structure. We perform this modeling approach in the ground of driver behavior in Dilemma Zone (DZ).

The model introduced in this study aims at capturing human learning process and mimicking drivers' realistic behavior while encountering yellow light indication. Drivers' knowledge about the environment, their experience, and learning procedure is reflected in the architecture to build a realistic model of driver behavior considering abstracted structure of human brain. To accomplish this goal, human behavior modeling in DZ is handled considering this decision making process as a cognitive phenomenon. Underlying mechanisms and structures in human decision making process is investigated using cognitive science. Unified theories of cognition (UTCs) (Newell 1990) are applied to investigate memory structure and knowledge storage in human mind. The proposed human learning model can be used to evaluate different DZ-mitigation algorithms and advance signal settings to determine the most effective strategies. The agents that are trained using this model can also be used in simulation software for more realistic simulation of signalized intersections.

Our manuscript starts with a background on human choice behavior and learning. Then, model development is presented including the description of the human cognitive system and human learning model. Application of the model in DZ is shown in the following section including data collection, model construction, implementation and results. The last section provides conclusions and future research.

Background

Human choice behavior has been long studied by researchers mostly in the ground of playing games. One of the earliest effort in this regard is the "prospect theory" by Kahneman and Tversky (1979). This theory investigates people's choice behavior in one-shot decision situations while having complete knowledge of the outcome probability distributions of options (Ahn 2010). Human choice behavior models have been categorized in different groups, namely belief-based vs. choice reinforcement models, exploratory vs. exploitative decisions, and experience-based vs. prediction-based models. In belief-based models, players play based on some belief that they have formed about other players. Conversely, in choice reinforcement model, strategies are chosen based on their stock of reinforcement (Camerer and Hua Ho 1999). Exploratory vs. exploitative decisions refers to the two types of strategy selection; first to choose a strategy that resulted in the most payoff in the past (exploitative) and second to select a less familiar strategy in the hope for a higher payoff in the future (exploratory). The explore/exploit dilemma has been widely researched (for examples see (Daw, O'Doherty et al. 2006) and (Lee, Zhang et al. 2011)). The last categorical approach (experience-based vs. prediction-based) focuses on the difference of choice behavior when decision is made by relying on experience (experience-based) comparing to when it is made based on knowledge of the outcome probabilities (prediction-based). Human decision making research is mainly focused on prediction-based models, and little research is available regarding decision from experience (Hertwig, Barron et al. 2004).

Almost similar concept of experience-based learning process is observed in various studies by different terminologies; choice reinforcement models (Camerer and Hua Ho 1999), choices from experiment (Hertwig, Barron et al. 2004), and experiment-based mode (Ahn 2010) all revolve around a common definition of learning from reinforcement. Two groups of reinforcement (experience-based) models are recognized. In the earlier reinforcement models, choice probabilities are updated directly. In the second group, reinforcement or propensity of the choices is updated. The updating occurs through cumulating previous payoffs or averaging them (Camerer and Hua Ho 1999) . Camerer and Hua Ho (1999) remarked that cumulative approach is preferable. Roth and Erev (1995, 1998) introduced an adaptive dynamic model for human learning process in extensive-form games. A dynamic choice model of human determines how the probability of selecting each strategy evolves over time in response to gaining experience (Roth and Erev 1995). The concept of their model is that players increase the probability of choosing strategies with previous success.

In this research effort human choice behavior and learning is modeled by integrating machine learning and human learning methods. Machine learning and human learning are tied concepts. Generally, rational inference principles of machine learning that try to find the best solution are not able to capture human learning process given human errors and not always optimal decisions. Some branches in the field of machine learning such as Bayesian Belief Network (BBN) are trying to capture human behavior. Although Bayesian models are applicable to mimic human behavior when dealing with uncertainty, it is difficult to build an accurate model. Another machine learning technique close to human behavior modeling is reinforcement learning approach (Lee and Son 2009). Reinforcement Learning (RL) methods have not been developed to describe human behavior, yet some research efforts has been toward applying RL methods to human decision behavior (Ahn

2010). Lee and Son (2009), in an attempt to compensate for the deficiency of Bayesian Belief Network (BBN) and reinforcement learning, integrated both approaches to an innovative learning model for human behavior against a dynamically changing complex environment (Lee and Son 2009). The model was a part of a Belief-Desire-Intention (BDI) human decision-making framework that they were working on (Lee and Son 2008, Zhao and Son 2008). The connection between human learning and machine learning related topics has been always of researchers' interest. As an example Castro, Kalish et al. (2008) attempted to answer the question of "Can machine learning be used to enhance human learning?" in the context of human category learning. Another example is a series of research investigating how the concept of intrinsic motivation in human learning transfers to artificial reinforcement learning (RL) system (Singh, Barto et al. 2004, Barto and Şimşek 2005, Stout, Konidaris et al. 2005, Singh, Lewis et al. 2010). However, there are many questions yet to be answered.

