# Modeling driver behavior and their interactions with driver assistance systems

Ning Li

A dissertation
submitted in partial fulfillment of the
requirements for the degree of

Doctor of Philosophy

University of Washington

2019

Reading Committee:

Linda Ng Boyle, Chair

Youngjun Choe

Shuai Huang

Program Authorized to Offer Degree:
Industrial and Systems Engineering

University of Washington

## Abstract

# Modeling driver behavior and their interactions with driver assistance systems

Ning Li

Chair of the Supervisory Committee:
Chair and Professor Linda Ng Boyle
Industrial & Systems Engineering and Civil & Environmental Engineering

As vehicle automation becomes increasingly prevalent and capable, drivers have the opportunity to delegate primary driving task control to automated systems. In recent years, significant efforts have been placed on developing and deploying Advanced Driver Assistance Systems (ADAS). These systems are designed to work with human drivers to increase vehicle safety, control, and performance in both ordinary and emergent situations. Current ADAS are mainly presented in rule-based or manually programmed design based on the summary and modeling of pre-collected human performance data. However, the pre-fixed system with limited personalization may not match human drivers' needs, which may arise the driver's dissatisfaction and cause ineffective system improvement. Human-centered machine learning (HCML) includes explicitly recognizing this human operator's role, as well as re-constructing machine learning workflows based on human working practices. The goal of this dissertation is to build a novel driver behavior modeling framework to understand and predict interactions with the driver assistance system from a human-centered perspective. It can lead not only to more usable machine learning tools but to new ways of improving the driver assistance systems.

A driving simulator study was conducted to evaluate drivers' interactions with Forward Collision Warning (FCW) system. Gaussian Mixture Model (GMM) clusterization was used to identify different driving styles based drivers' driving performance, secondary task engagement, eye glance behavior and survey information. The impact of the FCW system on the different driving styles was also evaluated and discussed from three perspectives: initial reaction, distraction types, and safety benefits. A driver behavior model was also built using inverse reinforcement learning. Lastly, the timing prediction of FCW using driving preference was compared to the algorithm from a traditional FCW system.

The findings of this study showed that ADAS without human feedback may not always bring positive safety benefits. Learning driver's preference through inverse reinforcement learning could better account for future scenarios and better predict driver behavior (e.g., braking action). This algorithm can be incorporated into real world in-vehicle warning systems such that the feedback and driving styles of the human operator are appropriately considered.

# TABLE OF CONTENTS

Page

# LIST OF FIGURES

# LIST OF TABLES

# GLOSSARY

ACC: Adaptive Cruise Control ADAS

BIC: Bayesian Information Criterion

ADAS: Advanced Driver Assistance System

ANOVA: Analysis of Variance

CI: Confidence Interval

DRT: Detection Response Task

EOR: Eyes-Off-Road

GD: Glance Duration

FCW: Forward Collision Warning

GLMM: Generalized Linear Mixed Model

GMM: Gaussian Mixture Model

IRB: Institutional Review Board

IRL: Inverse Reinforcement Learning

IVIS: In-Vehicle Information System

LMM: Linear Mixed Model

MDP: Markov Decision Process

MPH: Miles Per Hour

NADS: National Advanced Driving Simulator

NHTSA: National Highway Traffic Safety Administration

RL: Reinforcement Learning

RT: Reactiom Time

TDRT: Tactile Detection Response Task

TTC: Time to Collision

# ACKNOWLEDGMENTS

First, I would like to express my sincere gratitude to my advisor, Prof. Linda Ng Boyle, for her guidance and encouragement throughout these years. It all started in Spring 2016 when she offered me such a great opportunity to join the Human Factors and Statistical Modeling lab. Under her supervision, I learned how to define research questions, find solutions, publish papers and present results.

Besides my advisor, I would like to thank the rest of my dissertation committee members Prof. Youngjun Choe, Prof. Shuai Huang and Prof. Anind K. Dey for their great support and invaluable advice for dissertation work.

Thanks are also due to the Toyota Collaborative Safety Research Center for their financial support that I received for my PhD research.

I would like to thank my lab mates that include Chun-Cheng Chang, Tianshu Feng, Edith Guo, Steven Hwang, Haena Kim, Klaas Fiete Krutein, Jundi Liu, Erika Miller for making my experience in the Human Factors and Statistical Modeling lab and graduate school exciting and fun. I also appreciate for all the undergraduate research assistants who helped me conduct the driving studies. They are Juan Gonzalez, Zack Oakley, Warren Sprecher, and Tiffany Yam.

Last but not least, I would like to express my deepest gratitude to my family and my husband, Haoran Cai. This dissertation would not have been possible without their continued patience, and endless support.

# Chapter 1

# INTRODUCTION

## *1.1 Problem statement*

As vehicle automation becomes increasingly prevalent and capable, drivers have the opportunity to delegate primary driving task control to automated systems. Significant efforts have been placed on developing and deploying Advanced Driver Assistance Systems (ADAS). These systems are designed to work with human drivers to increase vehicle safety, control, and performance in both ordinary and emergent situations.

Current Advanced Driver Assistance Systems (ADAS) are mainly presented in rule-based or manually programmed design based on the summary and modeling of pre-collected human performance data. However, this pre-fixed system with limited personalization may not match human drivers' needs, which may arise the driver's dissatisfaction and cause ineffective system improvement.

Human drivers may develop different behavior adaptations when interacting with ADAS. The differences may be caused by different driving styles. As driving styles summarizes the habitual way of driving for a individual driver or a group of drivers, the conflict between driver assistance and driving styles could impact the driver behavior adaptation. Driving styles usually develop through the mixture influence from individual, socio-economic, and technological factors. The understanding of how these factors impact the development of driving style provides the potential and basis for the personalized ADAS. Traditional driving styles research mainly relied on the self-report information by collecting driver behavior related questionnaires. Time series observation of steering, speed and headway can implicitly reflect the driving styles (Black et al., 2011; Macadam, 2003). There is limited research in identifying driving styles based time-series observational data (e.g., vehicle kinematics, secondary task engagement, eye glance data), and how driving styles could impact drivers behavior adaptation when interacting with the ADAS is not thoroughly investigated.

There may be many different reasons for the formalization of the certain driving style. Näätänen and Summala (1976) proposed that it relates to the driver's preference, such as getting to destinations safely, arriving as fast as possible, keeping up with normal traffic flow, seeking the thrill of speeding, or even engaging with secondary tasks. How to quantify and evaluate the driver's preference was not widely discussed in the past research. Quantifying the driver's preference would be helpful in improving current ADAS system design and bring positive safety benefits for human drivers.

Human-centered machine learning (HCML) includes explicitly recognizing this human work, as well as re-constructing machine learning workflows based on situated human working practices, and exploring the collaboration of humans and systems. Machine learning from human-centered perspective could help to focus and guide how machine learning and system design can stay grounded in human needs. It can lead not only to more usable machine learning toostas but to new ways of improving driver assistance system.

## *1.2 Goal*

The goal of this dissertation is to build a driver behavior modeling framework that can understand and predict interactions with the driver assistance system from a human-centered perspective. This approach can lead to more usable machine learning tools as well as provide new ways of improving the driver assistance system. This study seeks to address the following research questions:

- **Research Question 1**: Can we identify the driving styles based on driver behavior data?
  - This study focuses on capturing and identifying the driving styles based on drivers' driving performance, secondary task engagement, eye glance behavior, and survey information. The data is from a driving simulator study that was designed and conducted with a scenario including lead vehicle decelerating under different conditions.
- **Research Question 2**: How do drivers adapt to the FCW system based on the driving styles?
  - Unlike the previous study, driver's adaptation to ADAS system is discussed based on driver characteristics (e.g., age, gender). This study aims to evaluate the driver's adaptation to an FCW system based on driving styles from three aspects: initial reaction, distraction, and safety benefits.

- **Research Question 3**: Can we learn driving preferences based on simulator data?
  - Driver's behavior varies, but the driving preference is relatively stable to achieve a short time goal. A perception-decision-action perspective was utilized to understand driver behavior when interacting with the vehicle. Driver preference is learned as a reward function given observed time series data by applying Inverse Reinforcement Learning.
- **Research Question 4**: Can we predict when the driver should brake based on their driving preferences?
  - This study compares the braking action timing prediction by using driving preference with traditional FCW system. The difference between these two mechanisms is evaluated and discussed.

# Chapter 2

# BACKGROUND AND LITERATURE REVIEW

## *2.1 Vehicle automation*

### *2.1.1 Levels of automation*

As vehicle automation becomes increasingly prevalent and capable, drivers have the opportunity to delegate control of the primary driving task to automated vehicles. SAE (2016) provides a taxonomy with detailed definitions for six levels of driving automation, ranging from no driving automation (level 0) to full driving automation (level 5). Each level describes the responsibilities of the vehicles that can take over from the drivers, and how the vehicles and the drivers interact with each other. The following are the specific SAE definitions for each level:

- **Level 0 - No Automation** The driver performs all driving tasks.
- **Level 1 - Driver Assistance** The driver still perform the majority of driving tasks, vehicle can provide some driving assist features (e.g., lateral control).
- **Level 2 - Partial Automation** The vehicle can provide some automated functions, like acceleration and steering, but the driver must supervise the system and monitor surroundings all the time.

- **Level 3 - Conditional Automation** The driver is not required to monitor the environment all the time, but the driver must be ready to respond to a request from the vehicle to intervene.

- **Level 4 - High Automation** The vehicle is capable of performing all driving functions under certain conditions. The driver may have the option to control the vehicle.

- **Level 5 - Full Automation** The vehicle is capable of performing all driving functions under all conditions. There is no need for the driver to intervene.

The evolution of vehicle automation aims to deliver greater driving safety by taking over the control of driving task from the human drivers. With less involvement of human drivers in the driving loop, the likelihood of human error occurrence decreases. However, in the transition from the low level to the high level of automation (up to level 4 automation), the drivers still have to be ready to intervene when needed. Failure of intervention would lead to the increase of driving risk. Therefore, a human-centered design idea is essential when improving the vehicle systems. In order to make the intervention from the human drivers successfully and effectively, it is critical to consider the individual difference of the human drivers and monitor the real-time status of the human drivers. For higher levels of automation, it is extremely important to track drivers' state and ensure that drivers are in the loop for responding appropriately in critical situations.

### *2.1.2 Advanced Driver Assistance Systems, ADAS*

Advanced Driver Assistance Systems (ADAS) are intelligent systems designed to enhance driving safety by providing assistance to the drivers with primary driving task. The assistance functions from ADAS include alerting drivers of potential hazard situations, intervening with partial vehicle control, and providing full control for a period of time. In recent years, significant emphasis and efforts have been placed on the development and implementation of Advanced Driver Assistance Systems (ADAS). These systems are designed to work with the human drivers to increase vehicle safety, control, and performance in both ordinary and emergent situations. Several examples are explained as following:

- **Adaptive Cruise Control (ACC)** Adaptive cruise control (ACC) is an automotive feature for road vehicles that automatically adjusts the vehicle speed to maintain a safe distance from vehicles ahead (Marsden et al., 2001).

- **Lane Departure Warning (LDW)** Lane Departure Warning (LDW) is a mechanism which warns the driver if the vehicle is leaving its lane with visual, audible, and/or vibration warnings.

- **Forward Collision Warning (FCW)** A Forward Collision Warnings System (FCWS) is designed to alert drivers of the potential collision risk when an obstacle is detected.(Lee and Peng, 2005).

Although the ADAS provide supports for specific parts of the driving tasks, the human drivers and the system share the control of the vehicle all the time. Unsuccessful transition of driving control from the system to the human driver could reduce the safety benefits and may lead to the increase of crash risk. It is important to design the functions provided by the ADAS to be feasible, accessible, and adaptable for the human drivers.

### *2.1.3 Car-following scenario*

As one of the most common scenario in transportation research, car-following scenario is observed in manual driving, assisted driving, and self-driving vehicles. Car-following captures the fundamental activity of driving following the lead vehicles safely in the traffic stream.

Rear-end collision is a common crash occurrence in car-following scenario. It refers to the situation that the lead vehicle is stopped or moving very slowly before the crash. It has a significant impact on traffic flow and traffic safety. In 2016, it accounted for 6.8% of the 34,439 fatal crashes in the US (Institute, 2017). To reduce the risk of the vehicle crash in the car-following scenario, many vehicle technology applications are developed based on the car-following research. ADAS, such as Adaptive Cruise Control (ACC), partially replaces the control of vehicle accelerator in order to reduce the hazard from the human driver misperspection. Forward Collision Warning (FCW), provides alerts to the human operators of the impending collisions.

Car-following is also an essential component of micro-simulation models. By focusing on car-following, researchers can investigate the individual driver behavior as well as global traffic flow from a microscopic perspective. The car-following behavior describes the behavior of a vehicle while following a lead vehicle. It consists of two aspects: vehicle kinematics (e.g., speed, acceleration) and human operator performance (e.g., reaction delay, imperfect perception). Existing car-following models (e.g., Gazis-Herman-Rothery (GHR) model, Fuzzy-logic model, Helly's model, Intelligent Driver Model (IDM)) mostly focus on vehicle kinematics rather than the human operator performance, thus these models are incapable of capturing varying human operator driving behaviors (i.e., driving styles and risk-anticipating preference) in car-following scenario (Chandler et al., 1958; Wu et al., 2000; Helly, 1959; Treiber et al., 2000). Given the importance of human factor in the car-following scenario, it is necessary to integrate the current car-following model by considering human operator performance.

### *2.1.4 Forward Collision Warning (FCW) system*

Rear-end collisions account for approximately 29 percent of all crashes each year (Lee et al., 2007). In order to reduce rear-end or forward collisions, great efforts have been placed on the development of Rear-end collision avoidance systems (RECAs). RECAs had been shown as a promising approach to help drivers avoid these crashes (Lee et al., 2002). Forward Collision Warning (FCW) system is one typical type of RECAs, and it is designed to warn drivers of an impending forward or rear-end crash so that drivers can return their attention to the critical driving situations. Thus, it has the potential to reduce the occurrence of rear-end collisions. An FCW system can detect the vehicles and obstacles in front of the host vehicle. If a fixed threshold of collision risk is exceeded (e.g., Time to Collision, TTC), an alert is issued.

Timing of alerts in an FCW system is based on a parametric physical model estimated from experiment data. However, this type of design has two potential issues. First, it is difficult to generalize for varying environmental situation. Weather condition could impact the time needed for avoiding a collision. Weather-related factors, especially rainy conditions, were found to affect crash frequencies (Jung et al., 2011). Besides, this design of FCW alerts does not account for the drivers attention to the driving task. If the driver is distracted, the driving performance is degraded, such as reduced headway distance and greater lane position variability, the driver's capability to respond to these alerts is also negatively impacted. Many studies have shown that driver distraction is believed to be a factor in a substantial percentage of collisions (Lee et al., 2007; Lees and Lee, 2007; Bunn et al., 2005).

## *2.2 Driver performance*

Performance measures evaluate the driver's ability to perform the driving task for a specific context and road condition. These measures provide insights on the driver's ability to maintain speed, distance, and lane position (da Silva, 2014). Furthermore, performance measures are essential for evaluating safety and improving vehicle systems. In general, the ideal selections of performance measures should be chosen based on the types of systems that are evaluated, and the tasks that would significantly affect driver behaviors.

A brief introduction on various performance measures used to evaluate the performance of drivers is discussed in this section. They are divided into: 1) vehicle performance measures

2) operator performance measures. 3) physiology measures.

### *2.2.1 Vehicle performance measures*

- *Longitudinal control* usually focuses on the control of distance and time, as it requires the driver's ability to perceive and attend to the situation while driving. Speed, as one example of longitudinal control measures, aims to prevent vehicle collisions and maintain steady traffic flow. It has been widely studied as a dependent variable in transportation research (Regan et al., 2008). Typical speed related measures include mean, maximum, quantile values of speed, variability such as standard deviation of speed. Several studies indicate that mean speed decreases when drivers are engaged with phone call (Green et al., 1993; Reed and Green, 1999). Furthermore, Haigney et al. (2000) showed that the variation of driving speed increase when drivers are exposed or distracted by cell phone usage. When it comes to the driver's interaction with in-vehicle information system, Srinivasan and Jovanis (1997)'s study shows that manually controlling in-vehicle navigation system would lower the mean speed, while Gärtner et al. (2001) indicate that the speech input for Driver Information System (DIS) has a smaller impact on the variation of speed when compared with manual input.

  Speed is a good performance measure that is dependent on the individual driver, as high speed and dramatically speed change indicate the drivers' inability to speed control (Regan et al., 2008). However, in real life situation, individual speed measures may be constrained by the high volume of traffic and other on-road environment conditions, which makes speed measure insensitive to reflect individual performance and behavior change.

- *Lateral control* refers to the control of side-to-side or sideways movement. Lane keeping, one of the commonly used lateral control measures, aims to measure the position of a traveling vehicle on the road as related to the center of the lane. The most commonly used lateral position metrics include mean lane position, standard deviation of lane position, and number of lane exceedences (LANEX). The ability of lane keeping control is used as a measure for evaluating the effects of in-vehicle systems on driving performance. Engström et al. (2005); Peng et al. (2014) show that performing secondary tasks would negatively affect drivers' lane keeping ability, especially when they are involved in high visual demand tasks, such as cell phone texting. Furthermore, Tijerina et al. (1998) conclude that drivers who were using manual input to navigation system tend to have a larger standard deviation of lane position and a greater number of lane exceedences compared to those using voice input.

#### *2.2.2 Operator performance measures*

- *Event detection and reaction time* aim to measure crash involvement of the drivers directly. Event detection and reaction time have been widely used for ADAS and in-vehicle information systems, including number of missed/detected events, response time to specific events. Reaction time to the leading vehicle's braking lights is used to evaluate the driver's vigilance during driving when automated systems are engaged (Rudin-Brown and Parker, 2004; Shen and Neyens, 2017). Response Time (RT) to Tactile Detection Response Task (TDRT) is considered to be a sensitive surrogate test for driver attention and cognitive demand for non-driving related tasks(Hsieh et al., 2015). Our previous study shows that participants have longest respond time to the TDRT when interacting with the in-vehicle navigation system with visual mode, as it takes time to interpret text on a visual display while also simultaneously attending to the TDRT stimuli.

### *2.2.3 Physiology measures*

Physiological measures provide insights on the driver's peripheral and central nervous system during driving. Physiology measures include heart rate, eye movement and pupil dilation, respiratory rate, and electroencephalogram (EEG); these have been widely studied and applied (Hjortskov et al., 2004; Sodhi et al., 2002; Kim et al., 2015; Wang et al., 2015). Hjortskov et al. (2004) shows that heart rate variability is a more sensitive and selective measure of mental stress. Particularly, Reid and Colle (1988) claims that heart rate and heart rate variability vary significantly when the user approaches the workload limit where cognitive capacity is fully utilized, resulting in degraded performance. Sodhi et al. (2002)'s study uses eye positions and pupil diameters as the indicators of attentional focus; their experiment results show that longer eye-off-road durations were observed in radio-tuning and rearview mirror checking tasks, but not in the odometer checking task. Kim et al. (2015)'s study tracks participants' breath rates and the duration of breathing-in and breathing-out to represent different driving states and uses this information to design their driving intervention algorithm. EEG signals also have been used to keep tracking of drivers' attention level in (Wang et al., 2015).

## *2.3 Importance of driver preference*

Driver preference, in this dissertation, refers to the driver's choice in speed and distance in the car-following scenario. The preferred driving speed and headway distance can be maintained through accelerating and decelerating by switching between accelerator pedal and brake pedal. It is important to consider driver preference because it affects the driver behavior when interacting with vehicle intelligent system and transportation infrastructure. Lachapelle (2006) concluded that drivers adjust the speed and headway relying on driver preference. It was also showed that driver preference could impact the route and paths choice (Macadam, 2003). In order to better evaluate ground vehicle steering systems, Black et al. (2011) created steering preference metric based on driver behavior. Furthermore, driver preference is associated with the acceptance of intelligent systems and traffic safety. Hoffman et al. (2003) demonstrated how well the algorithm of collision warning system and user interface can be tailored to the driver's preferences.

Driver preference, as discussed in (Hoffman et al., 2003), decides the success of the Forward Warning Collision system. Besides, Ahie et al. (2015) pointed out that driver preference was the source of the traffic conflict, such as dangerous overtaking.

With the rapid development of vehicle automation, a significant number of advanced driver assistance system (ADAS) are designed to improve vehicle control and the safety of the driver and the passengers. Many studies of ADAS have focused on real-time and correct identification of the driver's intention to improve the capability and acceptance of the system to the drivers. Tran and Firl (2014) considered driver preference (i.e., turning left or right) in the context of a Monte Carlos method. They employed this method to predict possible trajectories at urban intersection that involves obvious multi-modalities and non-linearities, which allows the incremental prediction of possible trajectories in situations where unimodal estimators such as Kalman Filters would not work well. Their proposed framework is evaluated experimentally in urban intersection scenarios using real-world data. Sezer et al. (2015) formalized the problem of vehicle interaction at an intersection merging scenario as an intention-aware motion planning problem using Mixed Observability Markov Decision Process (MOMDP). By considering driver's preference and intention, it is demonstrated that using intention-aware planning improves prediction performance in comparison to the traditional algorithm by lowering accident probability and intersection navigation duration. In addition to driver's intention at complicated traffic scenarios, modality is also an important factor that should be addressed in the design of in-vehicle information system. Kim et al. (2012) explores the efficacy of multi-modal cues for providing route guidance information to adjust different driver preference; further, they find that the full combination of visual, auditory, and haptic feedback is generally most useful to reduce way-finding errors.

## *2.4 Driving assistance system with human feedback*

Driver preference can be gathered through written questionnaires (Mazzae et al., 2004). However, this approach could delay the procedure of vehicle engineering development and testing. Human feedback can also be collected without directly person-in-person communication. Time-series observation of steering, speed and headway can implicitly reflect the driver preference (Black et al., 2011; Macadam, 2003). Human feedback oriented systems have been widely studied and implemented in web applications and conversational dialogue systems. Koren (2010) proposed a modified collaborative filtering algorithm for recommendation systems which can dynamically model not only the customer's preference, changing product perception, and popularity. Furthermore, researchers in conversation dialogue systems are dedicated to developing systems that can learn user preferences, improve task completion, or adapt dialogue strategies to an individual during a conversation. Linden et al. (1997) presents their Automated Travel Assistant, a prototype of the model that interactively builds flight itineraries by starting with minimal information about the user's preferences, and then improving the recommendations after user-interactions.

Unlike the web-based applications, driving is more complicated with safety and time-critical scenarios. Inappropriate or even misleading adaptive functions from user-adaptive driving systems may bring serious risks. Jameson (2009) presents a study in which the effects of different levels of in-vehicle adaptation are analyzed based on the performance of drivers under driving simulator condition. Their experiments indicate that adaptive user interfaces can be a practical means of supporting the driver, but also that the adaptation level of these systems has to be designed very carefully in order to avoid undesired system behavior, particularly in non-routine tasks and unfamiliar driving situations. Further, Jamson et al. (2008) studied the effects of moving from a non-adaptive to an adaptive forward collision warning(FCW) system that adjusted the timing of its alarms according to each driver's reaction time. Their experiment shows that all drivers benefited in terms of improved safety from both FCW systems. Furthermore, non-aggressive drivers (low sensation seeking, long followers) did not display a preference to the adaptive FCW over its non-adaptive one, while aggressive drivers (high sensation seeking, short followers) were demonstrated from benefits of the adaptive system.