Research efforts regarding drivers' decision making modeling in DZ have used machine learning techniques such as probabilistic and statistical approaches. In most studies, likelihood of stopping and going (e.g., (Olson and Rothery 1961, Allos and Al-Hadithi 1992)), stop/go decision and red-light running violation (e.g., (Elmitiny, Yan et al. 2010)), deceleration rate and brake-response time (e.g., (Gates, Noyce et al. 2007)) are investigated as a function of some influential factors such as distance to the intersection at the onset of yellow. For example, taking a probabilistic approach, Li and Abbas (2010) introduced a dilemma hazard model based upon the previous studies on drivers' response to the yellow onset, vehicle kinematics, and a Monte Carlo simulation framework. The proposed model assigns a hazard weight to each vehicle located in dilemma zone, and it was calibrated and validated with the vehicle trajectory data collected at a high-speed signalized intersection. Some researchers added fuzzy approaches to probabilistic and statistical models of drivers' decision and probability of stopping or going (e.g., (Kikuchi, Perincherry et al. 1993, Hurwitz, Wang et al. 2012)).

Although considerable research has been done related to human choice behavior and dilemma zone modeling, no human learning approach has been taken to model driver behavior in dilemma zone. The novel aspect of this study is to take the cognitive architecture of human learning process, and integrate it into a reinforcement learning model to produce a human learning model in dilemma zone. Our approach brings new insights in agent based modeling technique by providing more realistic model of the human learning process.

Model development

Human brain results from many years of evolving and adapting to different environments. It includes several smaller centers constituting a system to synchronize and manage various functions (Minsky 1993). Learning in human is a process of receiving data, comprehend it, store it in memories, and retrieve it in future events. Different disciplines such as psychology, anthropology, and artificial intelligence have studied cognitive science separately in their own area resulting in descriptions of regularities in behavior and theories to explain these regularities (Lehman, Laird et al. 2006). To integrate microtheories provided by every individual discipline, and draw a big picture of human cognition, Newell, one of the founders of Artificial Intelligence, introduced unified theories of cognition (UTCs) (Newell 1990). UTCs presents the full range of human cognition by introducing a single system of several mechanisms for all of cognitive behavior (Newell 1990). Decision making is one of the areas that is covered by unified theories of cognition.

Human cognitive system

In this study, underlying mechanisms in driver decision making in DZ is investigated using human cognition architecture. According to UTCs, memory structure includes two main components of working memory (short-term memory) and long-term memory as shown in Figure 36. Three different types of long-term memories are distinguished, namely procedural, semantic, and episodic. Procedural memory is about how and when to do things such as how to drive a car. Semantic memory consists of facts about the world (i.e., things one "knows") such as knowing that cars have four wheels. Episodic memory consists of things one "remembers" (i.e., specific situations one has experienced) such as a car accident. Working memory holds the knowledge that is most relevant to the current situation (i.e., what is true at this instant of time). Long-term memories are interacting with working memory to produce actions (Lehman, Laird et al. 2006). Human mind is in connection with the environment through perceptual system of senses and action generation using muscles (Newell 1990).

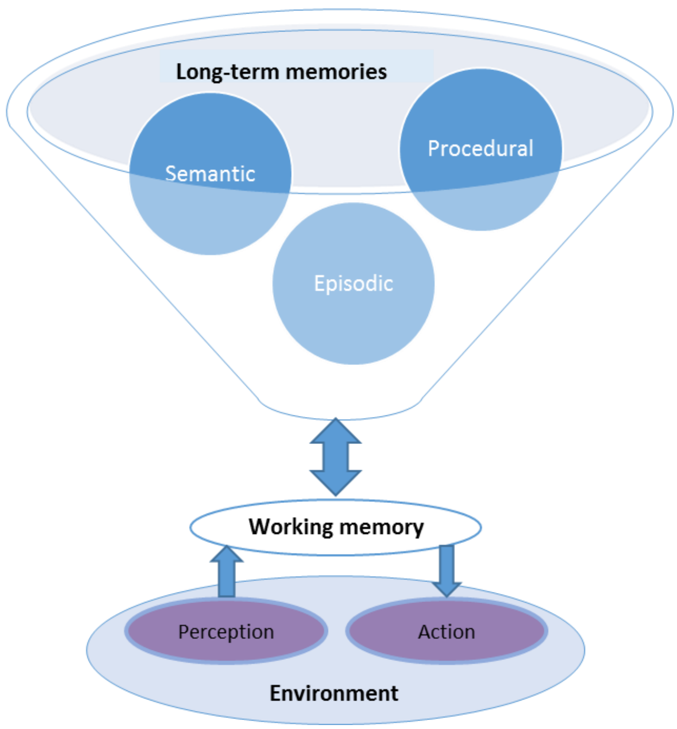


Figure 36: Human cognitive system

Human learning model

We use the memory structure in UTCs to model driver's cognitive mechanism and knowledge structure in DZ. Reinforcement learning technique that is incorporated to human learning in this study is Q-learning.

Q-learning is an off-policy temporal-difference control algorithm that was developed by Watkins (1989) (Sutton and Barto 1998). It is one of the most widely used RL algorithms. The algorithm finds a policy that maps traffic states to their optimal actions. In our research scope, optimal policy means acting as close as possible to the represented driver's actions. The quality of state-action is represented in Q-values.

For every episode until the final state is reached, the algorithm starts with initialization of the first state and Q-table (action-value function) that includes Q-values. An action is chosen based on Q-values using one of the action selection methods such as ε-greedy. The Q-values are updated with the following recursive equation:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha[r + \lambda max_a Q(s_{t+1}, a) - Q(s_t, a_t)]$$

Where, $Q(s_t, a_t)$ is the Q-value at stage t (the value of taking action a from state s at stage t), α is the learning rate ranging from 0 to 1, λ is discount factor ranging from 0 to 1 which determines the present value of the future rewards , and r is the reward function of performing a_t in s_t (Sutton and Barto 1998). The reward function have the $r^{Positive}$ value when the action is the same as the real action and $r^{Negative}$ otherwise.

The proposed human learning model is demonstrated in Figure 37. Procedural memory is related to "how to do things", which corresponds to updating Q-table in Q-learning method. In procedural memory, the learning mechanism starts with the initialization of the Q-table and initial state. Then, the action is chosen, and the Q-table is updated. This procedure is performed until the final state is reached. In case there is no learning from experience involved, this procedure is a pure machine learning in which the action selection is done applying the ε-greedy method. Human learning and experience comes to play in the form of episodic memory component. Episodic memory contains the knowledge related to the things that the driver has experienced and remembers. Propensity of drivers to stop or go formed as a result of their previous experience, affects the action selection in the procedural memory. However, the human brain is associated to memory decay; meaning that when an event happens, the attribute related to that event will vanish as time passes. The model of the memory decay used in this study is discussed in the following section. After updating the Q-table is finished, the trained Q-table is stored in the semantic memory. Semantic memory is involved with the things one knows. If a new knowledge, information, or experience become available to the driver, the process is repeated. Working memory is connected to all three other types of memory. Working (short-term) memory is related to the current task, and the knowledge in it is replaced when the current task changes. Any distractions or emotions influence the working memory. A distracted driver would act differently form a normal driver given the same amount of knowledge and experience. Working memory is the component of the memory structure in contact with the external environment. New knowledge and information that are sensed through the sensory system feed the long term memory (including semantic, episodic, and procedural).