## *2.5 Gaps in literature*

Advanced driver assistance systems (ADAS) aim to assist the driver in the driving process with safe interactive interface. It has been improving significantly in the automotive industry due to the rapid development of sensor technology. However, current ADAS mainly focus on reacting to the context of the vehicle and surrounding environment, while driver, who is tightly involved in the whole driving process, has been excluded from the consideration in the system design. Besides, this limitation of current ADAS can not perfectly handle the potential safety risk due to increased drivers' engagement of secondary tasks during driving. Therefore, ADAS with considering the driver's input is essential in the autonomous driving field as it not only considers driving contexts but also actively reacts to drivers' varying driving states. This dissertation takes Forward Collision Warning(FCW) systems as an example to investigate the problem: how to keep human in the loop of ADAS in a varying environment with safe-critical intervention.

Driver individual differences in terms of interacting with ADAS was mainly discussed based on driver characteristics and personalities, such as age (Ziefle et al., 2008; Trübswetter and Bengler, 2013; Reimer, 2014), gender (Son et al., 2015) and driving experience (Mueller and Trick, 2012; Underwood et al., 2002). However, the impacts of ADAS on drivers with different driving styles were rarely investigated. Driving style, as defined in (Sagberg et al., 2015), refers to habitual way of driving, which is characteristic for a driver or a group of drivers. It often develops through the mixture influence from individual, socio-economic, and technological factors. The understanding of how these factors impact the development of driving style provides the basis for personalized ADAS (Cho et al., 2006; Xiong et al., 2012). However, driving styles are often inferred from self-reported data (e.g., driving behavior questionnaires) (Xiong et al., 2012; Peng and Boyle, 2015). Identifying the driving styles based the collected time series data is still new. This dissertation will identify the driving styles based on driver behavior data that was collected from a controlled driving simulator study. Specifically, identifying the driving styles of how drivers react to safety-critical braking events is the focus of this work.

Personalized or adaptive ADAS aims to adjust the driver assistance functions to the driver's need. Many studies had discussed the potential of adaptive ADAS to improve safety and user satisfaction. Hajek et al. (2013) demonstrated the technological possibility of adjusting driver workload while the drivers are interacting with Active Cruise Control (ACC) system. Their experiment showed that workload-adaptive cruise control (WACC) revealed a safety advantage over the traditional ACC system in terms of low rate of deceleration. Lane Keeping (LK) system of adjusting driver distraction status was considered to increase driving safety through the field experiments conducted by (Blaschke et al., 2009). Furthermore,Jamson et al. (2008) investigated the effectiveness and acceptance of Forward Collision Warning (FCW) systems that adjusted the timing of its alarms based on drivers reaction time. Their study compared the different impacts of adaptive FCW on aggressive and non-aggressive drivers: non-aggressive drivers did not display a preference to the adaptive FCW or the original FCW, while aggressive drivers were benefited from the adaptive system. With the development of adaptive driver assistance systems, drivers may develop two different behavior adaptations when interacting with driver assistance systems in terms of driving performance: positive and negative. Positive behavior adaptation is the ideal situation when human drivers drive more safely with the aid of ADAS, while negative behavior adaptation refers to the case that drivers disuse these systems and further degrade the driving performance. This dissertation is also aimed to understand how drivers adapt to the FCW systems in terms of driving styles, time exposure, and secondary task engagement.

Drivers behavior adaptation to the FCW system may vary due to different driving styles. The mismatch between the warning from FCW system and the braking timing estimation from the human driver could lead to delay in reaction, inappropriate braking action, unsafe engagement of secondary task and distrust in the FCW system. Driving styles in this dissertation mainly were reflected as how drivers react to a braking event, this habitual behavior is developed by the process of reinforcement, as mentioned in (Sagberg et al., 2015). There may be many different reasons why such driving behavior occurs. Näätänen and Summala (1976) proposed that it relates to the motives, such as getting to destinations safely, arriving as fast as possible, keeping up with normal traffic flow, seeking the thrill of speeding, or even engaging with secondary tasks. How to quantify and evaluate the driver's motives was not widely discussed. Reward function, used in reinforcement learning, is inferred given an observed behavior from the observed subject. Ziebart (2010) discussed the driver's preference of route choice and proposed reward function to represent driver preference by considering factors such as weather, day of time, and cost. Besides, Shimosaka et al. (2014) investigated the reward function of risk anticipation and defensive driving from urban driving across the intersection. By adapting the similar techniques from previous studies, this dissertation applies the idea of learning driver preference in a braking event as reward function and investigates the individual difference of reward functions. Furthermore, driving preference is used to predict the personalized braking timing, the predicted timing and the traditional FCW timing is compared and discussed in this dissertation.

## *2.6 Research aims*

This dissertation aims to build a novel driver behavior modeling framework to understand and predict interactions with the driver assistance system from a human-centered perspective. It can lead not only to more usable machine learning tools but to new ways of improving the driver assistance system. The following research questions are addressed in this work:

- **Research Question 1**: Can we identify the driving styles based on driver behavior data?
  - This study focuses on capturing and identifying the driving styles based on drivers' driving performance, secondary task engagement, eye glance behavior, and survey information. The data is from a driving simulator study that was designed and conducted with a scenario including lead vehicle decelerating under different conditions.
- **Research Question 2**: How do drivers adapt to the FCW system based on the driving styles?
  - Unlike the previous study, the driver's adaptation to ADAS system is discussed based on driver characteristics (e.g., age, gender). This study aims to evaluate the driver's adaptation to an FCW system based on driving styles from three aspects: initial reaction, distraction, and safety benefits.
- **Research Question 3**: Can we learn driving preferences based on simulator data?
  - Driver's behavior varies, but the driving preference is relatively stable to achieve a short time goal. A perception-decision-action perspective was utilized to understand driver behavior when interacting with the vehicle. Driver preference is

learned as a reward function given observed time series data by applying Inverse Reinforcement Learning.

- **Research Question 4**: Can we predict when the driver should brake based on their driving preferences?
    - This study compares the braking action timing prediction by using driving preference with traditional FCW system. The difference between these two mechanisms is evaluated and discussed.

# Chapter 3

# EXPERIMENT DESIGN

This chapter outlines the driving simulator experiment that was used for this study. The experiment was conducted at the University of Washington, Seattle, WA, in April - June 2019. A Forward Collision Warning (FCW) system was used to study driver behavior (e.g., braking behavior) and driver-system interaction. An In-Vehicle Information System (IVIS) was used to induce visual and manual distractions. The driving simulator was used to collect driving performance measure and vehicle kinematic information, an eye-tracking system was used to capture eye glance behaviors, and questionnaire before the experiment was used to quantify risky anticipation and questionnaire after the experiment was used to collect user satisfaction of FCW. The study was approved by the Institutional Review Board (IRB) at University of Washington. Informed written consent was obtained from each participant at the beginning of the study.

A 2 (Assistance condition: FCW on, FCW off) x 2(Task mode: No Secondary task, Secondary task) within-subjects design was used with age group and gender as blocking factors.

## *3.1 Participants*

Participants came from a pool of volunteers that responded to an advertisement placed online. Among these individuals (from the Seattle area), 24 participants were randomly selected from three age groups (25-34, 35-44, 45-54) with an equal number of males and females in each age groups (see Table 3.1).

All participants were required to hold a valid US driver license and a certain amount of driving experience. Younger age group (25 - 34) were required to have driven in the US for at least one year, while middle age group (35 -44) and older age group (45 - 54) are required to have driven in the US for at least three years. Participants were compensated $20 per hour for attending the experiment and extra compensation was provided based on their performance of the secondary task.

| **Age Group** | **Male** | **Female** | **Total** |
|---|---|---|---|
| 18-34 | 4 | 4 | 8 |
| 35-44 | 4 | 4 | 8 |
| 45-54 | 4 | 4 | 8 |

Table 3.1: Number of Participants in Each Group

Figure 3.1: Driving Simulator Used for the study

## 3.2 *Apparatus*

### *3.2.1 Driving simulator*

A National Advanced Driving Simulator (NADS) miniSim (version 2.2.1) fixed-based quarter cab driving simulator was used in this study (see Figure 3.1). It includes three 48-inch monitors (sony displays, 1920 x 1080 resolution) placed approximating 2m from the drivers' eye point. The simulator projected images with a visual field. Data was collected from the simulator at 60 Hz.

The miniSim software Tile Mosaic Tool, TMT, (version 1.7.5.4) was used for creating the visual environment and Interactive Scenario Authoring Tool, ISAT, (version 1.8.0) was used for developing the scenario logic.

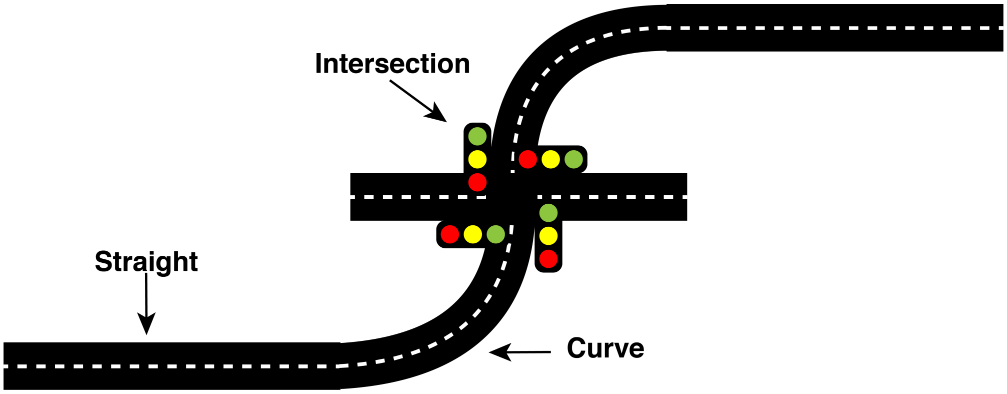


Figure 3.2: Snippet of driving scenario roadway

### *3.2.2 Driving task*

The driving scenario is an undivided two-lane (one lane in each direction) rural road with one lead vehicle in the same lane and path as the host vehicle and coming traffic on the other lane. The route map (shown in Figure 3.2) included straight segments, curved segments and intersections

There were two versions of the driving scenario, denoting as A and B (shown in Figure 3.3). Version A has FCW on condition following by the FCW off condition; version B has FCW on condition first and FCW off condition as the second. Except that, these two versions are identical in terms of driving distance, road and traffic conditions.

In the experiment, each participant completed two drives with pre-assigned scenario version combination (i.e., AA, AB, BA, and BB). Each drive took 20-30 minutes to complete, which varied among individuals.

Participants were instructed to drive at the post speed limit of 60 miles per hour (mph). Once the driving speed was greater than 70 mph or lower than 50 mph for more than 10 sec-

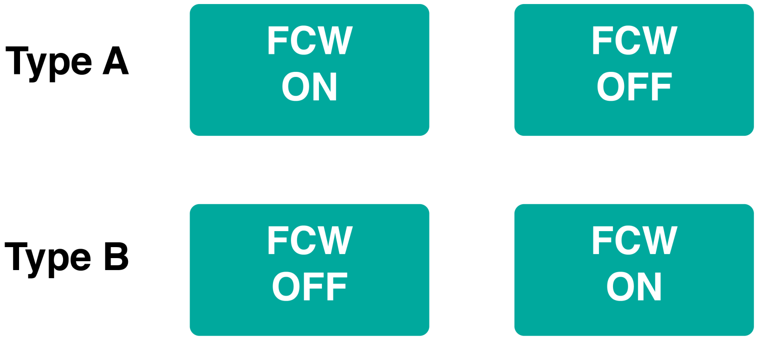


Figure 3.3: Two versions of driving scenarios

onds, participants would receive auditory instructions, either "Speed violation" for exceeding speed 70 mph or "Please drive up to 60 mph" for speed lower than 50 mph. Participants have to follow a lead vehicle that braked at a rate of 0.2g (gravitational acceleration) [1] for 10 seconds. Before a lead vehicle-braking event, the lead vehicle speed was smoothly adjusted to obtain constant time headways of 2.2 seconds. After the lead vehicle braked and reduced the speed to 30 mph for 10 second, it would start smoothly accelerate to reach the target speed of 55 mph. There are 16 braking events within a drive, 10 of 8 braking events took place while participants were instructed to engage with secondary task. The timing of each braking event was unpredictable for participants to reduce the potential learning effect.

Each drive was partitioned into 16 different segments for data analysis; each segment was defined as the time period that the lead vehicle started smoothly adjusting speed to maintain constant time headways until the next time that lead vehicle started maintaining the constant time headways. There was 1 mile for participants to drive when switching between two experiment conditions (FCW on and FCW off).

---

[1] gravitational acceleration is the acceleration on an object caused by the force of gravitation

The practice drive, including both FCW on and FCW off conditions, and secondary task was provided for participants to get familiar with driving simulator manual driving as well as FCW alert and secondary task. Participant completed the practice drive until they felt familiar with the driving simulator and understood all experiment tasks. The practice drive usually took around 5 minutes.

Before entering the driving segment with FCW condition, participants were notified "Forward collision warning system is on". When switching between FCW on the condition to FCW off condition, participants were also notified "Forward collision warning system is off".

### *3.2.3 Secondary task*

A 7-inch touchscreen (shown in Figure 3.7) was mounted to the right side of the steering wheel for the driver. The touchscreen was used in the secondary task, which provided a controlled exposure to the visual, manual and cognitive distraction. This aims to simulate the daily interactions of IVIS, such as scanning a music playlist.

The secondary task used in the experiment was designed and modified based on (Donmez et al., 2007). It consisted of selecting a word match with the phrase "Discover Project Missions", from a list of 10 closely related phrases presented in the touchscreen. After an auditory instruction "Secondary task starts" notified the participants, the task interface was shown up with initial page. The display would stay blank after another audio "Secondary task ends, please focus on driving now" was played. The participant initiated the task by touching the ready button, then two phrases candidates were presented on display. The participant was able to go through all the 10 possible phrases by touching up and down arrow buttons and made a selection by touching the phase, confirmed the answer by hitting the “Submit” button. The correct answer should be the phrase that has either “Discover” first, “Project” second, or “Missions” third. There is only one correct answer among the 10 phases. For example, “Propane Discuss Missions” is the correct phrase as “Missions” is at the right position. After submitting the answer, the participant would receive feedback regarding correct and incorrect selections (see Figure 3.5)

Participants would receive 0.10 dollars for each correct selection, and lose 0.03 dollars for each incorrect one. This reward mechanism aims to increase the importance of secondary task engagement and provide them the incentive to perform to their best ability.

The whole process of the secondary task is self-paced. Participants were instructed to interact with IVIS only when they feel safe and comfortable doing so. Participants could decide when to interact with the IVIS within the secondary task segments. This leads to the evaluation of driver strategies under different FCW assistance conditions.

The secondary task was programmed in *Python (version 2.7.15).* User Datagram Protocol (UDP) was used for streaming data communication so that the touchscreen interaction was recorded and synced with the driving simulator.

### *3.2.4 Eye-tracking system*

A faceLAB$^{TM}$eye tracker (shown in Figure 3.7) was used to collect eye movement and glance behavior data by using two cameras. FaceLAB is a software package that uses a set of

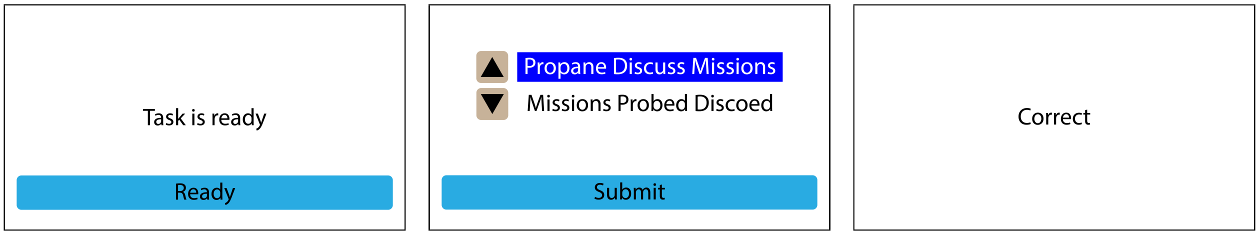


Figure 3.5: The interface of the secondary task shown in the touchscreen, initial page (left), working step page (middle) and result page (right)

cameras as a passive measuring device. The system is non-intrusive so that there's no need for participants to wear uncomfortable goggles or other sensing devices. With non-intrusive eye tracking system, the participants can drive as they normally do in daily life, which helps us collect the real eye movement data without any unnecessary alternation. The images from the cameras are processed and analyzed to summarize the characteristics of subject's face, including the position and orientation of head and eyes. Furthermore, the gaze directions of participants were analyzed and recorded.

Eye-tracking data was collected at 60Hz. Same as the secondary task, UDP was also used for streaming data communication between faceLAB and miniSim.

### *3.2.5 Questionnaire*

There are two questionnaires for the study: pre-experiment questionnaire and post-experiment questionnaire. The pre-experiment questionnaire covers the questions about the basic demographics (e.g., age, gender, education level) and driving experiences (e.g., How many miles did you drive last week?). The post-experiment questionnaire is an acceptance questionnaire (Van Der Laan et al., 1997), which aims to asses the usefulness and satisfaction of the FCW

Figure 3.7: The mini touchscreen (left) is used in the secondary task; the faceLAB™eye tracker system (right) is used for eye movement and glance behavior data collection

system.

### 3.3 Procedure

This is a 2 (Assistance condition: FCW on, FCW off) x 2(Task mode: No Secondary task, Secondary task) within-subjects design with age group and gender as blocking factors.

Participants recruitment was conducted online and through student outreach in Seattle, WA. All the experiment took place at the Human Factor Statistical Modeling Lab at University of Washington – Seattle.

Upon entering the test facility, participants were provided verbal information about the study and a consent form to review and sign. Once they provided consent, they were asked to complete the pre-experiment questionnaire. Participants would perform practice simulator drive to familiarize themselves with all conditions. Once participants were comfortable with driving in a simulator, the main drive began. Participants will have to complete a total

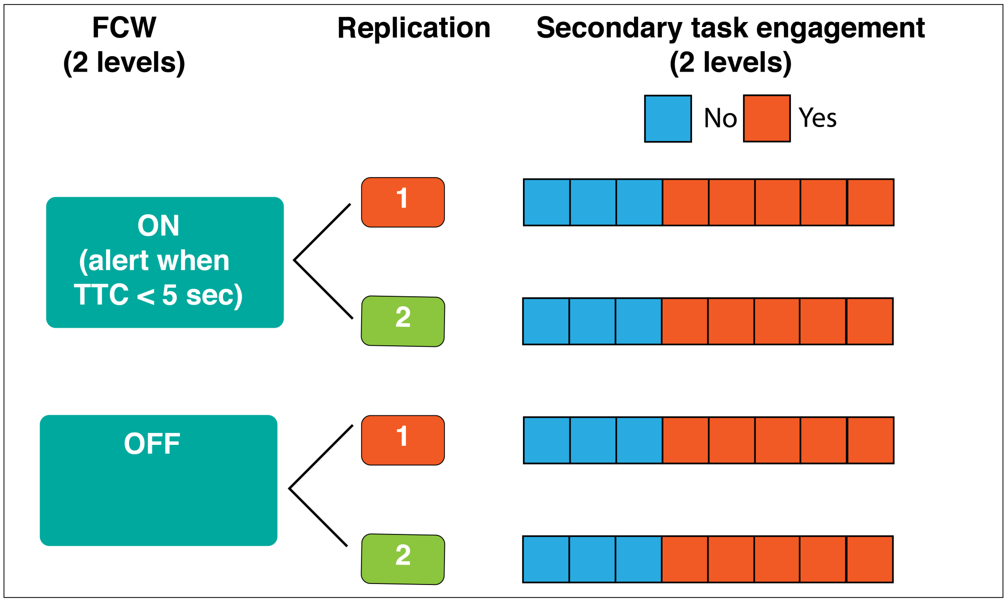


Figure 3.8: Assistance condition and secondary task arrangement for each drive

of two drives; each drive took around 20 minutes to complete varying among individuals. Within in each drive, participants drove with two assistance conditions: FCW on and FCW off. Participants would drive 1 mile between the condition switch. Within each condition, participants were required to complete 3 driving segments without the secondary task and 5 driving segments with the secondary task (See Figure 3.8).

Participants had to maintain the safe distance towards the leading vehicle under two conditions: FCW off and FCW on conditions. Under FCW off condition, participants would release the accelerator and brake based on their own judgment. With the assistance of FCW, participants will get a warning cue from programmed algorithm results when the Time To Collision (TTC) value is lower than 5 second.

Between each drive, participants would have 10 minutes break and completed the wellness questionnaire in the meanwhile. After completing all the experiment drives, participants had to complete the post-experiment questionnaire.

If a crash occurred or participant felt uncomfortable during the experiment, the experiment would immediately end.

## Chapter 4

# EXPERIMENT VARIABLE DEFINITION AND SUMMARY STATISTICS

This chapter presents the definitions of all the variables and summary statistics of the participants included in this study. The variables defined in this chapter come from four categories: driving performance, secondary task interaction, eye movement and glance and survey. The definitions of these variables apply across the dissertation. Descriptive statistics of the participants' demographics were evaluated to understand the difference between age and gender groups. It's important for evaluating the representability of the general driving population. Descriptive statistics of the secondary task provides a brief summary of the workload of the distraction and reflects the strategies of participants when interacting with FCW system. Collision is one direct traffic safety outcome, the summary statistics of collision is important for understanding the effectiveness of the FCW system.

## *4.1 Variable definition*

### *4.1.1 Driving performance*

- **Collision** (Yes/No): Collision is an binary measure that reflects if the participant successfully avoid the rear-end collision or not. It equals to "Yes" when the participant had crash during the whole experiment.

- **Maximum deceleration**: Maximum deceleration, in $m/s^2$, is defined as the highest deceleration (or lowest acceleration) value during a braking event. This is used to measure the braking intensity.

- **Accelerator release time**: Accelerator release time, in seconds, is defined as the time between the onset of the lead vehicle braking and the time that participant release the accelerator (See Figure 4.1). This is a direct measure of initial reaction from the participant in the braking event.

- **Accelerator-to-brake transition time**: Accelerator-to-brake transition time defines the duration starting from accelerator release to stepping on the brake pedal

- **Speed at accelerator release**: Speed at accelerator release, in $m/s$, is the speed when participant releases the accelerator during the braking event (See Figure 4.2).

- **Speed at brake**: Speed at brake, in $m/s$, is the speed when participant steps on the brake pedal during the braking event.

- **Standard Deviation of Lateral Position, SDLP**: Standard Devision of Lateral Position (SDLP), in inches, measures the difference between the center of the vehicle and the center of the lane. SDLP is computed based on Equation 4.1.1 (SAE, 2015).

$$SDLP = \sqrt{\frac{1}{T-1}\sum_{i=1}^{T}(x_i - \bar{x})^2} \tag{4.1}$$

where,

$x_i$ is $i^{th}$ observation of lane position,

$\bar{x}$ is the average lane position of the all the observations,

$T$ is the number of observations in the segment.

- **Time to Collision (TTC)**: Time to Collision (TTC), in seconds, is defined as shortest time to collision if the vehicles are to proceed with their current speeds. When the host vehicle is travelling at the same speed or lower speed of lead vehicle, TTC can be infinity. Due the systematic fault in driving simulator, TTC can also be infinity when the miniSim failed to identify the existence of the lead vehicle. the cutoff value is generally 20 seconds based on the definition of (SAE, 2015).

- **Minimum TTC**: Minimum TTC, in seconds, is defined as the shortest TTC during a braking event if the participant continue at the current speed in the same path (See Figure 4.3)

### *4.1.2 Secondary task interaction*

- **Number of Completed Tasks**: Number of completed tasks measures the engagement of the secondary task, as it's a self-paced task, participants can decide when to initialize the task and pause at any time they felt uncomfortable doing so. It measures the multitasking ability with and without FCW system assistance.

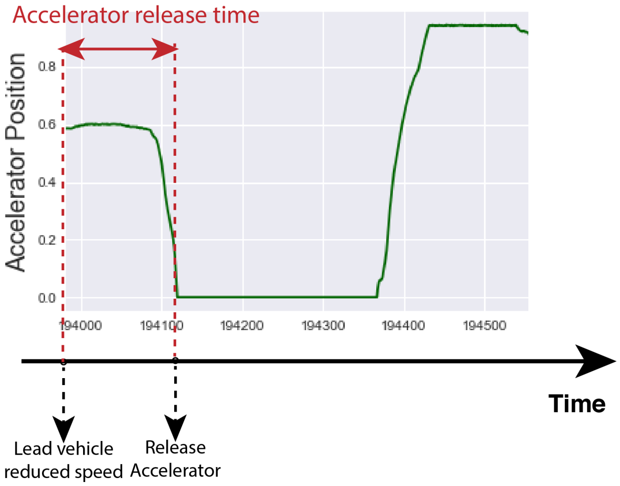


Figure 4.1: Visualization for the definition of variable accelerator release time

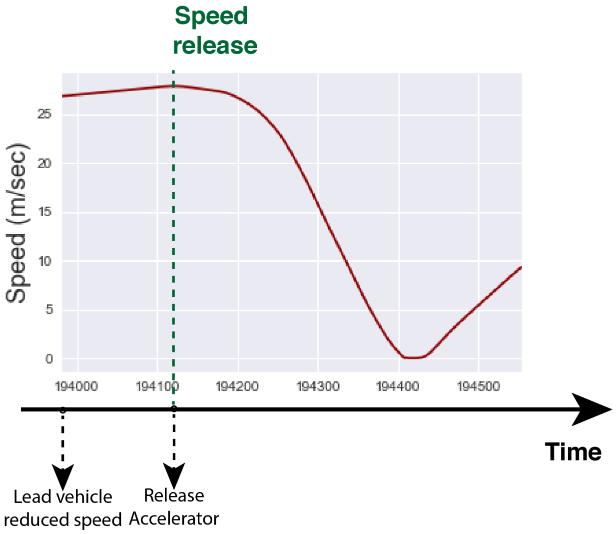


Figure 4.2: Visualization for the definition of variable accelerator release speed

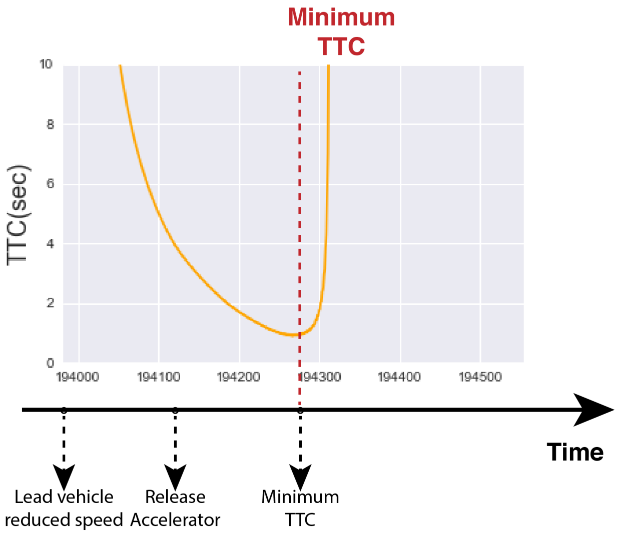


Figure 4.3: Visualization of the definition of minimum TTC

- **Number of touches to display**: Number of touches to display is defined as the total number of touchscreen operations during a braking event. It was used to evaluate the level of manual distraction. The larger Number of touches to display is associated with higher manual distraction.

- **Number of touches to display before Brake**: Number of touches to display before Brake is defined as the total number of touchscreen operations before participant stepping on the brake pedal during a braking event. This measures aims to evaluate the impact of FCW system on the driver's manual distraction behavior.

- **Number of touches to display after Brake**: Number of touches to display before Brake is defined as the total number of touchscreen operations before participant stepping on the brake pedal during a braking event. This measures is used to study if participants have any compensation behavior after they are interrupted by the sudden braking incident.

### *4.1.3 Eye movement and glance behavior*

Eye-off-road (EOR) is defined as any eye glance to the IVIS touchscreen. This measure aims to quantify the engagement of visual distraction.

- **Count of Eye-off-road, Count EOR**: Count of EOR is the total number of glance per trial.

- **Count of Long Eye-off-road , Count of Long EOR** Count of Long EOR is the total number of glance that duration exceeds 2.0 seconds.

- **Total Eye-off-road Time, TEORT**: Total Eye-off-road Time is the sum of all eye glance duration away from froward road view per trial (Equation 4.2).

- **Long Glance Duration Percent, LGP**: Long Glance Duration Percent is the proportion of glance duration that exceed 2.0 seconds (i.e., long glance) per trial (Equation 4.3).

- **mean Eye-off-road, mean EOR**: Mean EOR is the average glance duration per trial (Equation 4.4).

- **Maximum Eye-off-road, Maximum EOR**: Maximum EOR is the longest glance duration per trial (Equation 4.5).

$$TEORT_i = \sum_{j=1}^{N_i} EOR_{ij} \tag{4.2}$$

$$LGP_i = \frac{N_i > 2.0\ seconds}{N_i} \times 100 \tag{4.3}$$

$$MeanEOR_i = \frac{\sum_{j=1}^{N_i} EOR_{ij}}{N_i} \tag{4.4}$$

$$MaximuEOR_i = Max_{j \in \{1,\ldots,N_i\}}\{EOR_{ij}\} \tag{4.5}$$

where,

$i$ is the number of trial,

$EOR_{ij}$ is $j^{\text{th}}$ EOR duration in $i^{\text{th}}$ trial,

$N_i$ is the total number of EOR glances in $i^{\text{th}}$ trial.

### *4.1.4 Survey*

- **Miles Driven per Week**: Miles driven per week is collected from the response to the question "How many miles did you drive last week? " in the pre-experiment questionnaire.

- **Violation Frequency**: Violation Frequency is collected from the response to the question "How many moving violations have you had in the last 3 years ?" in the pre-experiment questionnaire.

### *4.2 Participants demographics*

The summary statistics of demographic information by age group is provided in Table 4.1 and Table 4.2. The average age for younger, middle, older age groups are 31.23 (SD=2.56), 39.33 (SD=3.88), 50.14 (SD=2.12) respectively, each age group has on average around 10 years age difference between each other, it indicates the representability of the participants from the three age groups. Their average ages of getting driver licenses across the three age groups are similar, they are 18.00 (SD=3.85), 17.04 (SD=1.66), and 18.27 (SD=2.87) for the younger, middle, older groups. Table 4.2 shows that the younger and middle age groups have similar miles to drive weekly, older age group has relatively fewer miles to drive weekly, but there is no distinct difference of violation frequency observed among these three age groups. The similarity of driving history controlled the confounding effect of driving experience. As age and driving experience were claimed to be highly correlated in previous literature research (Levy, 1990).

| **Age group** | **Age** | | **Years get license** | | **Education** | | | |
|---|---|---|---|---|---|---|---|---|
| | Avg. | Std. | Avg. | Std. | H.S. | Assoc. | Bach. | Grad. |
| 25-34 | 31.23 | 2.56 | 18.00 | 3.85 | 1 | 1 | 5 | 0 |
| 35-44 | 39.33 | 3.88 | 17.04 | 1.66 | 0 | 2 | 4 | 0 |
| 45-54 | 50.14 | 2.12 | 18.27 | 2.87 | 0 | 2 | 4 | 2 |

Table 4.1: Participant Demographics

| **Age group** | **Miles to drive weekly (miles)** | | **Violation Frequency** | |
|---|---|---|---|---|
| | Avg. | Std. | Avg. | Std. |
| 25-34 | 255.71 | 248.78 | 0.428571 | 0.78 |
| 35-44 | 318.57 | 151.9 | 0.571429 | 0.78 |
| 45-54 | 166.25 | 124.43 | 0.375000 | 0.74 |

Table 4.2: Participant Driving History

## *4.3 Collision*

Table 4.3 summarized the distribution of participants who had collision in this experiment. Older age group (45-54) has three participants that experienced collision during the experiment; overall 4 females and 2 males across all the age groups had a collision during the simulator experiment. Age and gender were considered as important factors contributing to the crash risk (Peck et al., 2008; Williams and Shabanova, 2003), the implicit driving style, however, may also be an essential factor that has not been widely discussed.

| **Age group** | **Female** | **Male** | **Total** |
|---|---|---|---|
| 25-34 | 0 | 1 | 1 |
| 35-44 | 2 | 0 | 2 |
| 45-54 | 2 | 1 | 3 |
| Total | 4 | 2 | 6 |

Table 4.3: Summary of collision over gender and age group

# Chapter 5

# CAPTURING AND IDENTIFYING DRIVING STYLES

This chapter presents the work of using a Gaussian Mixture Model to capture and identify different driving styles. The features used for modeling come from each individual driver's driving performance, secondary task engagement, eye glance behavior, and survey information. Therefore, each individual can be represented by a feature vector of these summary statistics from the above features. A Gaussian Mixture Model is applied to cluster these feature vectors, the optimal number of clusters is decided based on the Bayesian Information Criterion (BIC). The data used for the analysis of this chapter is collected from the driving simulator study in Chapter 3 that drivers followed a lead vehicle reducing speed under FCW off condition.

## *5.1 Methodology*

Data collected under FCW off condition is used to capture and identify the driving styles. The driving behaviors observed in this condition will not be affected or influenced by the FCW system. For that reason, this condition can also be used to better represent the daily driving styles of each individuals.

### *5.1.1 Feature definition*

Driving styles can be reflected in different aspects of the driving data. In order to have a better representation of driving styles, a total of 29 features from 4 categories were considered. Each feature was aggregated at participant level by the secondary task levels (no secondary task and secondary task). Table 5.1 summarized the features used for analysis in this chapter, detailed definition of each feature can be referred in Chapter 4.

### *5.1.2 Gaussian Mixture Model*

- **Model definition** The distribution of features $x$ related to the driver is assumed as a *mixture* of fixed $K$ component distribution $p_1, p_2, \ldots, p_K$:

  $$p(x) \quad = \quad \sum_{k=1}^{K} \phi_k p_k(x) \tag{5.1}$$

  where $w_k$ is the mixing weights, $w_k > 0$ and $\sum_k w_k = 1$.

  In mixture model, $w_k$ is usually formalized as $\phi_k = P(z = k)$ in a probability form, where $z$ is the **latent variable**. Therefore, Equation 5.1 can be reformulated as:

  $$p(x) \quad = \quad \sum_{k=1}^{K} Pr(z = k) p(x|z = k) \tag{5.2}$$

  $p(x|z = k)$ could be completely arbitrary distribution based on the modeling problems. In practice, **parametric mixture model** has been widely used, where $p(x|z = k)$ are all from the same parametric family, but with different parameters $\theta_k$.

- **Gaussian mixture model** (GMM) is considered in this study. For a Gaussian Mix-

| | **Number of features** | **Secondary task condition** | **Features** |
|---|---|---|---|
| **Driving performance** | 12 | No | Minimum TTC; Maximum deceleration;<br>SDLP; Speed at brake;<br>Speed at maximum brake force;<br>Speed at accelerator release |
| | | Yes | Minimum TTC; Maximum deceleration;<br>SDLP; Speed at brake;<br>Speed at maximum brake force;<br>Speed at accelerator release |
| **Secondary task interaction** | 3 | No | |
| | | Yes | Number of touches to display;<br>Number of touches to display before brake;<br>Number of touches to display after brake |
| **Eye movement and glance behavior** | 12 | No | LGP; Mean EOR; Maximum EOR;<br>Count of EOR; Count of Long EOR |
| | | Yes | LGP; Mean EOR; Maximum EOR;<br>Count of EOR; Count of Long EOR |
| **Survey** | 2 | No | Miles Driven per Week; Violation Frequency |
| | | Yes | |

Table 5.1: Summary of features used for identifying the driving styles

ture model with $K$ components, each component $p(x|z = k)$ is from Gaussian distribution family with mean $\vec{\mu}_k$ and variance parameters $\Sigma_k$. The mixture component weights are defined as $\phi_k$ for component $K$ with the constraint that $\sum_{k=1}^{K} \phi_k = 1$.

$$\begin{aligned}
P(\vec{x}) &= \sum_{k=1}^{K} \phi_k \mathcal{N}(\vec{x}|\vec{\mu}_k, \Sigma_k) && (5.3)\\
\mathcal{N}(\vec{x}|\vec{\mu}_k, \Sigma_k) &= \frac{1}{\sqrt{(2\pi)^k|\Sigma_k|}}(\vec{x} - \vec{\mu}_k)^T \Sigma_k^{-1}(\vec{x} - \vec{\mu}_k) && (5.4)\\
\sum_{k=1}^{K} \phi_k &= 1 && (5.5)\\
\phi_k &= Pr(z = k) && (5.6)
\end{aligned}$$

- **Learning the model** Denoting the parameters of GMM as $\vec{\theta} = (\phi, \mu, \Sigma)$. The GMM parameter $\vec{\theta}$ is estimated by using Maximum Likelihood Estimators (MLE). Given the training data $\{x^{(1)}, \ldots, x^{(m)}\}$, the log likelihood is shown as Equation 5.7.

$$\begin{aligned}
\ell(\vec{\theta}) &= \sum_{i=1}^{m} logp(\vec{x}^{(i)})\\
&= \sum_{i=1}^{m} log \sum_{k=1}^{K} Pr(z^{(i)}; \phi)\mathcal{N}(\vec{x}^{(i)}|\vec{\mu}_k, \Sigma_k) && (5.7)
\end{aligned}$$

As it's usually analytically impossible to find optimal solution of Equation 5.7 in a closed form, **Expectation maximization** (EM) is a numerical technique used for calculating the maximum likelihood estimation. The EM algorithm is an iterative algorithm, which can solve Equation 5.7 in two main steps: E step and M step, iteratively until the algorithm converges.

In E step, for each observation $i$ and component $k$, the component weight is assigned as Equation 5.8

$$w_k^{(i)} := p(z^{(i)} = k | x^{(i)}; \phi, \mu, \Sigma) \tag{5.8}$$

In M step, the parameters are updated accordingly based on Equation 5.9

$$\begin{aligned} \phi_k &:= \frac{1}{m} \sum_{i=1}^{m} w_k^{(i)} \\ \vec{\mu}_k &:= \frac{\sum_{i=1}^{m} w_k^{(i)} \vec{x}^{(i)}}{\sum_{i=1}^{m} w_k^{(i)}} \\ \Sigma_k &:= \frac{\sum_{i=1}^{m} w_k^{(i)} (\vec{x}^{(i)} - \vec{\mu}_k)(\vec{x}^{(i)} - \vec{\mu}_k)^T}{\sum_{i=1}^{m} w_k^{(i)}} \end{aligned} \tag{5.9}$$

- **Clustering** Given the model parameters, the probability that a data observation $x^{(i)}$ belongs to component $k$ is calculated using Bayes theorem (Equation 5.10).

$$p(z^{(i)} = k | x^{(i)}; \phi, \mu, \Sigma) = \frac{p(x^{(i)} | z^{(i)} = k; \mu, \Sigma) p(z^{(i)} = k; \phi)}{\sum_{j=1}^{K} p(x^{(i)} | z^{(i)} = j; \mu, \Sigma) p(z^{(i)} = j; \phi)} \tag{5.10}$$

- **Model selection** The number of components $K$ is a hypterparameter, which has great impact on the model results and inference. If $K$ is too small, it is difficult to identify the underlying clusters; if $K$ is too large, the model can be overfitted. The extreme case is that each observation point can be a single cluster, thus it is impossible to have insightful inference. Therefore, the Bayesian Information Criterion (BIC) is used for model selection (Biernacki et al., 2000).

- **Model initialization** Model initialization is important for solving GMM as it affects the learning convergence as well as the results. Bad initialization, such as assigning all the components with the same parameters, would never break apart the components. There's no optimal strategy to solve this issue. Initializing the components using K-means was used in this study.

## *5.2 Result*

For GMM in multivariate case, four different structures of covariance matrix were compared in this study:

- **spherical** Each component has its own single variance $\sigma_k^2$, the covariance matrix is formed as $\sigma_k^2 I$

- **diag** Each component has its own diagonal covariance matrix

- **tied** All components share the same covariance matrix, denoted as $\Sigma$

- **full** Each component has its own general covariance matrix, denoted as $\Sigma_k$

  From Figure 5.1, the model with 2 components and full covariance, which indicates that Each component has its own general covariance matrix, is optimal.

The participants were clustered into two groups: cluster 0 with 13 participants, cluster with 9 participants. The summary statistics of these two clusters are summarized as Table 5.2.

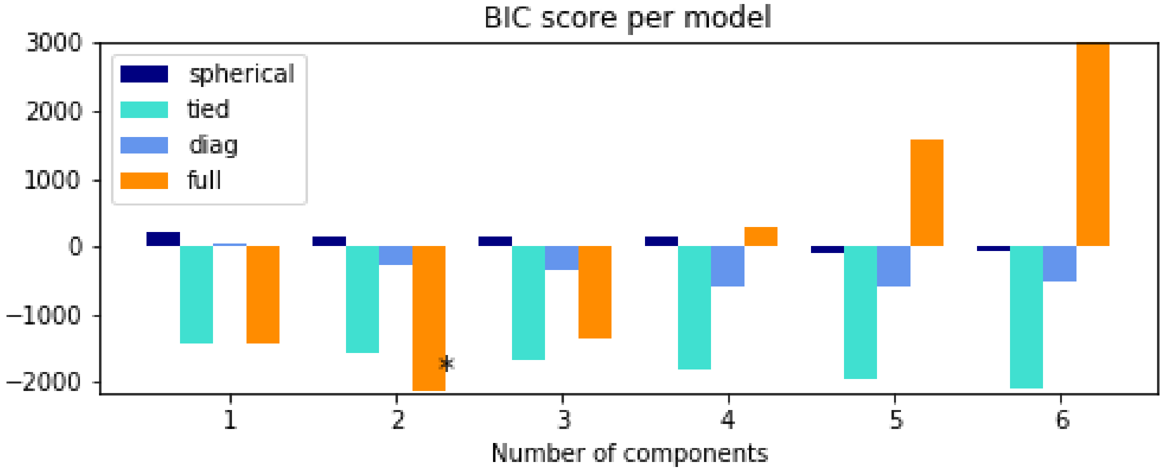
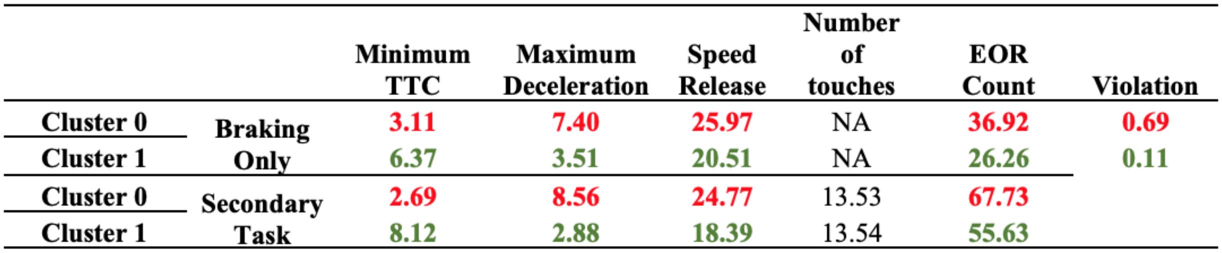
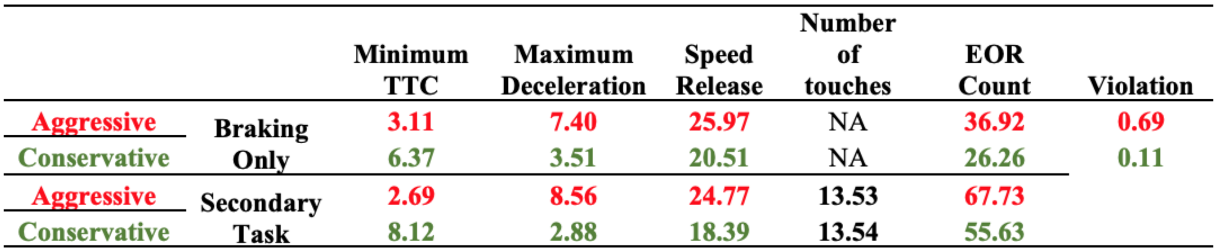


Figure 5.1: BIC score for GMM model selection



| | | Minimum TTC | Maximum Deceleration | Speed Release | Number of touches | EOR Count | Violation |
|---|---|---|---|---|---|---|---|
| **Cluster 0** | **Braking Only** | **3.11** | **7.40** | **25.97** | NA | **36.92** | **0.69** |
| **Cluster 1** | | **6.37** | **3.51** | **20.51** | NA | **26.26** | **0.11** |
| **Cluster 0** | **Secondary Task** | **2.69** | **8.56** | **24.77** | 13.53 | **67.73** | |
| **Cluster 1** | | **8.12** | **2.88** | **18.39** | 13.54 | **55.63** | |

Figure 5.2: Summary statistics of two driving style clusters



| | | Minimum TTC | Maximum Deceleration | Speed Release | Number of touches | EOR Count | Violation |
|---|---|---|---|---|---|---|---|
| **Aggressive** | **Braking Only** | **3.11** | **7.40** | **25.97** | NA | **36.92** | **0.69** |
| **Conservative** | | **6.37** | **3.51** | **20.51** | NA | **26.26** | **0.11** |
| **Aggressive** | **Secondary Task** | **2.69** | **8.56** | **24.77** | **13.53** | **67.73** | |
| **Conservative** | | **8.12** | **2.88** | **18.39** | **13.54** | **55.63** | |

Figure 5.3: Summary statistics of two driving style clusters: aggressive and conservative

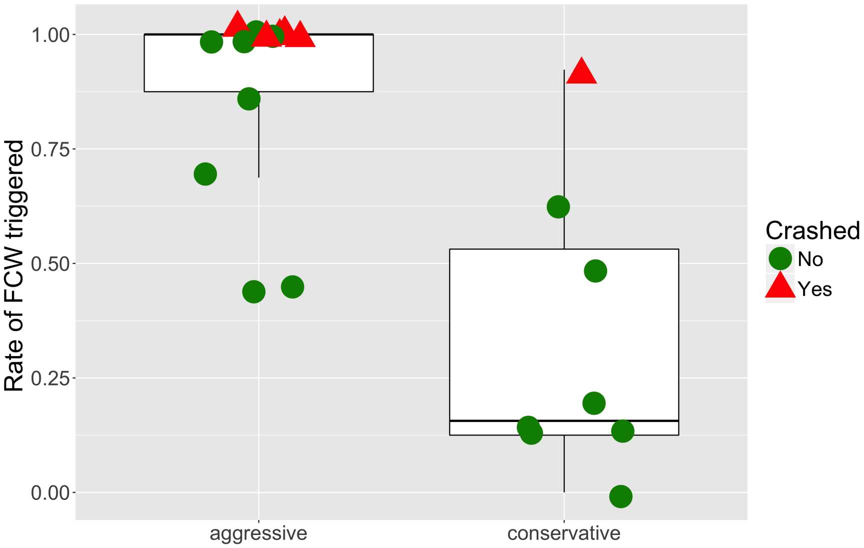
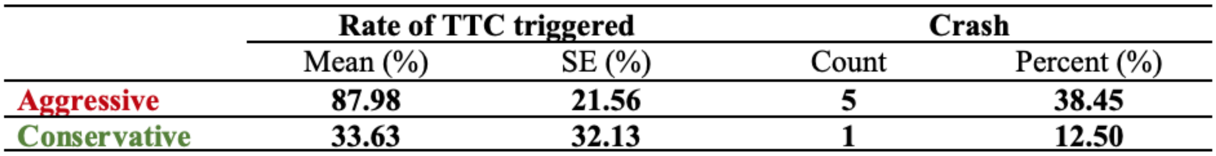


Figure 5.4: Rates of TTC triggered for drivers with different driving styles



| | Rate of TTC triggered | | Crash | |
|---|---|---|---|---|
| | Mean (%) | SE (%) | Count | Percent (%) |
| **Aggressive** | **87.98** | **21.56** | **5** | **38.45** |
| **Conservative** | **33.63** | **32.13** | **1** | **12.50** |

Figure 5.5: Rates of TTC triggered for two driving style clusters: aggressive and conservative

## *5.3 Discussion*

By comparing the summary statistics of these two clusters, two types of driving styles were identified: aggressive and conservative. The two different driving styles were discussed in terms of the seven metrics.