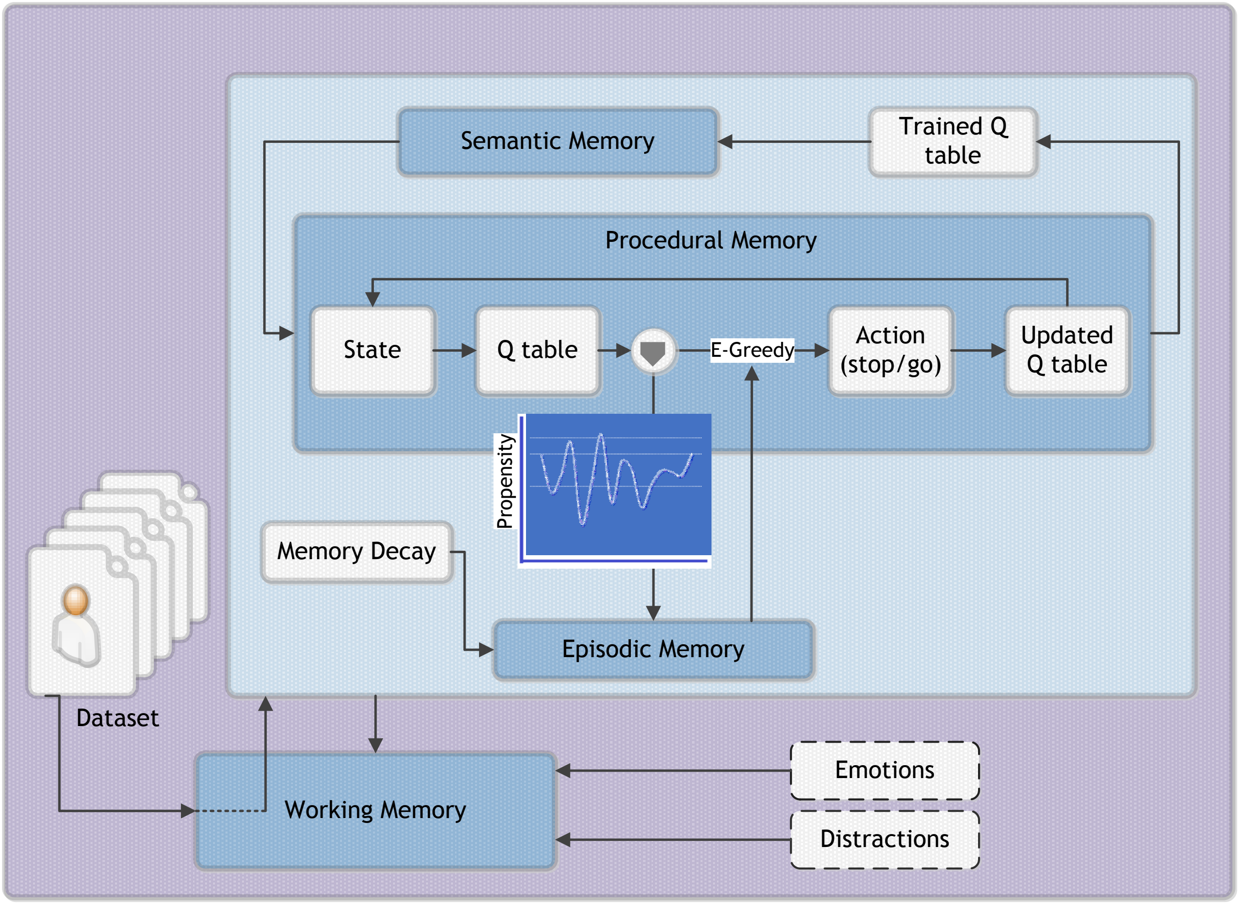


Figure 37: Human learning model

There are two robust properties of human learning remarked in the psychology literature, namely the "Law of Effect" and the "Power Law of Practice" (Roth and Erev 1995). The model presented here conforms to these properties. The "Law of Effect" defines that the choices that lead to positive results are more likely to be selected in the future. The "Power Law of Practice," is related to the learning curve, specifying that it is sharper at the beginning of the learning.

Memory decay (Forgetting)

Forgetting or recency effect shows the interaction between the law of effect (Thorndike 1898) and the power law of practice. It specifies that recent experience influence the choice of next strategy more than older experience (Roth and Erev 1995, Erev and Roth 1998).

The model of memory decay used in this study is Exponentially-Weighted Moving-Average (EWMA) with the following equation (Killeen 1994).

$$M_n = \beta * A_n + (1 - \beta) * M_{n-1}$$

Where, M_n is the memory at stage n, A_n is the relevant attribute, and β is the currency parameter ($0 \leq \beta \leq 1$). The currency parameter determines how much emphasis is on the most current event. Bigger β means giving less weight to older events.

Model application

Data collection

To examine the developed human learning model, we use a dataset collected from 34 drivers in a driving simulator study. The driving simulator is a DriveSafety DS-250 model. Every participant drives through a total of 50 intersections in 5 sessions of driving. Data collection takes into account the following variables that affects drivers decision in dilemma zone: (1) Time to intersection (TTI) at the onset of yellow (s) (levels: 2.5, 3.5, 4.5 sec), (2) Presence of police (levels: Yes, No), (3) Pavement condition (levels: Wet, Dry), (4) Other vehicle around (levels: No Vehicle, Back), and (5) Presence of side street queue (Levels: Yes, No).The experimental design of the study is an Adaptive Randomized Incomplete Block Split-plot (ARIBS) Design. We refer the readers to chapter 4 of this dissertation for a full description of the design and implementation. The following section focuses on a part of the simulator scenario design which is relevant to this study.

To account for drivers' learning in the experimental design of the simulator two main hypotheses were tested. Suppose a driver is approaching a signalized intersection encountering yellow light while in dilemma zone. The driver is monitored to recognize his/her decision. The first hypothesis is related to the situation in which the driver decides to stop. In this case, the adaptive design of the simulator provides the driver with a long yellow, so as the driver is waiting at the intersection, he/she may think that he could have made it through. The hypothesis to test is whether experiencing the long yellow will affect drivers' behavior at the following intersections or not. The second hypothesis is associated to the situation in which the driver decides to go. In this situation, signal setting is adapted in a way that the driver ends up running the red light. A flash and sound effect of taking a photo is provided while the driver is violating the signal. The hypothesis is to test if the driver behavior remains the same after this experience. Associated to these two scenarios, two learning variables (attributes) are generated that is used in the human learning model, namely LLY (learning-long yellow) and $LRLR$ (learning-red light running) with the value of 1 for the intersection under that specific scenario, and 0 otherwise.