- **Minimum TTC** Minimum TTC is defined as the shortest TTC during a braking event if the participant continues at the current speed in the same path. Larger minimum TTC indicates a safer situation. In general, the average minimum TTC for aggressive drivers is smaller compared with conservative drivers under both no secondary and secondary task situations. When engaged with the secondary task, the minimum TTC for aggressive drivers slightly decreased from 3.11 seconds to 2.69 seconds, while the conservative drivers increased the minimum TTC from 6.37 seconds to 8.12 seconds. This may indicate the different attitudes of engaging with the secondary task for drivers with different driving styles. Aggressive drivers could not maintain the safe minimum TTC when engaged in the secondary task, while conservative drivers stay more cautious and keep larger minimum TTC when distracted by the secondary task.

- **Maximum deceleration** Maximum deceleration, in $m/s^2$, is the maximum deceleration value during a braking event. High maximum deceleration is usually associated with severe braking, which increases the probability of having collision (Lee et al., 2002). Aggressive drivers have higher maximum deceleration values than conservative drivers. Especially when engaged with the secondary task, aggressive drivers had on average 8.56 $m/s^2$ maximum deceleration, while conservative drivers only had $2.88m/s^2$.

- **Speed release)** Speed Release (speed when releasing the accelerator pedal) is the initial speed when the driver releases the accelerator. It reflects the driver's ability of perspective risk management when following a lead vehicle. Aggressive drivers had higher speed at accelerator release, 25.97 $m/s$ and $24.77m/s$, under no secondary task and secondary task respectively. Both aggressive and conservative drivers reduced the speed release when interacting with the In-vehicle Information System (IVIS).

- **Number of touches to display** Number of touches to display is the total number of touchscreen operations per trial. It measures the manual distraction of secondary task. The larger number of touches to display, the more drivers were manually distracted. There is no difference in this metric among aggressive and conservative drivers.

- **Count of EOR** Count of Eye-off-road (EOR) accounts for the total number of eye glances on the touchscreen per trial. It is used to evaluate the level of visual distraction. Aggressive drivers had EOR more frequently than conservative drivers did within a trial.

- **Violation frequency** Violation Frequency measures the number of moving violations in the past three years. Aggressive driving style cluster has a higher value of violation frequency compared to conservative driving cluster.

- **Rate of TTC triggered** FCW alert is triggered once the TTC is less than 5 seconds.

The average rates of FCW triggered for aggressive and conservative drivers are 87.98% and 33.63%, respectively (See Figure 5.5) Besides, as observed in Figure 5.4, drivers with high rate of FCW triggered were more likely to have collision in the experiment.

Overall, participants from aggressive driving style cluster had smaller Minimum TTC, higher maximum deceleration, higher speed at accelerator release, and larger count of EOR. Furthermore, speed at accelerator release is negatively associated with minimum TTC: the higher speed at accelerator release, the smaller minimum TTC is. As aggressive drivers tend to maintain a higher speed, they had to experience severe braking situation and have higher crash risk due to the smaller minimum TTC. Aggressive and conservative drivers developed different safety compensation when engaging with the secondary task. Conservative drivers tended to have larger minimum TTC when distracted by the secondary task, while aggressive drivers were generally incapable of maintaining safe minimum TTC.

## Chapter 6

# DRIVERS ADAPTATION TO THE FCW SYSTEM BASED ON THE DRIVING STYLES

This chapter aims to study the driver's adaptation to the FCW system on different driving styles(aggressive and conservative) through Generalized Linear Mixed Model (GLMM). Unlike the previous research, driver's adaptation to ADAS system is discussed mainly based on driver characteristics (e.g., age, gender) and driving experience, this chapter aims to evaluate the driver's adaptation to an FCW system based on driving styles from three aspects: initial reaction, distraction, and safety benefits. Data collected from the driving simulator study under both FCW on and off conditions is used.

## *6.1 Methodology*

### *6.1.1 Explanatory variables*

- **Driving styles**: Aggressive and conservative driving styles. This feature is achieved by Chapter 5.

- **Assistance condition**: It has two levels: FCW is on and FCW is off.

- **Secondary task condition**: It has two levels: no secondary task condition and secondary task condition.

- **Triggered warning**: Once the TTC is lower than 5 seconds, participants received an auditory FCW alert from the system.

- **Trial number**: Trial number ranges from 1 to 8. It represents the driver's time exposure to the FCW system.

### *6.1.2 Dependent variables*

- **Accelerator Release Time (ART)**: Accelerator release time, in seconds, is defined as the time between the onset of the lead vehicle braking and the time that participant release the accelerator (See Figure 4.1). This is a direct measure of initial reaction from the participant in the braking event.

- **Accelerator-to-brake transition time**: Accelerator-to-brake transition time defines the duration starting from accelerator release to stepping on the brake pedal.

- **Number of touches to display**: The total number of touch operations to the mini-display when drivers were engaged with the secondary task.

- **Minimum TTC**: Minimum TTC, in seconds, is defined as the shortest TTC during a braking event if the participant continue at the current speed in the same path (See Figure 4.3).

- **mean Eye-off-road, mean EOR**: Mean EOR is the average glance duration per task (Equation 4.4).

### *6.1.3 Generalized Linear Mixed Model*

**Generalized linear mixed model** (GLMM) is proposed to study the association between the independent variables and dependent variables.

GLMM is an extension to the generalized linear model (GLM) in which the linear predictor contains random effects in addition to the usual fixed effects (Breslow and Clayton, 1993). It has been widely used in different statistical modeling problems, especially useful to handle a wide range of response distributions and a wide range of scenarios where observations have been sampled in groups rather than entirely independently.

The general form of the model (in matrix notation) is:

$$Y = X\beta + Z\gamma + \epsilon \tag{6.1}$$

Where $Y$ is a $N \times 1$ column vector, the response variable; $X$ is a $N \times p$ matrix of the $p$ predictor variables; $\beta$ is a $p \times 1$ column vector of the fixed-effects regression coefficients; $Z$ is the $N \times q$ design matrix for the $q$ random effects (the random complement to the fixed $X$); $\gamma$ is a $q \times 1$ vector of the random effects; and $\epsilon$ is a $N \times 1$ column vector of the errors, which is the part that is not explained by the model.

There are several reasons to consider GLMM for analyzing the relationships between explanatory variables and dependent variables .

- Driving performance is usually evaluated from a study with a fixed sample of subjects. Simply relying on the limited sample, it's not legitimately to conclude by treating factors as fixed effects, unless the whole population has been studied.

- Modeling fixed effects without considering potential random effects is inappropriate, which makes it impossible to derive conclusions about fixed effects. Because ignoring random effects causes the over-estimate of fixed effects variation, the large variation without regularization can be incorrectly interpreted and attributed to a subject.

- GLMM is more flexible compared to classic ANOVA approach, as it can handle non-Gaussian responses and complex grouping structures. Besides, it can also deal with the missing data problem, which is the prevalent issue in data collection of human behavior related information, while the traditional models may not.

GLMM will be used to assess the driving performance outcomes (e.g., Minimum TTC) and reaction time (e.g., Accelerator-to-brake transition time) given varying driving tasks and road scenarios. It can detect the significant factors that impact responses as well as accounting for the randomness among different subject groups, such as within individuals, within age groups, within gender (Donmez et al., 2007; Peng et al., 2014).

## *6.2 Result*

All model parameters were estimated using maximum likelihood and assessed at a significance level of 0.05. Significant variables were set in bold font. All data analysis and data visualization were conducted in R (version 3.3.2). The linear mixed effects model was fitted using the R package *lme4* (version 1.1-12), parameters in the model were tested using the package *lmerTest* (version 3.0-1).

### *6.2.1 Under FCW on condition*

**Accelerator Release Time (ART)** From Table 6.1 and Figure 6.1, there was no significantly difference of Accelerator Release Time (ART) between FCW on and FCW off conditions. While conservative drivers released the accelerator faster than aggressive drivers by 0.61 second (p−value = 0.02), which confirms with the difference of risk anticipation between these two groups. Besides, the accelerator release time decreased by 0.06 second (p−value = 0.03). As braking event was repeated multiple times, driving performance in terms of accelerator release time improved as participants had more exposure in this experiment.

| **Variable** | **Estimate** | **SE** | **t-statistics** | **p-value** | **95% CI** |
|---|---|---|---|---|---|
| (Intercept) | 2.31 | 0.17 | 13.21 | <0.00 | (1.96 , 2.65) |
| reference: Aggressive | - | - | - | - | - |
| **Conservative** | -0.61 | 0.27 | -2.25 | 0.02 | (-1.14 , -0.08) |
| **Trial Number** | -0.06 | 0.03 | -2.13 | 0.03 | (-0.10 , -0.00) |
| reference: FCW off | - | - | - | - | - |
| FCW on | -0.02 | 0.09 | -0.22 | 0.82 | (-0.20 , 0.16) |
| reference: Aggressive × Trial Number | - | - | - | - | - |
| Conservative × Trial Number | -0.06 | 0.04 | -1.53 | 0.13 | (-0.14 , 0.02) |

Table 6.1: Generalized Linear Mixed Model on Accelerator Release Time (ART)

**Accelerator to Brake Transition Time** Under FCW on condition, the accelerator to brake transition time increased by 0.53 second (p-value < 0.001). The mismatch of the

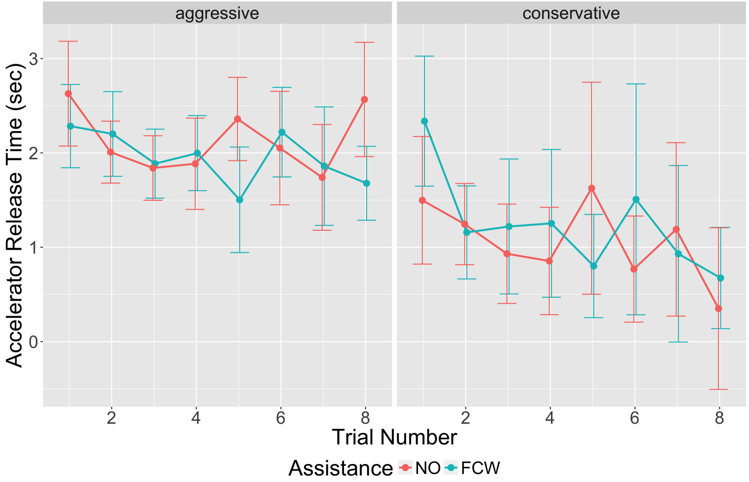


Figure 6.1: ART decreased as participants had more exposure in the experiment

actual FCW warning and the driver's expectation of FCW warning may cause the longer accelerator to brake transition time. As FCW is not triggered as expected, participants were hesitated and thus delayed stepping on the brake pedal. As trial number increased, the accelerator to brake transition time reduced gradually by 0.06 second, as the participants either gradually adapted their expectation for the FCW warning or became more cautious. Details can be referred in Figure 6.2 and Table 6.2.

**Number of touches to display** The relation between the number of touches to display and explanatory variables is analyzed by using generalized linear model with negative binomial regression, as negative biomial regression is for count variables, especially over-dispersed response variables.

Under FCW on condition, the number of touches to display generally reduced by 0.34 (p-value $< 0.001$) (see Table 6.3 and Figure 6.4). While no difference in terms of number of touches to display was observed between aggressive and conservative drivers.

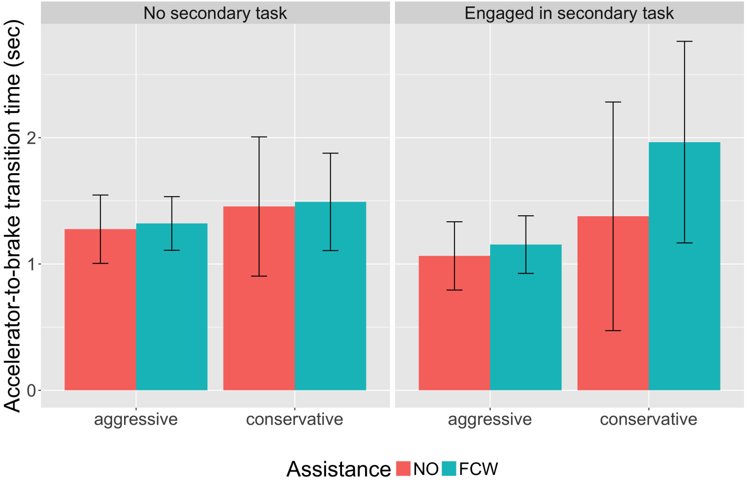


Figure 6.2: FCW increased the time that drivers stepped on the brake pedal.

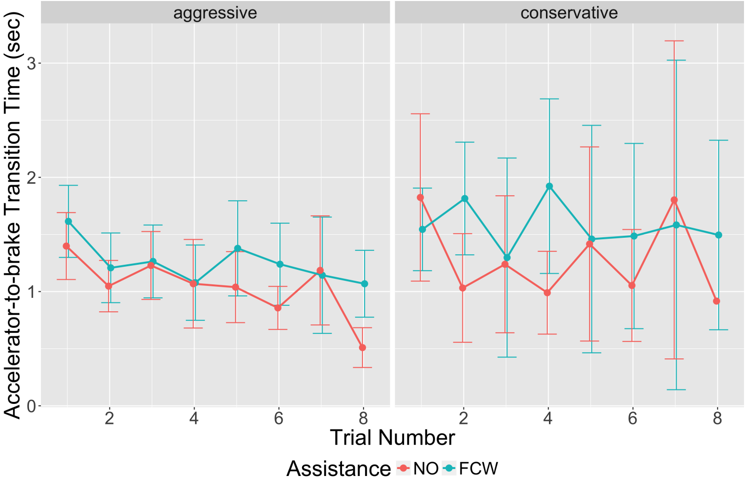


Figure 6.3: FCW increased the time that drivers stepped on the brake pedal over time

| **Variable** | **Estimate** | **SE** | **t-statistics** | **p-value** | **95% CI** |
|---:|---:|---:|---:|---:|---:|
| (Intercept) | 1.36 | 0.14 | 9.83 | 0.00 | (1.09 , 1.63) |
| reference: Aggressive | - | - | - | - | - |
| Conservative | 0.32 | 0.20 | 1.57 | 0.12 | (-0.08 , 0.71) |
| **Trial Number** | -0.06 | 0.01 | -3.73 | <0.001 | (-0.09 , -0.03) |
| reference: FCW off | - | - | - | - | - |
| **FCW on** | 0.53 | 0.12 | 4.29 | <0.001 | (0.29 , 0.78) |
| reference: FCW × Alert False | - | - | - | - | - |
| **FCW × Alert True** | -0.47 | 0.13 | -3.64 | < 0.001 | (-0.71 , -0.21) |

Table 6.2: Linear Mixed Model for Accelerator to Brake Transition Time

| **Variable** | **Estimate** | **SE** | **z-statistics** | **p-value** |
|---:|---:|---:|---:|---:|
| (Intercept) | 2.62 | 0.04 | 60.93 | <0.001 |
| reference: Aggressive | - | - | - | - |
| Conservative | 0.004 | 0.05 | 0.09 | 0.93 |
| reference: FCW × Alert False | - | - | - | - |
| **FCW on** | -0.34 | 0.06 | -5.25 | <0.001 |
| reference: FCW × Alert False | - | - | - | - |
| **FCW × Alert True** | 0.32 | 0.07 | 4.34 | <0.001 |

Table 6.3: Generalized linear model with negative binomial regression for number of touches to display

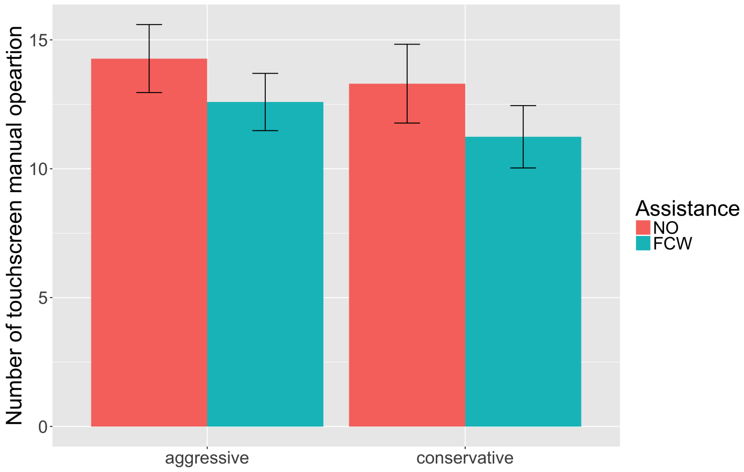


Figure 6.4: The frequency of manual distraction is reduced under FCW condition

### Mean EOR

Mean EOR was not significantly associated with driving styles and FCW condition (see Table 6.4). Under FCW on condition, mean EOR generally reduced by 0.15 second. Besides, conservative drivers had smaller mean EOR compared with aggressive driver, which is consistent with Chapter 5.

| | Estimate | SE | t-statistics | p-value | 95 % CI |
|---|---|---|---|---|---|
| (Intercept) | 2.60 | 1.70 | 1.53 | 0.12 | (-0.72 , 5.93) |
| reference: Aggressive | - | - | - | - | - |
| Conservative | -1.99 | 2.65 | -0.75 | 0.45 | (-7.18 , 3.19) |
| reference: FCW off | - | - | - | - | - |
| FCW on | -0.15 | 0.76 | -0.20 | 0.84 | (-1.65 , 1.34) |

Table 6.4: Liner Mixed Model for Mean Eye-off-road during the secondary task

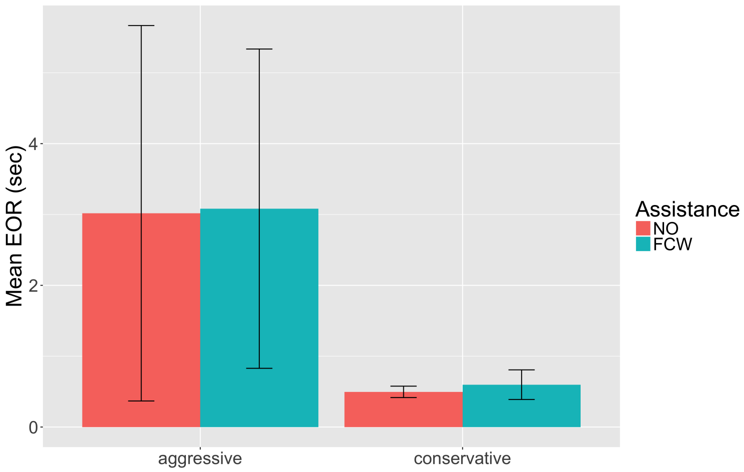


Figure 6.5: FCW condition did not significantly impact the average duration of EOR (sec) during the secondary task

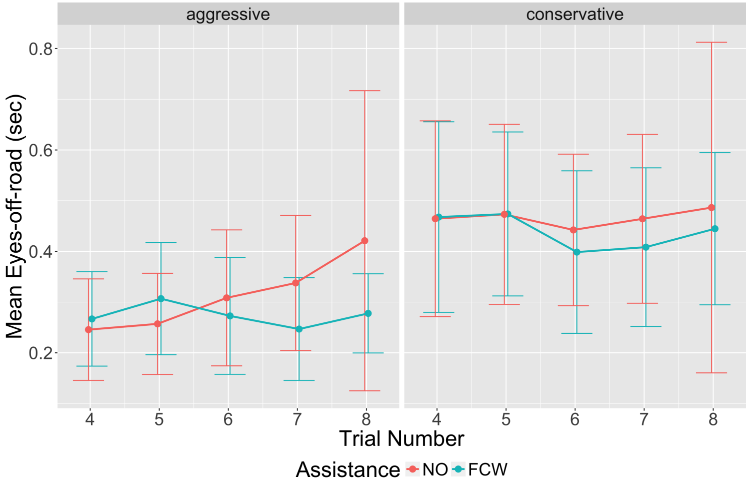


Figure 6.6: Average duration of EOR (sec) under FCW on condition reduced over time

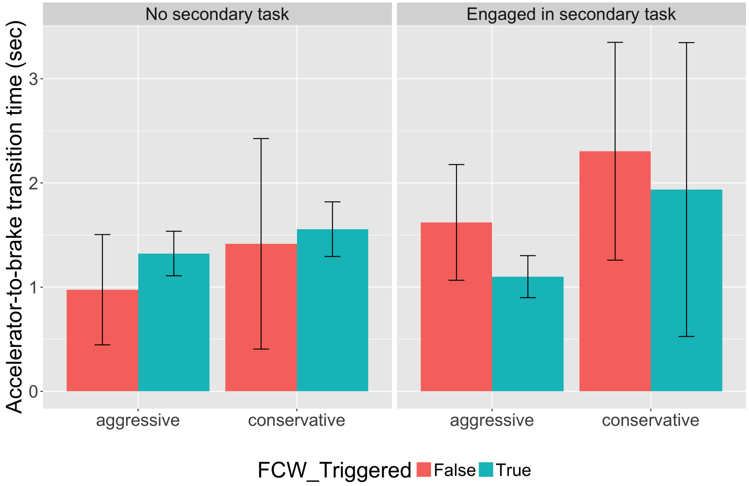


Figure 6.7: When the FCW warning is triggered, accelerator-to-brake transition time decreased.

### *6.2.2 When FCW is triggered*

Under FCW condition, it's also important to look into the driver's behavior specifically when FCW alert is triggered. It helps us understanding under what situation the FCW alert is triggered.

**Accelerator to brake transition time**

Table 6.2 showed that the accelerator to brake transition time decreased by 0.47 second (p-value $< 0.001$) as the FCW warning is triggered, but the accelerator to brake transition time was higher than FCW off condition by 0.06(=0.53-0.47) second. This indicates the immediate benefit of auditory FCW alert, as it could notify drivers of the current driving status and remind them to return to driving task immediately. However, drivers was not able to stay vigilance with the assistance of FCW system as they generally did without any assistance.

| | Estimate | SE | t-statistics | p-value | 95% CI |
|---:|---:|---:|---:|---:|---:|
| (Intercept) | 13.54 | 0.91 | 14.89 | $< 0.001$ | (11.75 , 15.32) |
| reference: Aggressive | - | - | - | - | - |
| **Conservative** | 1.42 | 0.44 | 3.25 | $< 0.001$ | (0.56 , 2.27) |
| reference: Alert False | - | - | - | - | - |
| **Alert True** | -0.83 | 0.38 | -2.17 | 0.03 | (-1.57 , -0.08) |
| **Trial Number** | 0.38 | 0.10 | 3.60 | $< 0.001$ | (0.17 , 0.58) |
| reference: FCW off | - | - | - | - | - |
| **FCW on** | 1.51 | 0.53 | 2.85 | $< 0.001$ | (0.47 , 2.56) |
| reference: Secondary task No | - | - | - | - | - |
| **Secondary task Yes** | -1.44 | 0.39 | -3.67 | $< 0.001$ | (-2.21 , -0.67) |
| **Speed at accelerator release** | -0.44 | 0.03 | -14.57 | $< 0.001$ | (-0.50 , -0.38) |
| reference: Conservative × Alert False | - | - | - | - | - |
| **Conservative × Alert True** | -1.69 | 0.55 | -3.07 | $< 0.001$ | (-2.77 , -0.61) |
| reference: FCW off × Trial Number | - | - | - | - | - |
| **FCW on × Trial Number** | -0.25 | 0.09 | -2.65 | 0.01 | (-0.43 , -0.07) |

Table 6.5: Generalized Linear Mixed Model for minimum TTC

**Minimum TTC** Minimum TTC is an important metric for evaluating safety benefits of ADAS. Higher Minimum TTC indicates lower risk of having collision (Donmez et al., 2007). It also negatively associated with the speed at accelerator release, which was confirmed by

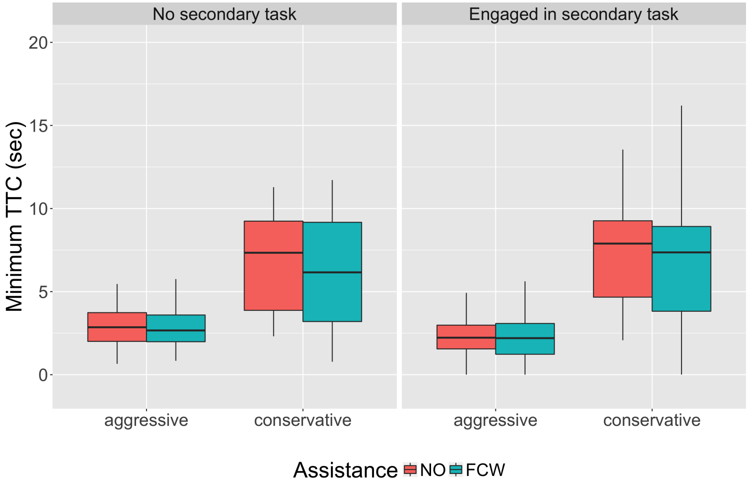


Figure 6.8: When the warning was triggered, it decreased the minimum TTC of conservative drivers.

Table 6.5. Higher speed release leads to lower minimum TTC. Compared with aggressive drivers, conservative drivers tend to have a larger minimum TTC under no FCW condition by 1.42 ($p$-value$< 0.001$), which indicates relatively safe. However, conservative drivers greatly reduced their minimum TTC by 1.69 seconds ($p$-value $<0.001$) when the FCW is triggered. Besides, when the drivers were engaged with the secondary tasks, the minimum TTC was reduced by 1.44 seconds ($p$-value $< 0.001$), it demonstrated the necessity of intervene from the driver assistance system. Last but not the least, as the drivers has more exposure to the system – trial number increases, the minimum TTC also increased by 0.38 second ($p$-value $< 0.001$), while under FCW is on condition, the minimum TTC increased by 1.26(=1.51-0.25) seconds at the first trial, gradually decreased by 0.25 ($p$-value $= 0.01$).

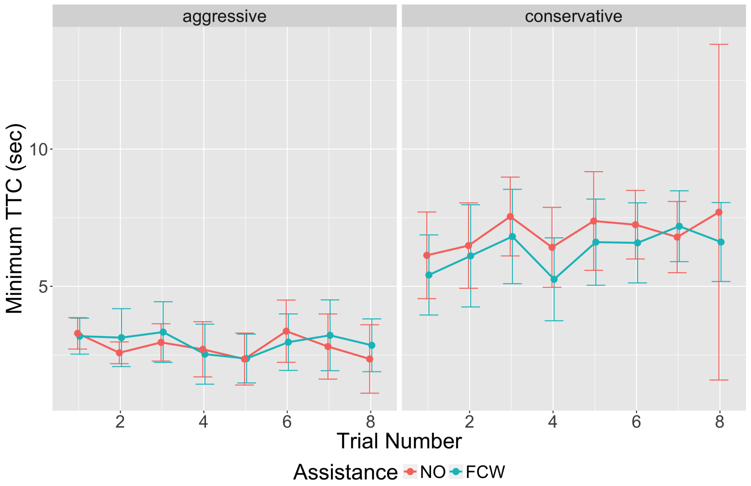


Figure 6.9: Minimum TTC for conservative drivers gradually increased over time

## *6.3 Discussion*

GLMM and GLM with negative binomial distribution were applied to evaluate the impacts of driving style, FCW condition, time exposure on dependent variables from three perspectives: initial reaction, distraction, and safety benefits.

- **Driving Styles**: As mentioned in Chapter 5, participants from aggressive driving style cluster had smaller Minimum TTC, higher maximum deceleration, higher speed at accelerator release, and larger count of EOR. Similar conclusions still apply when aggressive drivers drove under FCW condition. However, conservative drivers reacted to FCW differently. FCW condition increased the accelerator-to-brake transition time for conservative drivers, this may due to the mismatch of the expectation of FCW warning timing so that conservative drivers were hesitate and delayed stepping on the brake pedal.

- **FCW alert is triggered** The FCW alert is triggered once TTC is lower than 5 seconds. When FCW alert is not triggered, mismatch of the expectation of the warning cue caused drivers, especially conservative drivers, degenerate their initial reaction. When FCW alert was issued, drivers were aware of the severity of the driving situation, the release-to-brake transition time was largely reduced. It also greatly reduced the driver's distraction level. Drivers paused the engagement of secondary task visually and manually. However, the triggered FCW alert might not bring safety benefits for drivers, especially for the conservative drivers. Conservative drivers had reduced the minimum TTC when FCW alert is triggered.

- **Distraction**: The engagement of the secondary task largely reduced the minimum TTC, indicating the increased potential of having a collision. As discussed in many previous literature, engaging with the IVIS or cell phone usage is a main contributing factor for increasing on-road crash risk (Rakauskas et al., 2004; Fitch et al., 2013). Furthermore, under FCW on condition, drivers generally reduced visual and manual distraction through analyzing Mean EOR and number of touches to display.

- **Time exposure**: Over time, drivers become more familiar with the driving tasks and FCW system. Their driving performance also showed improvement. As they gain more experience, the driver's accelerator release time decreased (see Figure 6.1), and release-to-brake transition time decreased (see Figure 6.3), suggesting improvemenst over time. Further, the average Eyes-off-road (EOR) under FCW on condition also decreased over time (see Figure 6.6). In the first two trials with secondary tasks, aggressive drivers had higher average EOR with FCW, while conservative drivers had similar average EOR for both FCW on and off. However, starting from the third trial, both aggressive and conservative drivers had lower average EOR under FCW condition. Although the effect of FCW is not statistically significant in this current study, there is a trend that suggests that FCW could reduce visual distractions over time. The minimum TTC increased as the number of trials increased under FCW off condition (see Figure 6.9). Drivers were shown to gradually adapt to the braking task by driving more cautiously. However, the minimum TTC under FCW on condition was larger in the first trial, indicating a safety benefit with FCW. As the number of trials increased, the drivers gradually reduced the minimum TTC as they built up trust in the system. They also appeared to rely more on the FCW.In summary, as participants had more exposure to the system, they gradually adapted their expectation for the FCW warning and performed better.

## Chapter 7

# LEARN THE DRIVER'S UNDERLYING PREFERENCE GIVEN SIMULATOR DATA

The objective in this chapter is to understand driver behavior when interacting with the vehicle from a perception-decision-action perspective. Driving preference is learned as a reward function given observed time-series data by applying Inverse Reinforcement Learning.

Driving performance, physiologic metrics and cognitive performance can be explicitly measured, while human operators underlying preference and decisions are not visible, but this information plays an essential role on designing adaptive driving assistance system.

For example, in order to make old drivers to recognize and understand the task information quickly , different types of modalities can be to provide them the most suitable one to reduce distraction Lees et al. (2012). In car-following case, vehicle acceleration information can be observed and tracked, while drivers' intention for acceleration, deceleration and doing-nothing are not observable. The understanding and accurate prediction of the driver's intentions to brake will improve the design of warning systems (Wang et al., 2018; Aoude et al., 2012).

Underlying driver states and intentions can be represented in different ways. Driving style is the blueprint of drivers, which affects their driving behavior and driving trip choice. Hong et al. (2014) assessed different driving style based on collecting real-time data from smartphone sensors, which can provide real-time driver feedback to guide drivers to reduce aggressive driving behaviors. Driving routine preference reflects how they accomplish the purposeful repetitive tasks, such as how they drive through an intersection. (Aoude et al., 2012).

Drivers' states and intentions change over time, usually current states are not independent of previous states. Besides, when drivers are deeply engaged with secondary tasks, it's hard for them to dramatically disengage from secondary tasks and be fully ready for taking over a critical situation. Therefore,

This chapter aims to use real-time eye glance data to capture the driver's attention while driving. Vehicle kinematic data (i.e., relative speed and relative distance) and attention status were used to learn driving preference under car-following scenario. The data collected from the driving simulator study under FCW off condition was utilized.

## *7.1 Methodology*

### *7.1.1 Features definition*

- **Relative Distance**: Relative distance, in $m$, measures the distance between the lead vehicle and the host vehicle. The smaller relative distance is, the more emergent the braking event is.

- **Relative Speed**: Relative speed, in $m/s^2$, is defined as the speed difference between the host vehicle and the lead vehicle. The positive value means that the host vehicle travels faster than the lead vehicle, negative value indicates that the host vehicle is slower.

- **Distraction (Yes/No)**: Distraction status indicates if the driver is distracted away from primary driving task or not. This feature is identified by the eye glance data. If the driver has Eye-off-road, distraction status is set to be 1, otherwise 0.

- **Brake Action (Yes/No)**: Driver's braking action is defined based on "Brake Force" value with the cut-off value 18 pound, as the maximum brake force value in this driving simulator is 180 pounds. If the brake force is greater than 18 pound, braking action is set to be 1, otherwise 0.

### *7.1.2 Reinforcement learning*

Reinforcement learning is a type of human-centered machine learning that is influenced by behaviorist psychology. It is concerned with how agents ought to take action in an environment to maximize some cumulative reward (Sutton and Barto, 1998).

In car-following scenario (see Figure 7.1), the drivers precept what's going on from the outside environment, they made decisions based on their driving preferences, which are formed by long time driving experience and impacted by many factors, then the drivers take actions following their decisions.

A basic reinforcement learning model is the Markov Decision Process (MDP). MDP is particularly well suited for modeling driving performance because it explicitly models the individual's context, the actions that can be performed in that context, and the preferences people have for different actions in different contexts. A Markov decision process can be formalized as a tuple:

$$\mathcal{M}_{MDP} = (S, A, P(s^{'}|s,a), R(s,a), \gamma) \tag{7.1}$$

- $S$: a set of states $S(s \in S)$ represents all driving context(e.g. driver characteristics, driver workload, driving scenarios)
- $A$: action states set $A(a \in A)$ contains all the possible actions (e.g., braking) that agent can take.
- $P(s^{'}|s,a)$:$P(s^{'}|s,a)$ is the action dependent probability that describes the probability of next state $s^{'}$ when agent performs action $a$ in state $s$.
- $R(s,a)$:reward function $R(s,a)$ specifies the unity that driver get from performing action $a$ in state $s$.
- $\gamma$: $\gamma \in [0,1]$ is the discount factor, which represents the difference in importance of future rewards and present rewards.
- $\pi(s)$: policy from agent $\pi(s)$ specified the action $\pi(s)$that it will choose at state $s$. Finding the optimal policy is the key problem in learning MDP. The goal is to choose a policy $\pi(s)$ that can maximize the cumulative rewards, specifically a discounted sum over all horizon:

  $$\sum_{t=0}^{\infty} \gamma^t R_{a_t}(s_t, s_{t+1}) \quad \text{(where we choose } \ a_t = \pi(s_t) a_t = \pi(s_t))$$

Many studies have used reinforcement learning approach to model driver behaviors and destination planning (Banovic et al., 2016; Ziebart, 2010), but it is still a relatively new concept for modeling driving behavior. Current ADAS does not support user-adaptive function. For example, FCW sends collision warning based on prefixed threshold, which may not account for various driving contexts. Besides, the development of in-vehicle sensors makes modeling driver behavior in real-time possible. Therefore, this dissertation focuses on designing adaptive Forward Collision Warning (FCW) system as a study prototype to identify the optimized moment to interrupt drivers based on the past driving performance and real-time estimation of driver states.

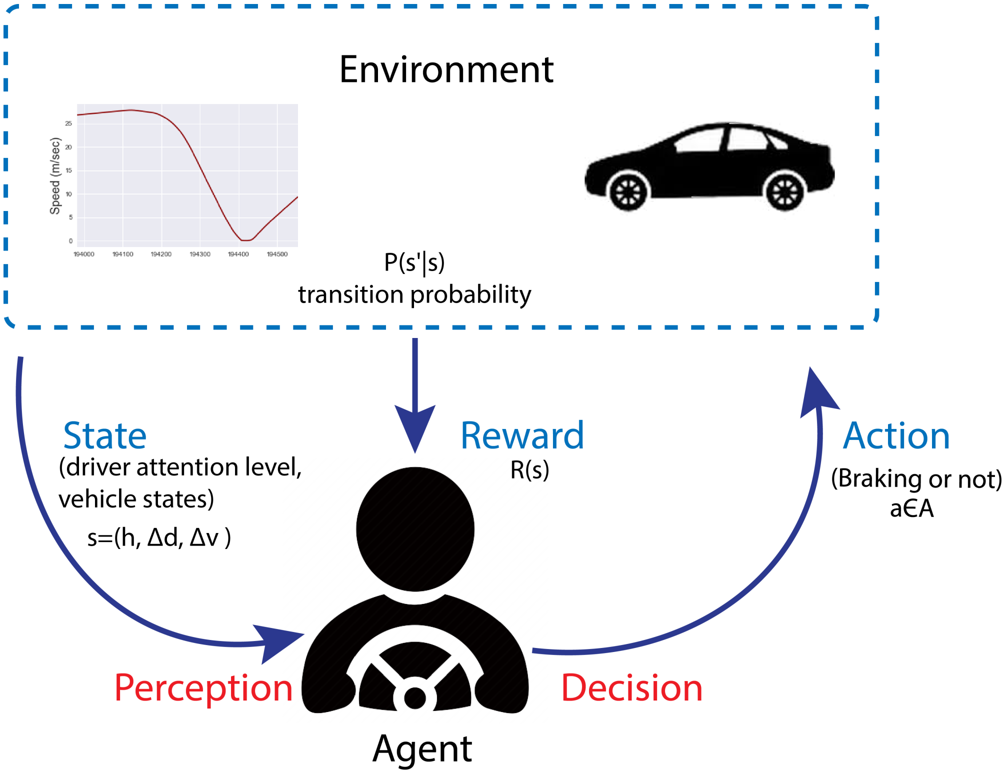


Figure 7.1: Reinforcement learning framework is used to model human-vehicle interaction. Drivers receive the vehicle state information, then choose the optimal actions by maximizing the reward.

In order to formulate FCW in an MDP framework, it is helpful to examine the full context that has been involved in driving. There are generally three components of driving context:

- **Environment**: including on-road traffic control and infrastructure and the climate conditions
- **Vehicle**: responsible for driving-related operations. Recently vehicle can collect sensor information and give drivers feedback.
- **Driver**: taking control of maneuvering, and supervisory control.

Figure 7.1 presents how to formulate driving control as a reinforcement learning framework. A driver observed the change in the state of the environment, and took actions with the purpose of maximizing the rewards. In the symbiotic system, the environment includes outside context and driving vehicle. Hence, the environment state is represented by both the human state (attention state) and the vehicle state(relative distance and the relative velocity). The driver decides when to brake. The interpretation of driver in model is equivalent to find the optimal mapping between situations (described by physical variables, such as speed, distance) and actions (warning signal).

In practice, the Markov decision process tuple in FCW will be:

- $S$: the states of the MDP are based on the context of both the driver (attention level) and the vehicle (relative distance and relative velocity), each state is a tuple $s = (h, \Delta d, \Delta v)$ where $h$ indicates human attention level (e.g., 0 represents not distracted and 1 represents distracted), $\Delta d$ denotes the relative distance between leading vehicle and driving vehicle, and $\Delta v$ denotes the relative velocity.

- $A$: action states set $A(a \in A)$ contains all the possible actions the agent can take (e.g., 0 indicates no warning, 1 indicates warning).

- $P(s^{'}|s,a)$:$P(s^{'}|s,a)$ is the action dependent probability that describes the probability of next state $s^{'}$ when agent takes $a$ in state $s$. The transition probability is assumed unknown at the beginning and it will be updated continuously during learning.

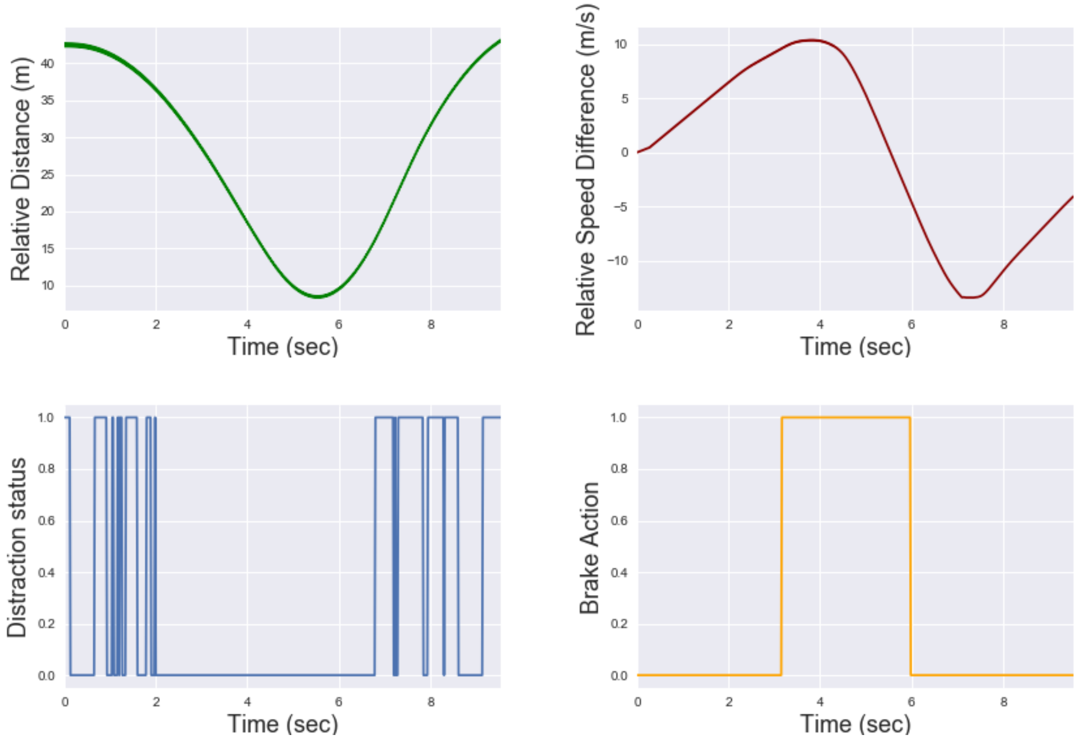


Figure 7.3: An example of time series data for a braking event

- $R(s,a)$:reward function $R(s,a)$ specifies the unity that agent get from performing action $a$ in state $s$.

- $\pi(s)$: policy from agent is mapping from situations $s = (h, \Delta d, \Delta v)$ to actions from agent(e.g. sending warning signal or not).

### *7.1.3 Time series data summary*

There are 16 braking events associated with each participant for those where no crash occurred. Figure 7.3 shows a sample of the time series for state variable, S=$(h, \Delta d, \Delta v)$ and the corresponding action time series data.

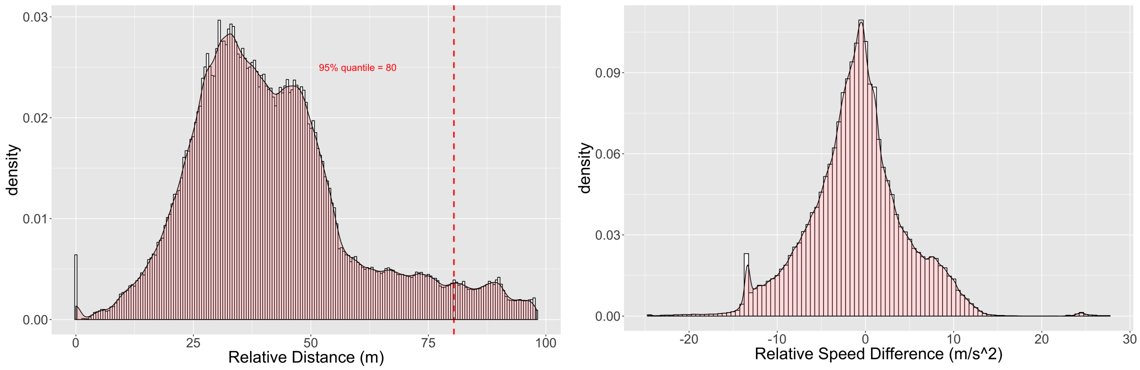


Figure 7.4: Distributions of relative distance $\Delta d$ and relative speed difference $\Delta v$ for the data

Visualization of $\Delta d, \Delta v$ was shown in Figure 7.4.

- Relative distance $\Delta d$: ranging from 0 to 1126 m.
  - The 95% quantile is 80 m
  - Extreme values were observed most likely due to simulator recording errors (about 5% of the data), these values had been bined seperately.
- Relative speed $\Delta v$: ranging from -30 to 27 $m/s$. Negative relative speed $\Delta v$ indicates the host vehicle is driving slower than the lead vehicles, positive relative speed $\Delta v$ indicates the host vehicle is driving faster.

### *7.1.4 Inverse Reinforcement Learning*

Given the states information and reward mechanism, driver behavior inference (e.g., acceleration or deceleration) is a typical reinforcement learning problem (see Figure 7.5). However, in this study, the reward mechanism of human drivers stays implicit. Designing the appropriate reward functions is a typically difficult problem. Different reward functions could impact the inference result as well as the convergence of the reinforcement learning algorithm (Kaelbling et al., 1996; Mazumder et al., 2018; Ye et al., 2018).

Through the simulator experiment, time-series data of states, including dynamic vehicle kinematics and driver distraction status was recorded. Along with state observation, the driver's behavior (e.g., acceleration, or deceleration) was also tracked. Learning the implicit reward mechanism from the time series data of states and actions is an inverse reinforcement learning problem (Abbeel and Ng, 2004) (see Figure 7.6).

Learning driver preference is assumed as a reward function $R(s)$ given some observed data. An individual driver is assumed to have a stable preference within a braking event as the average duration of a braking event is 18.68 seconds of a braking event from the collected data.