Model construction

The five aforementioned influencing factors (TTI, Presence of police, Pavement condition, Other vehicle around, and Presence of side street queue) constitute the state variables in the model. The action is the decision of the driver to stop or go.

To reduce the number of states, and overcome the challenge of data limitation, fuzzification is considered for state variable TTI. Two fuzzy sets are defined as "TTI is high (5.5 sec)" and "TTI is low (2.5 sec)" for state variable TTI. A triangular fuzzy membership function is used for fuzzy sets. The upper and lower bounds (5.5 and 2.5) are determined based on the boundary of dilemma zone. Membership functions for fuzzy sets "Low" and "High" are as follows:

$$\omega_{Low}(TTI) = \begin{cases} 0.9 & TTI \leq TTI_{lb} \\ \dfrac{TTI_{ub} - TTI}{TTI_{ub} - TTI_{lb}} & TTI_{lb} < TTI < TTI_{ub} \\ 0.1 & TTI \geq TTI_{ub} \end{cases}$$

$$\omega_{High}(TTI) = \begin{cases} 0.9 & TTI \leq TTI_{lb} \\ \dfrac{TTI - TTI_{lb}}{TTI_{ub} - TTI_{lb}} & TTI_{lb} < TTI < TTI_{ub} \\ 0.1 & TTI \geq TTI_{ub} \end{cases}$$

Where $\omega_{Low}(TTI)$ is the membership function for fuzzy set "TTI is low (2.5 sec)", $\omega_{High}(TTI)$ is the membership function for fuzzy set "TTI is high (5.5 sec)", TTI_{ub} is the upper bound of TTI (5.5 sec), and TTI_{lb} is the lower bound of TTI (2.5 sec). Although, the collected data for this study includes TTI equals 2.5, 3.5, and 4.5, TTI_{ub} was considered 5.5 to account for the total range of dilemma zone (2.5 to 5.5 sec) and improving the applicability of the model to future data. Application of the fuzzification technique reduces the number of states to 32 states for this study.

LLY and $LRLR$ (learning variables) are episodic memory attributes considered 1 for intersections that they are in effect and 0 otherwise. At every intersection the memory associated to these two learning variables are calculated using the memory decay equations as follows:

$$M_n^{LLY} = \beta^{LLY}\mu^{LLY}LLY_n + (1-\beta^{LLY})M_{n-1}^{LLY}$$

$$M_n^{LRLR} = \beta^{LRLR}\mu^{LRLR}LRLR_n + (1-\beta^{LRLR})M_{n-1}^{LRLR}$$

Where, M_n^{LLY} and M_n^{LRLR} are the memory associated to learning variables at intersection n, β^{LLY} and β^{LRLR} are the currency parameters, μ^{LRLR} and μ^{LLY} are learning coefficients ($0 \le \mu \le 1$) to show the difference between learning effects derived from different learning scenarios (for example the effect of red light running experience on the future decision of a driver to stop or go could be more than the effect of experiencing the long yellow), and LLY_n and $LRLR_n$ are the learning variables at intersection n. In this recursive equation, M_0^{LLY} and M_0^{LRLR} refer to initial memory contents associated to learning variables. It assumes initial values prior to the available data, and is related to the drivers driving experience, personality, and background.

M_n^{LLY} and M_n^{LRLR} are used to calculate “Propensity” of the driver to stop or go according to the following equation:

$$PropS_n = (1 + \gamma^{LLY}M_n^{LLY} + \gamma^{LRLR}M_n^{LRLR})/2$$

Where, $PropS_n$ is the propensity of the driver to stop at intersection n, γ^{LLY} and γ^{LRLR} are weighting parameters which determine how memory attributes change the propensity of the driver ($-1 \le \gamma \le 1$). Propensity of the driver to go at intersection n ($PropG_n$) is then calculated as $1 - PropS_n$.

Model implementation and results

Multimethod Simulation Software, Anylogic, is used to construct the model (see Figure 38).