The reward function for a single state follows a linear form (see Equation 7.1.4).

$$R(s) = \sum_{i=1}^{n} \theta_i f_s^i = \vec{\theta}^T \mathbf{f}_s \tag{7.2}$$

Where $\vec{\theta} \in \mathcal{R}^n$ is reward weight vector, $\mathbf{f}_s \in \mathcal{R}^n$ is a feature vector representation of state $s$.

Therefore, the reward for the time series $\zeta = \{s_1, s_2, \ldots, s_T\}$ is defined as the sum of all the individual reward for each observed state $s_i$ (see Equation 7.1.4).

$$reward(\zeta) = \sum_{s_j \in \zeta} \vec{\theta}^T \mathbf{f}_{s_j} \tag{7.3}$$

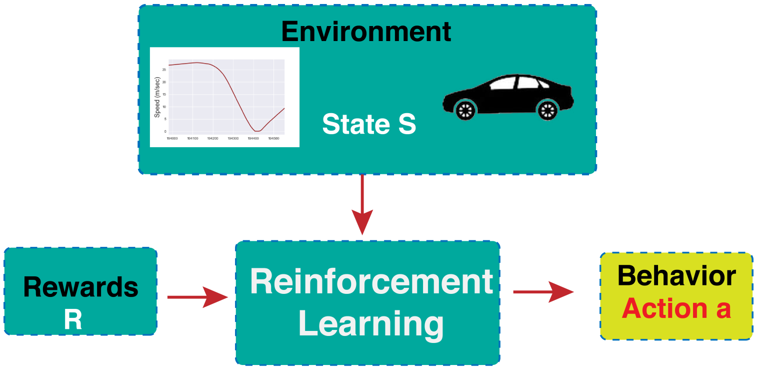


Figure 7.5: Drivers observe state $s$ and then perform action $a$ based on their preference (represented by reward mechanism $R$)

According to Maximum Entropy IRL (Ziebart, 2010), a distribution is considered over the entire class of possible behaviors (see Equation 7.4). The path with highest probability is considered as the optimal path. The optimized weight parameter $\theta^*$ is learned by maximizing the log likelihood $\ell$ (Equation 7.5). Then the reward function $R(s)$ is calculated given the estimated $\theta^*$ through Equation 7.1.4.

$$P(\zeta|\theta) = \frac{e^{-reward(\zeta|\theta)}}{\sum_{\zeta'} e^{-reward(\zeta'|\theta)}} \tag{7.4}$$

$$\begin{aligned} \theta^* &= \operatorname*{argmax}_{\theta} \ell(\theta) \\ &= \operatorname*{argmax}_{\theta} \Pi_i \frac{e^{-reward(\zeta|\theta)}}{\sum_{\zeta'} e^{-reward(\zeta'|\theta)}} \end{aligned} \tag{7.5}$$

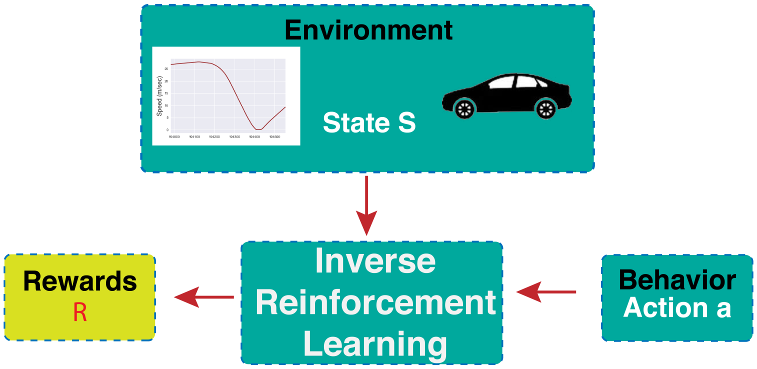


Figure 7.6: Learn the reward function $R$ from time series data collected from driving simulator

### *7.1.5 Model setup*

The simulator data collected under FCW off condition was used. The range of relative distance within a braking event is from 0 to 1126 m. Relative speed difference varies from -30 $m/s$ to 27 $m/s$. Distraction status is a binary variable, it equals to 1 when driver is distracted, otherwise 0.

- State space $S = (h, \Delta d, \Delta v)$
  - Relative distance $\Delta d$ ranging from (0, 1126) is divided into intervals $(\Delta d_1, \ldots, \Delta d_4)$, specifically
    - $\Delta d_i = [(i-1) \times 20, i \times 20)$, where $i = 1, \ldots, 4$
    - $\Delta d_5 = [80, \infty)$
  - Relative speed difference $\Delta v$ ranging from (-30, 27) is divided into intervals $(\Delta v_1, \ldots, \Delta v_5)$, specifically

    - ∗ $\Delta v_1 = [-30, 0)$
    - ∗ $\Delta v_i = [(i-2) \times 5, (i-1) \times 5)$, where $i = 2, \ldots, 4$
    - ∗ $\Delta v_5 = [15, \infty)$
  - Distraction status $h$ equals to 1 when participant has eyes off road, otherwise 0.
  - By considering all the interaction between each variable, the dimension of feature for representing a state is $50(=5 \times 5 \times 2)$.

- Action space $A = \{0, 1\}$
  - 0 indicates no brake, 1 indicates stepping on brake pedal

- 80% of the data was used as training data, the 20% of the data is hold for test.

## *7.2 Result*

The preliminary results were visualized as heatmap (Figure 7.7 and Figure 7.8). The darker color is associated with larger reward value for the state.

### *7.2.1 Aggressive drivers*

Using participant with PID 103 as an example. Under undistracted status, maintaining relative distance between $40 - 60$ m and relative speed difference between $5 - 10m/s$ is the optimal as it was assigned with the largest instant reward value (see the left picture of Figure 7.7). However, when driver is distracted, the preferable relative distance is still between $40 - 60$ m, but the relative speed difference reduced to $0 - 5m/s$.

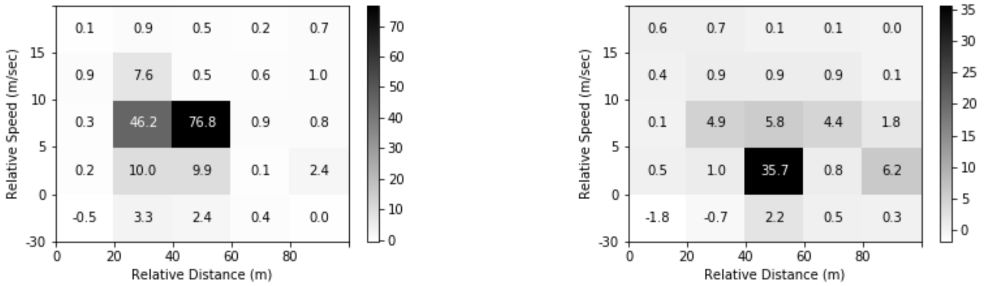


Figure 7.7: Heatmap of reward function under undistracted (left) and distracted (right) status for aggressive driver with PID 103

### *7.2.2 Conservative drivers*

Using participant with PID 120 as an example. Under undistracted status, maintaining relative distance between $40 - 60$ m and relative speed difference between $0 - 10m/s$ is the optimal as it was assigned with the largest instant reward value (see the left picture of Figure 7.8). However, when driver is distracted, the preferable relative distance is still between $40 - 60$ m, but the relative speed difference reduced to negative, which indicates that conservative drivers prefer driving slower than the lead vehicle.

## *7.3 Discussion*

- **Difference between aggressive and conservative drivers** By comparing the reward functions from aggressive and conservative drivers, these two drivers prefer maintaining similar relative distance towards the lead vehicle. Furthermore, both drivers reduced the relative speed difference when they were distracted. However, the big difference reflects the speed choice. In general, aggressive driver prefers higher rela-

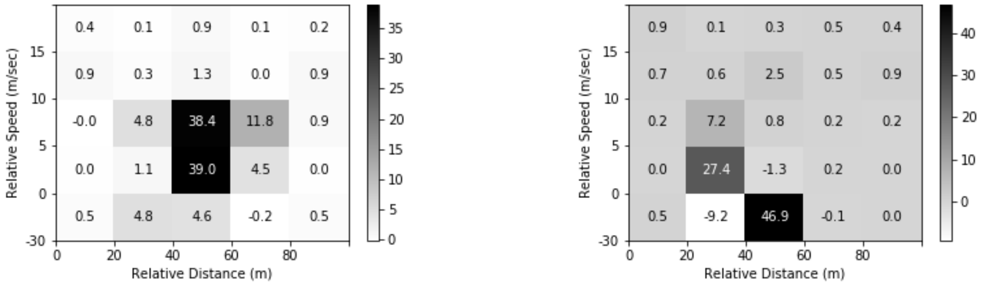


Figure 7.8: Heatmap of reward function under undistracted (left) and distracted (right) status for conservative driver with PID 120

tive speed than conservative driver at both distracted and undistracted status. When conservative drivers were distracted, they prefer compensating their speed by driving slower than the lead vehicle. This is acceptable in the driving simulator study, but it could be dangerous for the traffic flow in the daily driving situation.

- **Preferred driving state** Based on the data collected from the simulator, the range of relative distance within a braking event is from 0 to 1126 m. Relative speed difference varies from -30 $m/s$ to 27 $m/s$. The safest state is when $\Delta d$ is greater than 80 m, $\Delta v$ is less than 0 $m/s$ and driver stays undistracted status. This perfect and ideal state is not preferable among the participants attending this experiment. Previous research of developing advanced driver assistance system aims to keep drivers maintaining a safety zone; however, the assumption about safety state without considering the driver's preference impacts the satisfaction and acceptance of the system (Elmalaki et al., 2018).

- **Individual difference** As shown in Appendix A, each driver has a different preferred state under distracted and undistracted status. This individual difference could be Incorporated for designing ADAS to improve the user trust and acceptance.

# Chapter 8

# PREDICT WHEN THE DRIVER BRAKES USING UNDERLYING PREFERENCE

How to make drivers effectively respond to system warning at a critical situation is important for driving safety. Inappropriate interventions or interruptions while driving can be quite dangerous, as they can increase driver workload and degenerate primary driving task performance. Optimizing appropriate intervention time for a driver is critical for system design.

The traditional FCW system measures the time-to-collision based on the relative distance and the relative velocity of the front object. If the Time-to-Collision (TTC) is below a certain threshold, system provides an alert and displays a visual alert, prompting the driver to apply the brakes. The fixed threshold is set based on multiple experiments capturing the average population-level response and feedback. Unfortunately, making a phone call, texting, talking with passengers can cause distraction and delay the driver's response (Regan et al., 2008; Horberry et al., 2006; Lansdown et al., 2004; Hancock et al., 2003; Boyle et al., 2013). This motivates us to investigate the adaptive FCW system which adapts to individual response based on their preference, which is learned from Chapter 7.

This chapter compares the braking action timing prediction by using driving preference (from Chapter 7) with traditional TTC-based FCW system. The difference between these two mechanisms is evaluated and discussed.

## *8.1 Methodology*

### *8.1.1 Features definition*

- **Relative Distance**: Relative distance, in $m$, measures the distance between the lead vehicle and the host vehicle. The shorter relative distance is, the more emergent the braking event is.

- **Relative Speed**: Relative speed, in $m/s^2$, is defined as the speed difference between the host vehicle and the lead vehicle. The positive value means that the host vehicle travels faster than the lead vehicle, negative value indicates that the host vehicle is slower.

- **Distraction (Yes/No)**: Distraction status indicates if the driver is distracted away from primary driving task or not. This feature is identified by the eye glance data. If the driver has Eye-off-road, distraction status is set to be 1, otherwise 0.

- **Brake Action (Yes/No)**: Driver's braking action is defined based on "Brake Force" value with the cut-off value 18 pound. If the brake force is greater than 18 pound, braking action is set to be 1, otherwise 0.

### *8.1.2 Reinforcement learning*

Chapter 7 described how to formulate driving control as a reinforcement learning framework. A driver observed the change in the environment, and then took actions with the purpose of maximizing the rewards. In Chapter 7, the reward function and transition probabilities of the MDP model are calculated from the observed time series data. Q-values $Q(s,a)$ is the expected utility starting in $s$, taking action $a$. $Q(s,a)^*$ is defined as Equation 8.1.2. The expected value of $Q(s,a)^*$ can be estimated from the sampling approach, which can be updated iteratively based on Equation 8.1.2 until the algorithm converges.

The probability that the driver take action $a$ at state $s$ is denoted as $\pi(s,a)$, calcualted as Equation 8.1.2 by applying softmax over the Q-values. the Q-values for each state vary by individuals as they have different reward mechanism. The estimated probability is helpful for easily comparing the optimal state across all the individual drivers.

$$Q^*(s,a) \quad = \quad \sum_{s^{'}} P(s^{'}|s,a)(R(s,a,s^{'}) + \gamma max_{a^{'}} Q^*(s,^{'} a^{'})) \tag{8.1}$$

$$Q_{k+1}(s,a) \quad \longleftarrow \quad \sum_{s^{'}} P(s^{'}|s,a)(R(s,a,s^{'}) + \gamma max_{a^{'}} Q_k(s,^{'} a^{'})) \tag{8.2}$$

$$\pi(s,a) \quad = \quad \frac{e^{Q^*(s,a)}}{\sum_{a^{'}} e^{Q^*(s,a^{'})}} \tag{8.3}$$

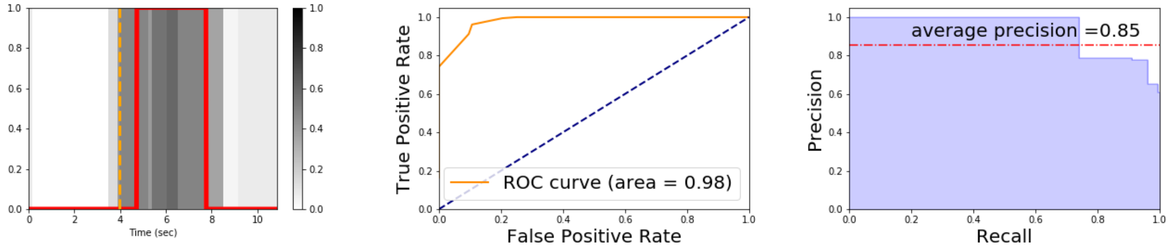


Figure 8.1: Predicted and Actual data comparison (left); ROC Curve with AUC=0.96 (middle); Precision Recall Curve with average precision = 0.85 (right)

## *8.2 Result*

Taking the participant with PID 103 as an example, the predicted and actual braking action probability is shown in Figure 8.1.

The left plot of Figure 8.1 demonstrated the probability that a driving controller (human or system) should take action over time. The darker the color is, the higher the likelihood that the operator should take braking action. The area in color gray suggests that driver should brake and reduce speed during this period. The yellow dashed line marks the earliest moment that an alert should be delivered if the controller is not taking necessary action (e.g., stepping on the brake pedal). The red lines marked the actual brake action of the participant from 4.5 seconds to 8 seconds. The period of time was covered by the predicted time for braking.

The ROC curve and Precision-Recall Curve demonstrated the potential of using individual preference to predict braking action with high precision and high sensitivity.

## *8.3 Discussion*

The result section demonstrated the technical possibility of predicting the timing when the driving controller should take braking action by incorporating the driver's preference. In order to compare and evaluate the difference between the driver's preference based algorithm and TTC-based algorithm, two examples from aggressive and conservative drivers were visualized in Figure 8.2. The suggested predicted alert timing in the dashed yellow line and the actual FCW alert cue in red. Distraction status, brake force, acceleration position, and the probability predicted by considering individual driving preference were visualized for more insights.

- **Aggressive driver** As shown in the left plot of Figure 8.2, aggressive driver brake more severely (Brake force reaches the maximum value 180 pounds) due to the late FCW alert issued by the traditional TTC based algorithm. Even though the driver detected the potential collision risk by releasing the accelerator before the FCW alert, it was still too late for taking a safe braking action. The yellow dashed line was suggested by the new algorithm, and it was issued one second before the traditional FCW alert, it may provide enough braking time for the aggressive driver without performing hard brake.

- **Conservative driver** As shown in the right plot of Figure 8.2, the conservative driver did not receive any FCW alert during the experiment, because the TTC based algorithm took this case as a safe status since the TTC value did not exceed the fixed-threshold. However, due to the lack of the FCW warning, conservative drivers were constantly engaged with the secondary task and had a high frequency of eyes-off-road for this braking event. This is dangerous for real-life driving, as drivers compensate the driving performance for constantly engaging in distraction. Ths misuse of the FCW could bring the potential risk for collision. The yellow dashed line suggested by the new algorithm could be helpful to reduce the unnecessary engagement of the secondary tasks.

Overall, the suggested braking actions based on driving preference are earlier than the original FCW alert. Due to the delay of issuing FCW alert, the aggressive driver was distracted and had to take severe brake (brake force reaches to maximum brake force value). While the conservative driver was distracted constantly during the braking event. An on-road test by comparing these two algorithms would help understanding the driving performance, user acceptance, and behavior adaptation with the assistance of these two FCW systems.

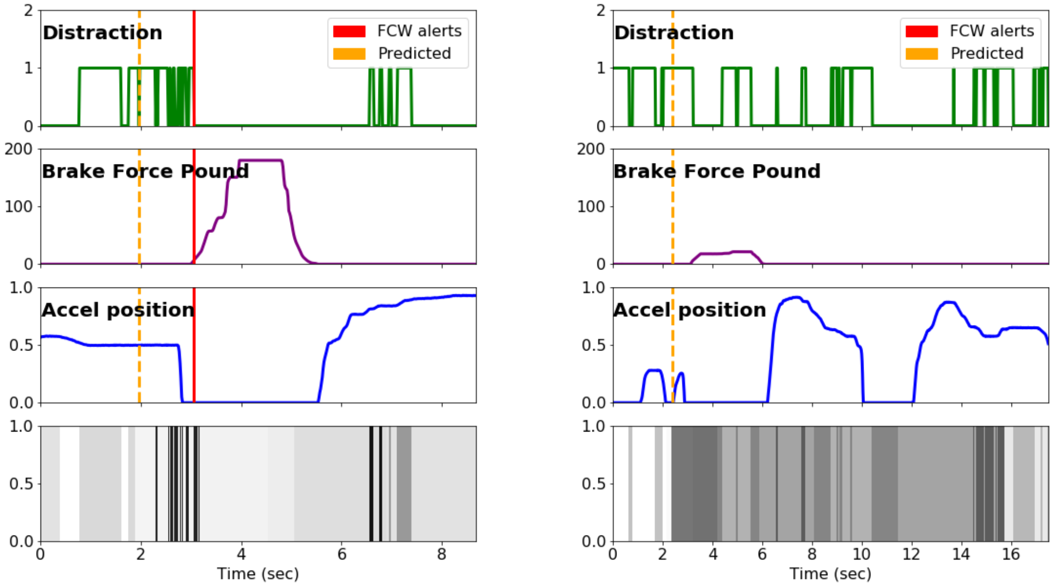


Figure 8.2: Demonstrated examples from aggressive driver (left) and conservative driver (right)

## Chapter 9

# GENERAL CONCLUSION

This chapter provides an overall summary of the findings from this dissertation, contributions, and future research.

### *9.1 Overall summary*

This goal of this dissertation is to build a novel driver behavior modeling framework to understand and predict interactions with the driver assistance system from a human-centered perspective. The FCW system was used as a study prototype to understand driver behavior and the interaction with the driver assistance system. A driving simulator study was conducted with two different FCW assistance conditions and secondary task engagement conditions. Driving styles were captured based on the data collected under FCW off condition. Driver's adaptation to the FCW system was evaluated based on the identified driving styles. Driver's braking behavior was formalized as Markov Decision Process, individual implicit driving preference towards braking behavior was represented as a reward function and learned by applying inverse reinforcement learning. The predicted braking action by considering driver preference was compared with the original FCW system. The key findings from this dissertation are summarized below:

- **Driving styles** Driving styles can be reflected in varying metrics. Four categories of features were used for capturing and identifying the difference in driving style. The four categories are driving performance, secondary task engagement, eye glance behavior, and survey. By applying Gaussian Mixture Model, 2 clusters are optimal. By comparing the summary statistics from these two groups, they were identified as aggressive and conservative groups. In general, aggressive drivers had smaller minimum TTC, larger maximum deceleration, higher speed at accelerator release, high frequency of EOR, higher violation frequency over the past years, and higher average rates of FCW triggered in the experiment.

- **Adaptation to FCW system** FCW system, as a driver assistance system, aims to raise the driver's awareness of potential rear-end crash risk and further bring safety benefits. The adaptation and interaction to the FCW system were discussed based on demographic information (e.g., gender, age) with the assumption that the driving experience and driving styles are highly associated with demographic information. Unlike the previous study, driving style identified in Chapter 5, was used to evaluate the adaption to the FCW system.

  - **Driving styles** Aggressive and conservative drivers reacted differently to the FCW system. FCW condition increased the accelerator-to-brake transition time for conservative drivers; this may due to the mismatch of the expectation of FCW warning timing so that conservative drivers delayed stepping on the brake pedal.

- **FCW alert timing** The FCW alert is triggered once TTC is lower than 5 seconds. When FCW alert is not triggered, mismatch of the expectation of the warning cue caused drivers, especially conservative drivers, degenerate their initial reaction. When FCW alert is issued, drivers were aware of the severity of the driving situation, the release-to-brake transition time was largely reduced. It also greatly reduced the driver's distraction level. Drivers paused the engagement of secondary task visually and manually. However, the triggered FCW alert might not bring safety benefits for drivers, especially for conservative drivers. Conservative drivers had reduced the minimum TTC when FCW alert is triggered.

- **Time exposure** In general, drivers were getting familiar with the driving tasks and FCW system as they had taken more trials. Their driving performance also improved. As they were getting more exposure to the experiment trials, the driver's accelerator release time decreased, release-to-brake transition time decreased, this indicated that drivers improved the initial reaction to the FCW system. Besides, the average EOR for both aggressive and conservative drivers decreased over time, it showed the trend that FCW could reduce the visual distraction over time. Furthermore, the minimum TTC also increased as the number of trials increased. Furthermore, average eyes-off-road reduced under FCW condition over time. It showed that drivers gradually received safety benefits from the FCW system. To sum up, as the participants had more exposure to the system, they gradually adapted their expectation for the FCW warning and performed better.

- **Driver preference** FCW alert timing is so critical that it leads to the different behavior adaptation to the FCW system. By formalizing the braking behavior as a Markov Decision Process (MDP), driver's preference was learned as a reward function. The visualization of reward functions reveals that the theoretical ideal state is not preferable among the participants attending this experiment. Advanced driver assistance system aims to keep drivers maintaining a safety zone; however, the inappropriate assumption about safety state without considering the driver's preference impacts the satisfaction and acceptance of the system.

- **FCW based on driving preference** Issuing the alert based on TTC does not account for individual difference. The suggested braking actions based on driving preference are earlier than the original FCW alert. The new algorithm captured the dynamics of the vehicle kinematics as well as the distraction status of the drivers. Due to the delay of issuing FCW alert based on the traditional FCW system, the aggressive driver was distracted and had to take severe brake (brake force reaches to maximum brake force value). While the conservative driver was distracted constantly during the braking event due to the failure of capturing driver attention status in the traditional FCW system. An on-road test by comparing these two algorithms would help understand the driving performance, user acceptance and behavior adaptation with the assistance of these two FCW systems.

Overall, through this dissertation work, ADAS without human feedback may not always bring positive safety benefits to the drivers. Inverse reinforcement learning proposed in this dissertation can learn driving preference from the time-series observation data of vehicle kinematics and eye glance data. Furthermore, the new FCW algorithm can successfully predict driver behavior (i.e., braking) by considering individual driving preference. The comparison between the new algorithm and the traditional FCW system could provide the implications for the design of new driving assistance warning system.

## *9.2 Study limitations and future research*

A limitation of the driving simulator study was the sample size. There were 24 participants from three age groups with an equal number of females and males recruited for this experiment. The sample size 24 was carefully chosen given the randomization of the scenario sequence. There were four possible orders for the driving scenario (see Chapter 3). These four possible orders required a minimum sample of four for each age group and gender. This sample size was large enough to capture significant differences in the effect of the FCW system and driving styles. However, for the outcomes that were not significant (FCW did not significantly impact Mean Eye-off-road), it is most likely due to insufficient power and large variability. In general, larger sample size is preferred as it can increase the precision of the effects estimation (Casella and Berger, 2002). Thus, a future driving simulator study with larger sample size (e.g., 48) could provide a more precise estimation of the effects and bring more insights on the factors that were not statistically significant for the current study.

The design of reward function is not trivial in reinforcement learning. The objective of inverse reinforcement learning is to learn the underlying reward structure based on observations. In Chapter 7, the reward function is assumed to be a weighted linear form of pre-selected features (see Equation 7.1.4). The linear form is the most interpretable as it shows the direct relations between the reward function and the state features. However, the reward structure can also be quite complex. From a parametric perspective, a non-linear form could also be considered. As pointed out in (Levine et al., 2010; Choi and Kim, 2013), a non-linear form of reward functions can capture the complex relationships between the state features. From a non-parametric perspective, Gaussian Processes (GPs) can also be applied to account for potentially complex, non-linear reward functions (Levine et al., 2011; Wulfmeier et al., 2015).

Driver's braking behavior in the car-following scenario was formalized as a Markov Decision Process (MDP) problem. However, it is recognized that there is a lot of unknowns associated with driver behavior and environmental conditions that can not be easily captured in a simulator study. MDP is capable of dealing with many stochastic states and uncertainty based on the Markov property. Other machine learning methods, such as logistic regression, Support Vector Machine (SVM), and random forest, may not be suitable for the varying-length sequential data. Future research could compare the prediction between MDP and other machine learning methods.

Subsequent research should compare the driving preference based FCW algorithm with the TTC based FCW algorithm. Chapter 8 used the data collected from the driving simulator study as examples to compare the brake timing predictions from these two algorithms. The new FCW algorithm is developed based on a reinforcement learning algorithm that uses driving preference as the reward. The simulator study for this dissertation was based on dry roads with clear skies. The advantage of the driving preference based FCW algorithm is that it can be used to infer behavior based on other road and weather conditions, as well as other environmental conditions.

The new FCW algorithm can adapt to each driver's needs as more data on each person is collected over time. Thus, an additional driving study (simulator or on-road) using this driving preference based FCW algorithm could be conducted to evaluate driver acceptance of this new system.

## *9.3 Contribution and publications*

### *9.3.1 Driving styles identification*

**Contribution:** As noted earlier, driving styles are usually inferred from self-reported data (e.g., driving behavior questionnaires). Identifying driving styles based on time series data is still a novel concept. Driving styles can be reflected in varying metrics. The four categories used in this study are driving performance, secondary task engagement, eye glance behavior and driver history. This dissertation used a Gaussian Mixture Model to capture and identify different driving styles based on driver behavior data. The data was collected from a controlled driving simulator study. Specifically, a two cluster solution was identified as optimal based on the Bayesian Information Criterion (BIC). By comparing the summary statistics from these two groups, they were identified as either aggressive and conservative. In general, aggressive drivers had smaller minimum TTC, larger maximum deceleration, higher speed at accelerator release, high frequency of EOR, and higher violation frequency over the past years.

**Impact:** Driving style is an important component of driving behavior. It relates to the way drivers choose to drive, and further impacts the way that driver interact with assistance systems and traffic infrastructure.

**Publication:** The paper will summarize the work conducted to capture two driving styles: aggressive and conservative. In general, aggressive drivers had smaller minimum TTC, larger maximum deceleration, higher speed at accelerator release, high frequency of EOR, and higher violation frequency over the past years. This work is being prepared for submission to *Transportation Research Part F* (Li and Boyle, in preparation).

### *9.3.2 Driver's adaptation to the FCW system*

**Contribution:** FCW systems are designed to alert the driver of potential rear-end crashes. In previous studies, the adaptation and interaction to the FCW system were discussed based on demographic information (e.g., gender, age) with the assumption that the driving experience and driving styles are highly associated with demographic information. Unlike previous studies, this work focused on the use of driving styles to evaluate adaptation to the FCW system. The driving styles were identified using non-FCW associated data. Aggressive and conservative drivers reacted differently to the FCW system. Furthermore, mismatch of the expectation of the warning cue caused drivers, especially conservative drivers, to have degraded driving performance. When FCW alert is issued, drivers were aware of the severity of the driving situation by stepping on the brake pedal much quicker. It also greatly reduced the driver's distraction level. Drivers paused the engagement of secondary task visually and manually. As drivers became more familiar with the driving tasks and FCW system, their driving performance also improved. Participants would gradually adapt their expectation for the FCW warning and performed better over time.

**Impact:** Human drivers adapt differently when interacting with ADAS. The differences may be caused by different driving styles. Past studies have not fully captured the impact of driving styles and adaptation behavior as drivers interact with ADAS. However, these findings have implications for safety and user acceptance of ADAS.

**Publication:** This work aims to study the driver's adaptation to the FCW system on different driving styles (aggressive and conservative) through Generalized Linear Mixed Model (GLMM). Driver's adaptation to the FCW system was evaluated based on driving styles from three aspects: initial reaction, distraction, and safety benefits. Data used for this work was collected from the driving simulator study under both FCW on and off conditions. This work is being prepared for submission to *Transportation Research Part F* (Li and Boyle, in preparation).

### *9.3.3 Driver preference based FCW system*

**Contribution:** FCW alert timing is so critical that it affects the driver's interaction with the FCW system. The braking behavior was formalized as a Markov Decision Process, driving preference is learned as a reward function given the time-series data. Learning the implicit reward mechanism from the time series data of states and actions is an Inverse Reinforcement Learning(IRL) problem. Maximum Entropy IRL was applied to solve the optimal reward function based on the collected data. The visualization of a reward matrix reveals that the theoretical ideal state is not practical and preferable among the participants attending this experiment. Each individual has a different preference for the optimal safe state. Advanced driver assistance system aims to keep drivers maintaining a safety zone; however, the assumption about safety state without considering the driver's preference impacts the acceptance of the system. Furthermore, the suggested braking actions based on driving preference are earlier than the original TTC-based FCW alert. The new algorithm captured the dynamics of the vehicle kinematics as well as the distraction status of the drivers.

**Impact:** Driver preference affects the driver behavior when interacting with intelligent vehicle systems and the transportation infrastructure. It is important to account for driver preference in the design of ADAS. The driver preference based FCW system could enhance driver safety and the driver's acceptance.

**Publication:** This work aims to understand driver behavior when interacting with the FCW system from a perception-decision-action perspective. Driving preference is learned as a reward function given observed time-series data by applying Maximum Entropy Inverse Reinforcement Learning. Real-time eye glance data was used to capture the driver's attention status while driving. Both Vehicle kinematic data (i.e., relative speed and relative distance) and attention status were used for learning driving preference under the car-following scenario. The data collected from the driving simulator study under FCW off condition was utilized. This work is being prepared for submission to *IEEE Transactions on Intelligent Transportation Systems* (Li and Boyle, in preparation).

# BIBLIOGRAPHY

Pieter Abbeel and Andrew Y Ng. Apprenticeship learning via inverse reinforcement learning. In *Proceedings of the Twenty-first International Conference on Machine Learning*, page 1. ACM, 2004.

Liv M Ahie, Samuel G Charlton, and Nicola J Starkey. The role of preference in speed choice. *Transportation Research Part F: Traffic Psychology and Behaviour*, 30:66–73, 2015.

Georges S Aoude, Vishnu R Desaraju, Lauren H Stephens, and Jonathan P How. Driver behavior classification at intersections and validation on large naturalistic data set. *IEEE Transactions on Intelligent Transportation Systems*, 13(2):724–736, 2012.

Nikola Banovic, Tofi Buzali, Fanny Chevalier, Jennifer Mankoff, and Anind K Dey. Modeling and understanding human routine behavior. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*, pages 248–260. ACM, 2016.

Christophe Biernacki, Gilles Celeux, and Gérard Govaert. Assessing a mixture model for clustering with the integrated completed likelihood. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 22(7):719–725, 2000.

J Black, E Iyasere, and J Wagner. Creation of a driver preference objective metric to evaluate ground vehicle steering systems. In *Proceedings of the 2011 American Control Conference*, pages 1867–1872. IEEE, 2011.

C Blaschke, F Breyer, B Färber, J Freyer, and R Limbacher. Driver distraction based lane-keeping assistance. *Transportation Research Part F: Traffic Psychology and Behaviour*, 12 (4):288–299, 2009.

LN Boyle, JD Lee, Y Peng, M Ghazizadeh, Y Wu, E Miller, and J Jenness. Text reading and text input assessment in support of the nhtsa visual-manual driver distraction guidelines. Technical report, 2013.

Norman E Breslow and David G Clayton. Approximate inference in generalized linear mixed models. *Journal of the American Statistical Association*, 88(421):9–25, 1993.

Terry L Bunn, Svetla Slavova, TW Struttmann, and SR Browning. Sleepiness/fatigue and distraction/inattention as factors for fatal versus nonfatal commercial motor vehicle driver injuries. *Accident Analysis & Prevention*, 37(5):862–869, 2005.

George Casella and Roger L Berger. *Statistical inference*, volume 2. Duxbury Pacific Grove, CA, 2002.

Robert E Chandler, Robert Herman, and Elliott W Montroll. Traffic dynamics: studies in car following. *Operations Research*, 6(2):165–184, 1958.

JH Cho, HK Nam, and WS Lee. Driver behavior with adaptive cruise control. *International Journal of Automotive Technology*, 7(5):603–608, 2006.

Jaedeug Choi and Kee-Eung Kim. Bayesian nonparametric feature construction for inverse reinforcement learning. In *Twenty-Third International Joint Conference on Artificial Intelligence*, 2013.

Fátima Pereira da Silva. Mental Workload, Task Demand and Driving Performance: What Relation? *Procedia - Social and Behavioral Sciences*, 162(Panam):310–319, 2014. ISSN 18770428. URL `http://linkinghub.elsevier.com/retrieve/pii/S1877042814063137`.

Birsen Donmez, Linda Ng Boyle, and John D Lee. Safety implications of providing real-time feedback to distracted drivers. *Accident Analysis & Prevention*, 39(3):581–590, 2007.

Salma Elmalaki, Huey-Ru Tsai, and Mani Srivastava. Sentio: Driver-in-the-loop forward collision warning using multisample reinforcement learning. In *Proceedings of the 16th ACM Conference on Embedded Networked Sensor Systems*, pages 28–40. ACM, 2018.

Johan Engström, Emma Johansson, and Joakim Östlund. Effects of visual and cognitive load in real and simulated motorway driving. *Transportation research part F: Traffic Psychology and Behaviour*, 8(2):97–120, 2005.

Gregory M Fitch, Susan A Soccolich, Feng Guo, Julie McClafferty, Youjia Fang, Rebecca L Olson, Miguel A Perez, Richard J Hanowski, Jonathan M Hankey, and Thomas A Dingus. The impact of hand-held and hands-free cell phone use on driving performance and safety-critical event risk. Technical report, 2013.

Ulrich Gärtner, Winfried König, and Thomas Wittig. Evaluation of manual vs. speech input when using a driver information system in real traffic. 2001.

Paul Green, Eileen Hoekstra, and Marie Williams. On-the-road tests of driver interfaces: examination of a route guidance system and a car phone. *University of Michigan Transport Research Institute, Washington, DC*, page 89, 1993.

DE Haigney, RG Taylor, and SJ Westerman. Concurrent mobile (cellular) phone use and driving performance: task demand characteristics and compensatory processes. *Transportation Research Part F: Traffic Psychology and Behaviour*, 3(3):113–121, 2000.

W Hajek, I Gaponova, KH Fleischer, and J Krems. Workload-adaptive cruise control–a new generation of advanced driver assistance systems. *Transportation Research Part F: Traffic Psychology and Behaviour*, 20:108–120, 2013.

Pete A Hancock, M Lesch, and Lisa Simmons. The distraction effects of phone use during a crucial driving maneuver. *Accident Analysis & Prevention*, 35(4):501–514, 2003.

Walter Helly. Simulation of bottlenecks in single-lane traffic flow. 1959.

Nis Hjortskov, Dag Rissén, Anne Katrine Blangsted, Nils Fallentin, Ulf Lundberg, and Karen Søgaard. The effect of mental stress on heart rate variability and blood pressure during computer work. *European Journal of Applied Physiology*, 92(1-2):84–89, 2004.

Josh Hoffman, John D Lee, and Elizabeth M Hayes. Driver preference of collision warning strategy and modality. 2003.

Jin-Hyuk Hong, Ben Margines, and Anind K Dey. A smartphone-based sensing platform to model aggressive driving behaviors. In *Proceedings of the 32nd annual ACM conference on Human factors in computing systems*, pages 4047–4056. ACM, 2014.

Tim Horberry, Janet Anderson, Michael A Regan, Thomas J Triggs, and John Brown. Driver distraction: The effects of concurrent in-vehicle tasks, road environment complexity and age on driving performance. *Accident Analysis & Prevention*, 38(1):185–191, 2006.

Li Hsieh, Sean Seaman, and Richard Young. A surrogate test for cognitive demand: tactile detection response task (tdrt). Technical report, SAE Technical Paper, 2015.

Insurance Information Institute. Facts + Statistics: Highway safety. `https://www.iii.org/fact-statistic/facts-statistics-highway-safety`, 2017. [Online; accessed 19-July-2019].

Anthony Jameson. Adaptive interfaces and agents. *Human-Computer Interaction: Design Issues, Solutions, and Applications*, 105:105–130, 2009.

A Hamish Jamson, Frank CH Lai, and Oliver MJ Carsten. Potential benefits of an adaptive forward collision warning system. *Transportation Research Part C: Emerging Technologies*, 16(4):471–484, 2008.

Soyoung Jung, Xiao Qin, and David A Noyce. Modeling highway safety and simulation in rainy weather. *Transportation Research Record*, 2237(1):134–143, 2011.

Leslie Pack Kaelbling, Michael L Littman, and Andrew W Moore. Reinforcement learning: A survey. *Journal of Artificial Intelligence Research*, 4:237–285, 1996.

SeungJun Kim, Jin-Hyuk Hong, Kevin A Li, Jodi Forlizzi, and Anind K Dey. Route guidance modality for elder driver navigation. In *International Conference on Pervasive Computing*, pages 179–196. Springer, 2012.

SeungJun Kim, Jaemin Chun, and Anind K. Dey. Sensors Know When to Interrupt You in the Car. *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems - CHI '15*, pages 487–496, 2015. ISSN 1076-898X. URL `http://dl.acm.org/citation.cfm?doid=2702123.2702409`.

Yehuda Koren. Collaborative filtering with temporal dynamics. *Communications of the ACM*, 53(4):89–97, 2010.

Gerard Lachapelle. Driver response analysis in car-following scenarios using differential global positioning system. Technical report, 2006.

Terry C Lansdown, Nicola Brook-Carter, and Tanita Kersloot. Distraction from multiple in-vehicle secondary tasks: vehicle performance and mental workload implications. *Ergonomics*, 47(1):91–104, 2004.

John D Lee, Daniel V McGehee, Timothy L Brown, and Michelle L Reyes. Collision warning timing, driver distraction, and driver response to imminent rear-end collisions in a high-fidelity driving simulator. *Human Factors*, 44(2):314–334, 2002.

K Lee and H Peng. Evaluation of automotive forward collision warning and collision avoidance algorithms. *Vehicle System Dynamics*, 43(10):735–751, 2005.

Suzanne E Lee, Eddy Llaneras, Sheila Klauer, and Jeremy Sudweeks. Analyses of rear-end crashes and near-crashes in the 100-car naturalistic driving study to support rear-signaling countermeasure development. *DOT HS*, 810:846, 2007.

Monica N Lees and John D Lee. The influence of distraction and driving context on driver response to imperfect collision warning systems. *Ergonomics*, 50(8):1264–1286, 2007.

Monica N Lees, Joshua Cosman, John D Lee, Shaun P Vecera, Jeffrey D Dawson, and Matthew Rizzo. Cross-modal warnings for orienting attention in older drivers with and without attention impairments. *Applied Ergonomics*, 43(4):768–776, 2012.

Sergey Levine, Zoran Popovic, and Vladlen Koltun. Feature construction for inverse reinforcement learning. In *Advances in Neural Information Processing Systems*, pages 1342–1350, 2010.

Sergey Levine, Zoran Popovic, and Vladlen Koltun. Nonlinear inverse reinforcement learning with gaussian processes. In *Advances in Neural Information Processing Systems*, pages 19–27, 2011.

David T Levy. Youth and traffic safety: the effects of driving age, experience, and education. *Accident Analysis & Prevention*, 22(4):327–334, 1990.

Greg Linden, Steve Hanks, and Neal Lesh. Interactive assessment of user preference models: The automated travel assistant. In *User Modeling*, pages 67–78. Springer, 1997.

Charles C Macadam. Understanding and modeling the human driver. *Vehicle System Dynamics*, 40(1-3):101–134, 2003.

Greg Marsden, Mike McDonald, and Mark Brackstone. Towards an understanding of adaptive cruise control. *Transportation Research Part C: Emerging Technologies*, 9(1):33–51, 2001.

Sahisnu Mazumder, Bing Liu, Shuai Wang, Yingxuan Zhu, Lifeng Liu, and Jian Li. Action permissibility in deep reinforcement learning and application to autonomous driving. In *2018 SIGKDD Conference on Knowledge Discovery and Data Mining (KDD)*, 2018.

Elizabeth N Mazzae, Thomas A Ranney, Ginger S Watson, and Judith A Wightman. Hand-held or hands-free? the effects of wireless phone interface type on phone task performance and driver preference. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, volume 48, pages 2218–2222. SAGE Publications Sage CA: Los Angeles, CA, 2004.

Alexandra S Mueller and Lana M Trick. Driving in fog: The effects of driving experience and visibility on speed compensation and hazard avoidance. *Accident Analysis & Prevention*, 48:472–479, 2012.

Risto Näätänen and Heikki Summala. Road-user behaviour and traffic accidents. *Amsterdam, Netherlands: North-Holland*, 1976.

Raymond C Peck, Michael A Gebers, Robert B Voas, and Eduardo Romano. The relationship between blood alcohol concentration (bac), age, and crash risk. *Journal of Safety Research*, 39(3):311–319, 2008.

Yiyun Peng and Linda Ng Boyle. Driver's adaptive glance behavior to in-vehicle information systems. *Accident Analysis & Prevention*, 85:93–101, 2015.

Yiyun Peng, Linda Ng Boyle, and John D Lee. Reading, typing, and driving: How interactions with in-vehicle systems degrade driving performance. *Transportation Research Part F: Traffic Psychology and Behaviour*, 27:182–191, 2014.

Michael E Rakauskas, Leo J Gugerty, and Nicholas J Ward. Effects of naturalistic cell phone conversations on driving performance. *Journal of Safety Research*, 35(4):453–464, 2004.

Matthew P Reed and Paul A Green. Comparison of driving performance on-road and in a low-cost simulator using a concurrent telephone dialling task. *Ergonomics*, 42(8):1015–1037, 1999.

Michael A Regan, John D Lee, and Kristie Young. *Driver distraction: Theory, effects, and mitigation*. CRC Press, 2008.

Gary B Reid and Herbert A Colle. Critical swat values for predicting operator overload. In

*Proceedings of the Human Factors Society Annual Meeting*, volume 32, pages 1414–1418. SAGE Publications Sage CA: Los Angeles, CA, 1988.

Bryan Reimer. Driver assistance systems and the transition to automated vehicles: a path to increase older adult safety and mobility? *Public Policy & Aging Report*, 24(1):27–31, 2014.

Christina M Rudin-Brown and Heather A Parker. Behavioural adaptation to adaptive cruise control (acc): implications for preventive strategies. *Transportation Research Part F: Traffic Psychology and Behaviour*, 7(2):59–76, 2004.

SAE. Operational definitions of driving performance measures and statistics. Technical Report J2944 201506, 2015.

SAE. Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles. Technical Report J3016_201806, 2016.

Fridulv Sagberg, Selpi, Giulio Francesco Bianchi Piccinini, and Johan Engström. A review of research on driving styles and road safety. *Human Factors*, 57(7):1248–1275, 2015.

Volkan Sezer, Tirthankar Bandyopadhyay, Daniela Rus, Emilio Frazzoli, and David Hsu. Towards autonomous navigation of unsignalized intersections under uncertainty of human driver intent. In *Intelligent Robots and Systems (IROS), 2015 IEEE/RSJ International Conference on*, pages 3578–3585. IEEE, 2015.

Sijun Shen and David M Neyens. Assessing drivers' response during automated driver support system failures with non-driving tasks. *Journal of Safety Research*, 61:149–155, 2017.

Masamichi Shimosaka, Takuhiro Kaneko, and Kentaro Nishi. Modeling risk anticipation and defensive driving on residential roads with inverse reinforcement learning. In *17th International IEEE Conference on Intelligent Transportation Systems (ITSC)*, pages 1694–1700. IEEE, 2014.

Manbir Sodhi, Bryan Reimer, and Ignacio Llamazares. Glance analysis of driver eye movements to evaluate distraction. *Behavior Research Methods, Instruments, & Computers*, 34 (4):529–538, 2002.

Joonwoo Son, Myoungouk Park, and Byungkyu Brian Park. The effect of age, gender and roadway environment on the acceptance and effectiveness of advanced driver assistance systems. *Transportation Research Part F: Traffic Psychology and Behaviour*, 31:12–24, 2015.

Raghavan Srinivasan and Paul P Jovanis. Effect of selected in-vehicle route guidance systems on driver reaction times. *Human Factors*, 39(2):200–215, 1997.

Richard S Sutton and Andrew G Barto. *Reinforcement learning: An introduction*, volume 1. MIT press Cambridge, 1998.

Louis Tijerina, Edwin Parmer, and Michael J Goodman. Driver workload assessment of route guidance system destination entry while driving: A test track study. In *Proceedings of the 5th ITS World Congress*, pages 12–16, 1998.

Quan Tran and Jonas Firl. Online maneuver recognition and multimodal trajectory prediction for intersection assistance using non-parametric regression. In *Intelligent Vehicles Symposium Proceedings, 2014 IEEE*, pages 918–923. IEEE, 2014.

Martin Treiber, Ansgar Hennecke, and Dirk Helbing. Congested traffic states in empirical observations and microscopic simulations. *Physical Review E*, 62(2):1805, 2000.

Nicole Trübswetter and Klaus Bengler. Why should i use adas? advanced driver assistance systems and the elderly: knowledge, experience and usage barriers. 2013.

Geoffrey Underwood, Peter Chapman, Karen Bowden, and David Crundall. Visual search while driving: skill and awareness during inspection of the scene. *Transportation Research Part F: Traffic Psychology and Behaviour*, 5(2):87–97, 2002.

Jinke D Van Der Laan, Adriaan Heino, and Dick De Waard. A simple procedure for the assessment of acceptance of advanced transport telematics. *Transportation Research Part C: Emerging Technologies*, 5(1):1–10, 1997.