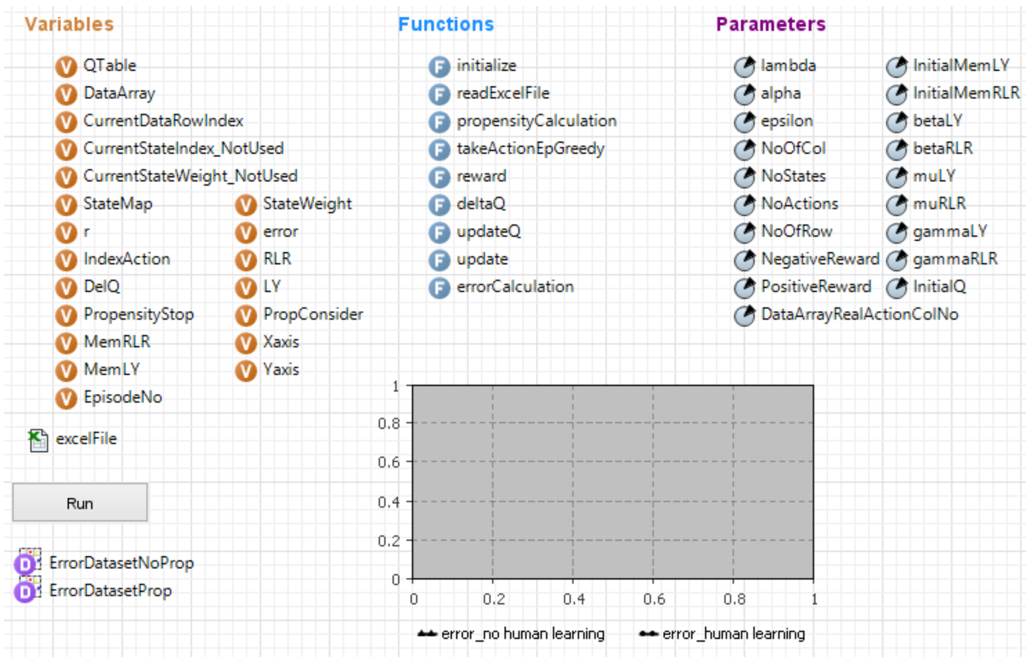


Figure 38: Model implementation in Anylogic

The model is run for the two following scenarios, and results are compared.

Scenario 1: No human learning is considered (only machine learning)

In this scenario, the Q-learning algorithm is applied. For every training iteration, the Q-table is trained using the agent data and according to the following equation:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha[r + \lambda max_a Q(s_{t+1}, a) - Q(s_t, a_t)]$$

Where, $Q(s_t, a_t)$ is the Q-value at stage t, α is the learning rate, λ is discount factor, and r is the reward function of performing a_t in s_t .

The training algorithm takes the following steps until the last state is reached:

- Initialization
- Taking action using ε-greedy
- Reward calculation
- Updating Q-table

The last updated Q-table is the final Q-table which is used to extract the optimum policy (here, optimum means closest policy to real actions by the agent).

Scenario 2: human learning (propensity inclusion) is considered

In this scenario, the propensity of stop/go is incorporated into the Q-learning algorithm in that before taking action, the Q-values are multiplied by the calculated propensity of the current state. This will affect the action selection by the algorithm.

Therefore, the training algorithm takes the following steps until the last state is reached:

- Initialization
- Propensity inclusion in Q-table
- Taking action using ε-greedy
- Reward calculation
- Updating Q-table

The model was trained for 3 agents (agent 8, 26, and 30). Table 11 shows the model parameter that led into the least error.

Table 11: model parameters setup

Parameter	Agent 8	Agent 26	Agent 30
λ	0.3	0.3	0.3
α	0.25	0.25	0.25
ε	0.1	0.1	0.25
β^{LLY}	0.2	0.2	0.2
β^{LRLR}	0.1	0.1	0.1
$r^{Negative}$	-1	-1	-1
$r^{Positive}$	+1	+1	+1
M_0^{LLY}	0.1	0.1	0.1
M_0^{LRLR}	0.1	0.1	0.1
μ^{LLY}	0.8	0.8	0.8
μ^{LRLR}	1	1	1
γ^{LLY}	0.2	-0.2	-0.2
γ^{LRLR}	0.35	-0.3	0.35

The error values associated to the two scenarios (human learning and no human learning) are illustrated in Figure 39, Figure 40, and Figure 41 for the 3 agents. Fifty training iterations were considered in training the agents. According to these figures, when human learning is considered, the human learning error values are lower through the training (the pink chart is located below the green chart in most of the points) and they merge faster. Error fluctuation is higher in agents 8 and 26 comparing to agent 30, though lower error values were achieved for agents 8 (12%) and 26 (16%) showing the difference between agents.

Figure 39: Error of the models for agent number 8

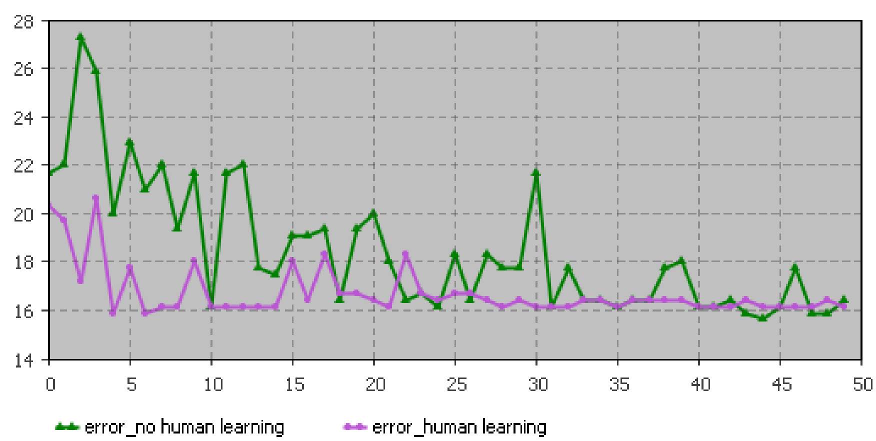


Figure 40: Error of the models for agent number 26

Figure 41: Error of the models for agent number 30

Comparison between pure machine learning model and human learning model shows that the human learning model was more promising as it resulted in lower error values, and faster merging process. Although collecting more data would result in a higher accuracy and lower error value, the trained model was deemed satisfactory since it illustrates the ability of the model to capture the driver's learning, and mimic drivers realistically. Another point to be mentioned is the difference between the models of different agents. It is important to account for this in simulation models by considering various agents representing different behavioral tendency by drivers. The model developed here provides a novel approach in developing human agents that can be implemented in commercial software packages for more realistic traffic behavior in evaluating existing conditions as well as new future implementations. This DZ human learning model can also be used in evaluation of different DZ-protection algorithms to come up with the best strategy that fits driver behavior the most.

Conclusions and future research

Understanding human behavior and learning process in traffic concepts such as dilemma zone issue can aid the development of crash mitigation strategies, safety countermeasures, and more realistic simulation models. This paper developed a human learning model by incorporating human memory structure and reconstructing a machine learning technique. The model recognizes the cognitive structure of human memory, and utilizes a reinforcement learning model to construct a human learning model. The model was applied to drivers' choice behavior and learning in dilemma zone. We combined the concept of cognitive architecture and human learning with the decision making process occurring at the onset of yellow at signalized intersections. The data for testing the model was obtained through a driving simulation experiment geared toward capturing driver learning process at the onset of yellow. Two scenarios were examined: the first model took into account the machine learning techniques, and the second one considered the human learning process. The result of the model showed that the human learning model provides a close matching to driver behavior (down to around 12% error) while merging faster than the pure machine learning model. The human learning model presented here can be used in developing simulation agents for evaluating different DZ-mitigation strategies.

The proposed methodology is able to improve the capability of agent based modeling techniques by mimicking driver behavior and learning process more realistically. The next step of this research is to optimize the model parameters and incorporate other modules of the human learning model such as emotions and distraction into the trained model. Moreover, the DZ human learning model will be applied to evaluate different DZ-protection algorithms. Applications of the developed model, other than DZ that was presented here, should also be investigated.

Acknowledgements

The authors wish to thank the Mid-Atlantic Universities Transportation Center and the Virginia Center for Transportation Innovation and Research (VCTIR) for sponsoring this study. The authors are solely responsible for the material contained in the paper and the views are not necessarily those of the supporting agencies.

CHAPTER 8 SUMMARY AND CONCLUSIONS

This dissertation investigates human choice behavior in dilemma zone with an emphasis on recognition of influential factors, learning process related to human cognition, and safety measures related to DZ conflicts. It provides a comprehensive review of the literature in regard to dilemma zone, influential factor, modeling approaches, prevention signal algorithms, safety surrogate measure, and human choice behavior.

To accomplish the goal of this research, in the first step, a driver survey was designed and administered in three states of Virginia, Maryland, and Pennsylvania. The main purpose of this survey was to identify the influential factors that affect driver's decision to stop or go at the onset of yellow. Twenty three factors were presented to participants to pick from as influential factors. Totally 1213 people participated in the survey with the age distribution ranging from 19 to 92 years old. A descriptive analysis was performed, and a summary of the participants' comments was provided. The result of influential factors revealed that out of 23 factors presented to participants, 9 of them are significant in all states.