Shouyi Wang, Yiqi Zhang, Changxu Wu, Felix Darvas, and Wanpracha Art Chaovalitwongse. Online prediction of driver distraction based on brain activity patterns. *IEEE Transactions on Intelligent Transportation Systems*, 16(1):136–150, 2015.

Wenshuo Wang, Junqiang Xi, and Ding Zhao. Learning and inferring a driver's braking action in car-following scenarios. *IEEE Transactions on Vehicular Technology*, 67, 2018.

Allan F Williams and Veronika I Shabanova. Responsibility of drivers, by age and gender, for motor-vehicle crash deaths. *Journal of Safety Research*, 34(5):527–531, 2003.

Jianping Wu, Mark Brackstone, and Mike McDonald. Fuzzy sets and systems for a motorway microscopic simulation model. *Fuzzy Sets and Systems*, 116(1):65–76, 2000.

Markus Wulfmeier, Peter Ondruska, and Ingmar Posner. Maximum entropy deep inverse reinforcement learning. *arXiv preprint arXiv:1507.04888*, 2015.

Huimin Xiong, Linda Ng Boyle, Jane Moeckli, Benjamin R Dow, and Timothy L Brown. Use patterns among early adopters of adaptive cruise control. *Human Factors*, 54(5):722–733, 2012.

Yingjun Ye, Xiaohui Zhang, and Jian Sun. Automated vehicle's behavior decision making using deep reinforcement learning and high-fidelity simulation environment. *arXiv preprint arXiv:1804.06264*, 2018.

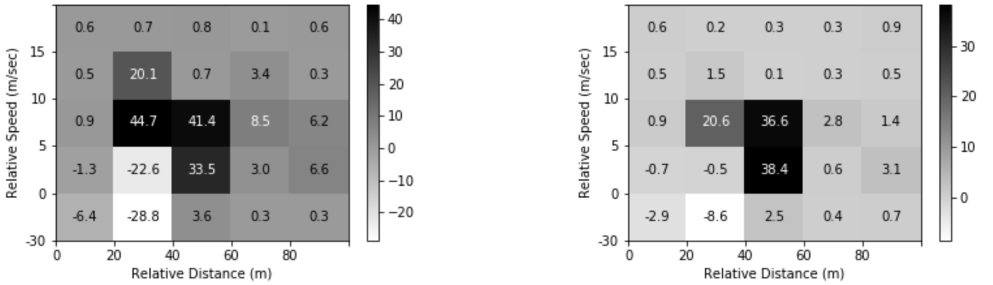
Brian D Ziebart. *Modeling purposeful adaptive behavior with the principle of maximum causal entropy.* Carnegie Mellon University, 2010.

Martina Ziefle, Preethy Pappachan, Eva-Maria Jakobs, and Henning Wallentowitz. Visual and auditory interfaces of advanced driver assistant systems for older drivers. In *International Conference on Computers for Handicapped Persons*, pages 62–69. Springer, 2008.

# Appendix A

# REWARD FUNCTIONS FOR ALL THE PARTICIPANTS

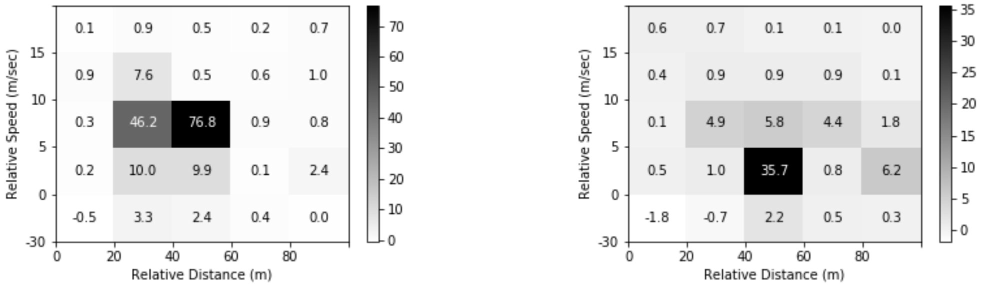
## *A.1 Aggressive drivers*



Undistracted

Distracted

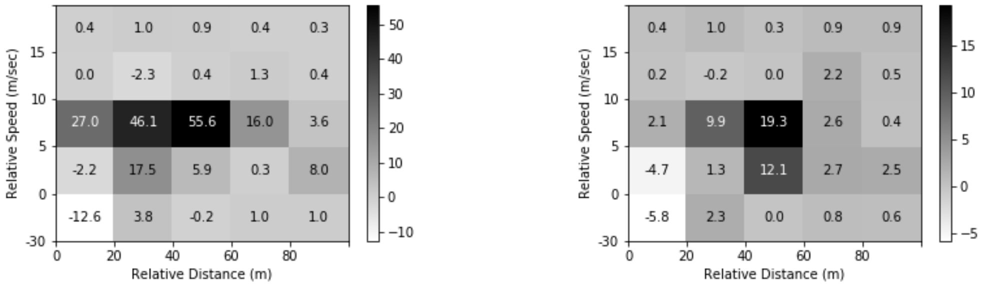
Figure A.2: PID 102



Undistracted

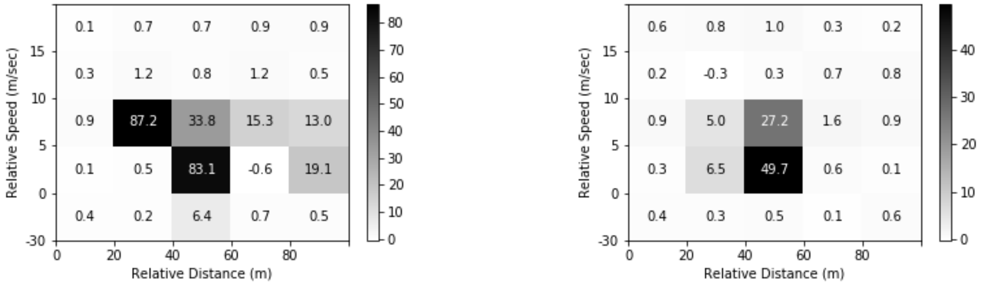
Distracted

Figure A.4: PID 103



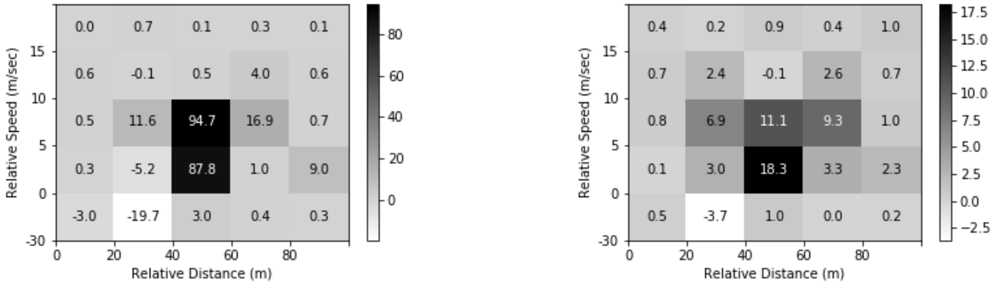
Undistracted Distracted

Figure A.6: PID 105



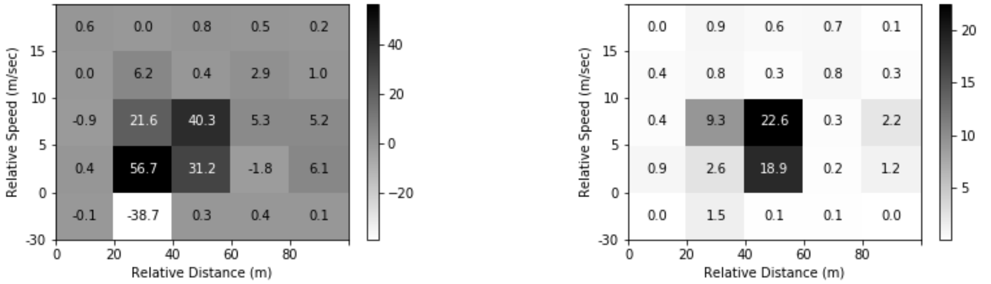
Undistracted Distracted

Figure A.8: PID 107



Undistracted Distracted

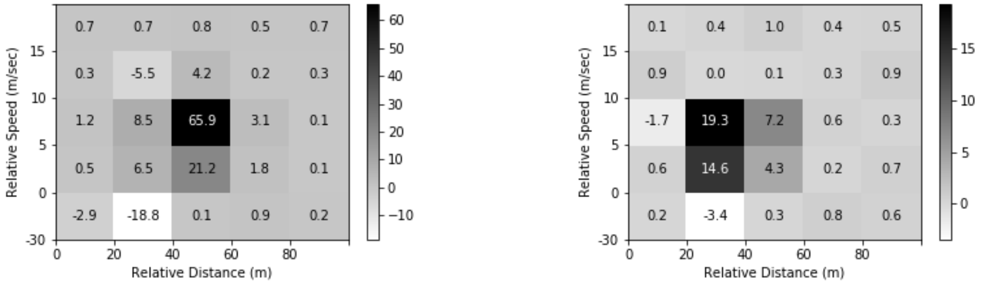
Figure A.10: PID 109



Undistracted

Distracted

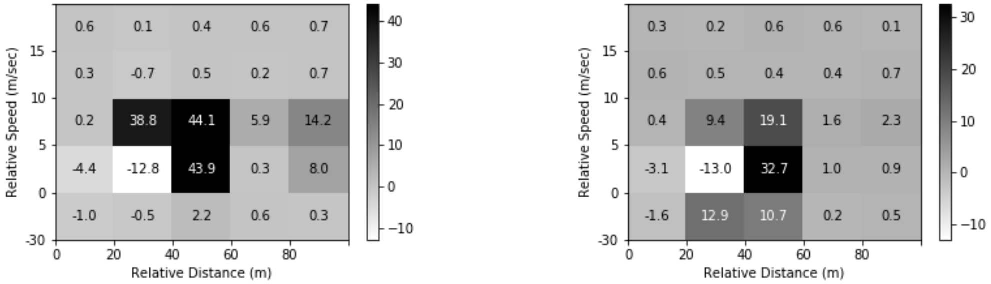
Figure A.12: PID 110



Undistracted

Distracted

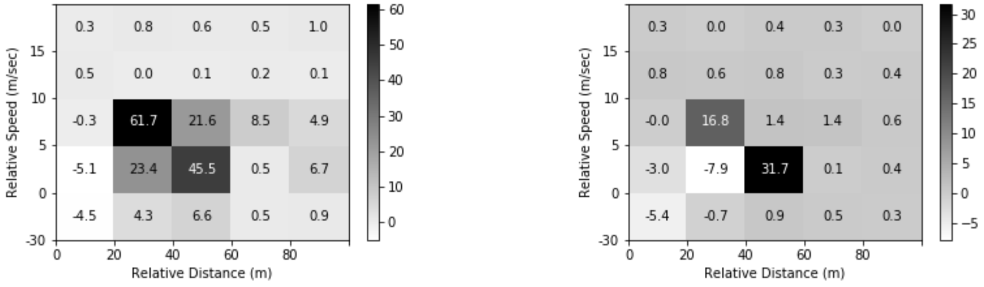
Figure A.14: PID 111



Undistracted

Distracted

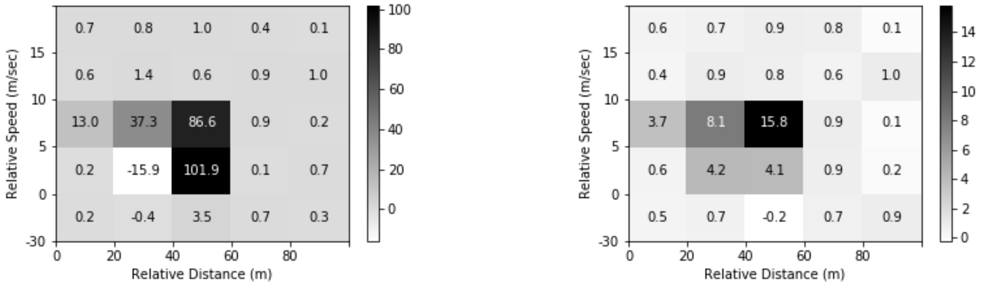
Figure A.16: PID 113



Undistracted

Distracted

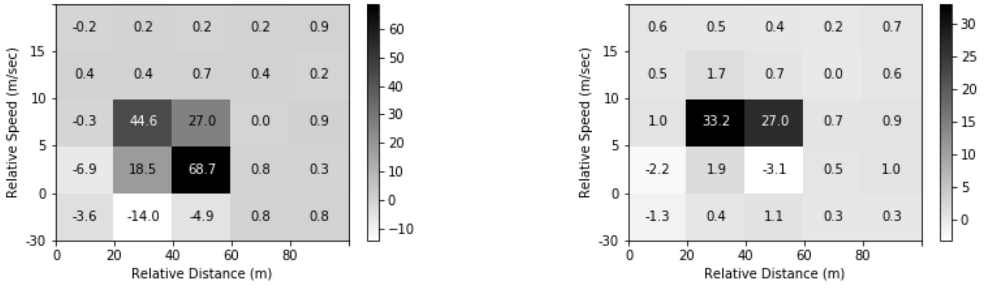
Figure A.18: PID 114



Undistracted

Distracted

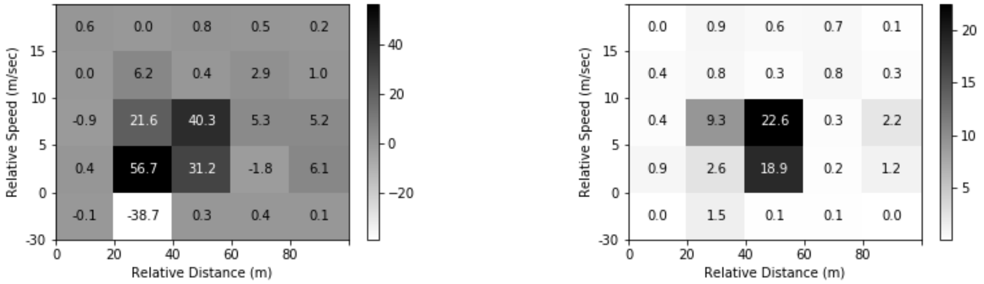
Figure A.20: PID 115



Undistracted

Distracted

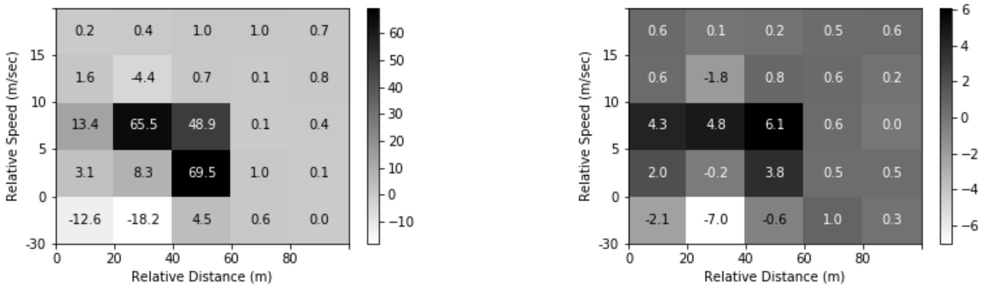
Figure A.22: PID 116



Undistracted

Distracted

Figure A.24: PID 110

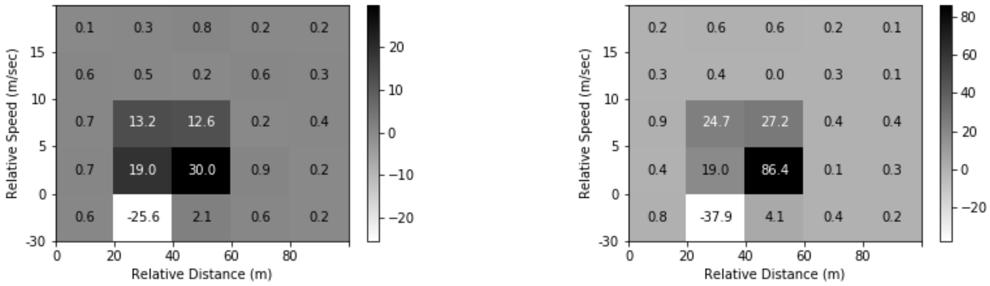


Undistracted

Distracted

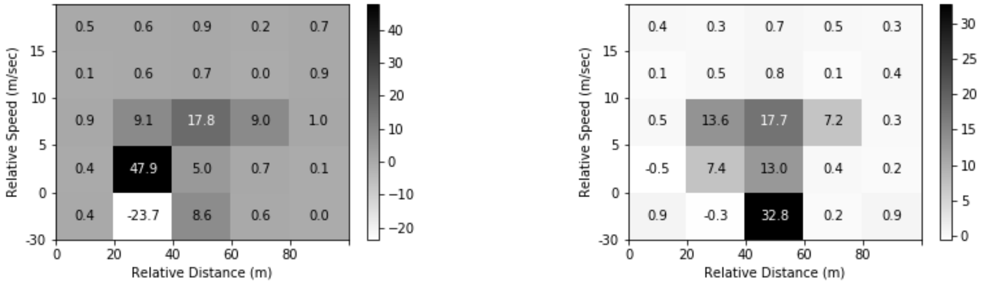
Figure A.26: PID 119

## A.2 Conservative driver



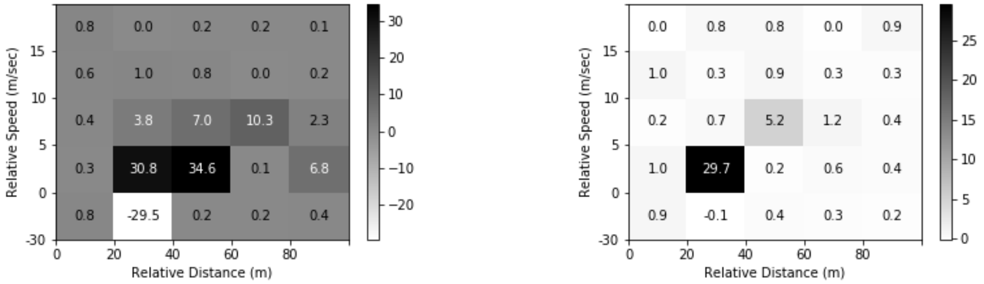
Undistracted Distracted

Figure A.28: PID 104



Undistracted Distracted

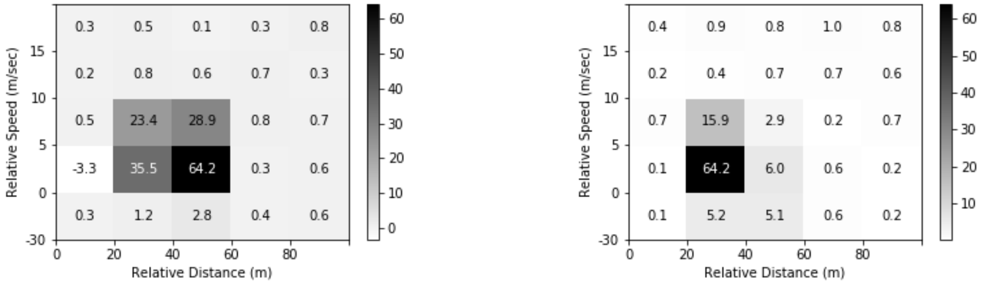
Figure A.30: PID 106



Undistracted

Distracted

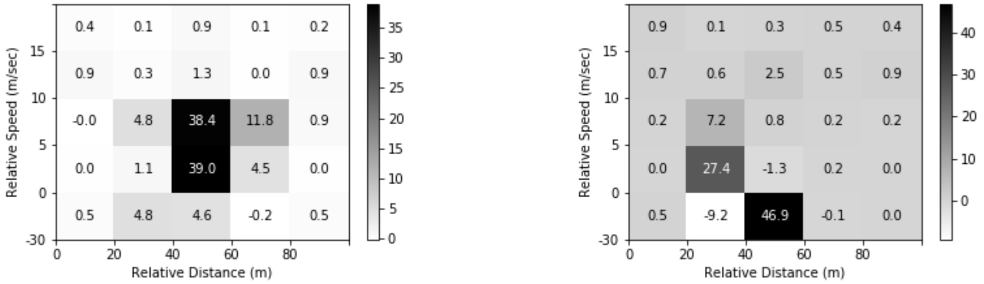
Figure A.32: PID 108



Undistracted

Distracted

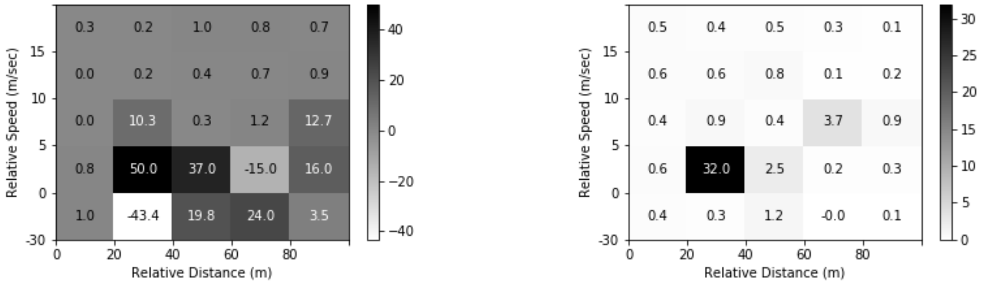
Figure A.34: PID 118



Undistracted

Distracted

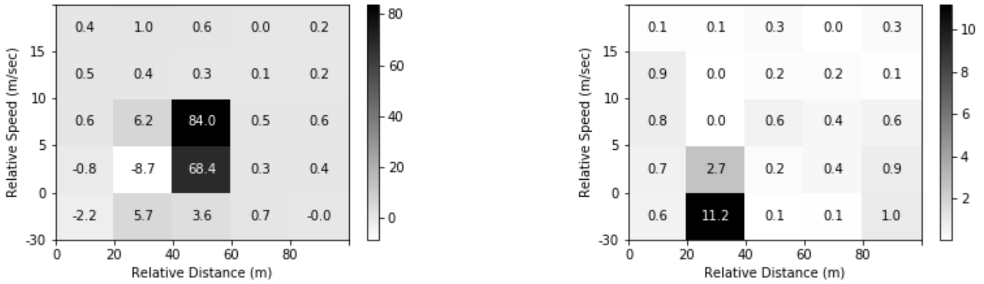
Figure A.36: PID 120



Undistracted

Distracted

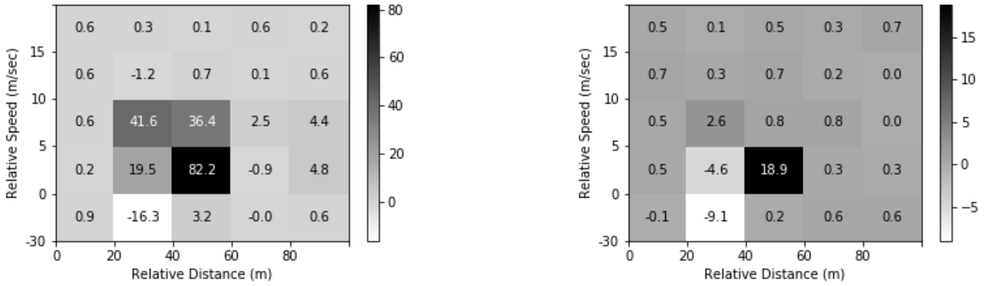
Figure A.38: PID 121



Undistracted

Distracted

Figure A.40: PID 122



Undistracted

Distracted

Figure A.42: PID 123