The results of the significant influential factors from the survey were applied in designing an adaptive experiment in a driving simulator study. The five factors taken into account were (1) Time to intersection (TTI) at the onset of yellow (levels: 2.5, 3.5, 4.5 sec), (2) Presence of police (levels: Yes, No), (3) Pavement condition (levels: Wet, Dry), (4) Other vehicle around (levels: No Vehicle, Back), and (5) Presence of side street queue (Levels: Yes, No). In addition to these five factors, another factor was considered to account for the learning process in drivers' decision making. The purpose here was to recognize the effect of drivers' positive or negative experience that they gain while passing through different intersection signal settings. An adaptive design was considered to implement the scenarios.

Three scenarios were generated to this effect. In the first scenario, approaching driver to the intersection observe a platoon of cars ahead which pass through the green signal at the intersection. The driver slows down anticipating that the green might end due to the large gap. The adaptive setting of the design extends the green for the driver. The hypothesis here is to see if the driver changes his behavior in the following intersections after this experiment. The second scenario is related to the time that driver encounter yellow while in DZ and decides to stop. In this case, a long yellow is presented to driver to see if this waiting experience would affect his future decisions. The last scenario is similar to the second one except that the driver decides to go. Then, the adaptive design of the experiment changes the signal to red so that the driver ends up running the red light. A camera flash effect and sound of taking a picture is presented to the red light runner. The effect of this experience in driver's future decisions is of the interest.

The experimental design of the study is an Adaptive Randomized Incomplete Block Split-plot (ARIBS) Design, and it was implemented in the DriveSafety DS-250 driving simulator. Totally, 34 participants completed the study. The statistical analysis was performed on the collected data. The results revealed that Pavement condition, TTI, Presence of police*TTI, Presence of side street queue*TTI are significant factors in drivers decision at the p=0.05 rate. Regarding learning hypothesis, short yellow and long yellow scenarios appeared to be significant. However, even in these cases that the drivers learn, their behaviors change toward safer actions by performing more stop decisions. Therefore, DZ-protection algorithms should not have any concerns regarding driver's learning process.

Later, a prediction model was constructed using Canonical Discriminant Analysis to predict drivers' decision in dilemma zone. Two time frames were considered. First one is during green immediately before yellow. The rationale is that if the drivers' decision could be predicted at this time frame, then a DZ-protection algorithm could use this prediction to provide a safer situation. The second time period is the first three seconds of yellow. The logic behind this scenario is that there is at least 2.5 sec yellow time and 0.5 sec all red time. Therefore, if the model predicts that the driver is going to proceed through, the all red could be extended to accommodate driver's decision and prevent a possible crash with the side street traffic. Two different simulator datasets were applied to construct the model. According to the results, the highest accuracy is obtained when the data is continuous in nature; meaning that it continuously monitors driver behavior as oppose to instantaneous data points. Regarding the time frame, the accuracy of the model is much higher for the time frame of three seconds after yellow. In this research, the highest accuracy of the model was 99.7%.

In the next step of this research effort, the dilemma zone safety conflict was evaluated using real-time field data. A safety assessment method was introduced resulting in a novel measure called Safety Surrogate Number (SSN) that provides a comprehensive picture of safety at signalized intersections. The analysis procedure was based upon the concept of time-to-collision extracted from real-time vehicle trajectory and speed data. The SSN was calculated using a histogram plot of time-to-collision frequencies shortly before, during, and shortly after the yellow intervals. This measure is served as a comparison ground to evaluate the level of safety at intersections.

In the last part, a human learning model was developed based on the cognitive architecture of human brain introduced in unified theories of cognition (UTCs). Components of the memory, knowledge storage, and experience usage were taken into account in constructing the model. The model which is an integration of machine learning and human learning was applied to dilemma zone problem. The driving simulator data was used to train the agents. The DZ human learning model led into faster-merging errors comparing to the machine learning technique.

This study is one of the first to address driver behavior and learning by focusing on human cognitive science and memory structure. The results of this study are of relevance for better dilemma zone modeling, assessment of intersection safety, and designing DZ mitigation strategies.

Future research

This research effort paved the road for subsequent contributions in driver behavior modeling and safety evaluation at signalized intersections. In the future, the SSN measure will be applied to evaluate DZ-protection algorithms. A new DZ-protection system is going to be installed at two intersections that are currently under study by vt-scores lab. Applicability of this novel measure will be examined using the real time data collection system. Driver behavior will also be investigated further as they are exposed to this protection strategy. Driver decision prediction model will be made, and results will be compared to the results of the driving simulator study. Moreover, the human learning model will be used to generate agents to be applied in traffic simulation software. A comparison will be conducted between machine learning-trained agents and human learning-trained agents. The parameters of the human learning model will also be optimized, and other modules will be added to the current model.

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