AN ANALYSIS OF NATURALISTIC DRIVER DATA IN EVALUATING VEHICLE LONGITUDINAL CONTROL SYSTEMS

THESIS

Presented in Partial Fulfillment of the Requirements for the Degree Master of Science in the Graduate School of The Ohio State University

By

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2017

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ABSTRACT

As vehicles with advanced driver assistance systems such as adaptive cruise control (ACC) become more common on the roads, many people have begun to raise concerns about their safety and control. The National Highway Traffic Safety Administration (NHTSA) is actively pursuing research in the performance and safety of different types of these systems in an effort to guide their development and to ensure that they are safe to the public. One fundamental aspect of this pursuit is gaining an understanding of human driver behaviors under normal driving conditions.

This document presents an analysis of naturalistic driver data as a means to gage the performance and guide development of vehicle longitudinal control systems such as ACC. First, an analysis of the steady-state behavior is discussed, using a frequency content based approach and method to study and extract significant amounts of data. Next, a method is proposed that uses this extracted data to stochastically replicate these behaviors over indefinitely long periods of time.

A second analysis of the same set of naturalistic data is also performed to guide the development of a simplified model of an ACC system based on a second-order single degree-of-freedom (SDOF) mass-spring-damper model. The study of the relationship between the behavior of the leading vehicle and the subsequent behavior of the following...
vehicle is of particular interest as it is used to gage the performance of the aforementioned ACC model under a series of three different inputs.
For Q-Row:

IBQQWT

WB

Ohio
ACKNOWLEDGEMENTS

My utmost thanks and gratitude go out to my advisor Dr. Gary Heydinger, not only for writing a letter of recommendation that ultimately led to my acceptance into the graduate program at The Ohio State University, but also for the insightful technical feedback and support on my research. I must also give thanks to my co-advisor Dr. Dennis Guenther for his unwavering guidance and support, encouraging me every step along the way and making sure I was keeping my head up when times were tough. A special shout out also goes out to Dr. Kiran D’Souza for his technical support.

I would also like to thank the National Highway Traffic Safety Administration (NHTSA) for supporting this research and the amazing staff at the Vehicle Research and Test Center (VRTC). Their knowledge and insight proved to be an invaluable asset in my studies and I am extremely grateful for their support. I would like to thank Josh Every, Sughosh Rao, Frank Barickman, Riley Garrott, Kamel Salaani, Chris Manganello, and John Martin for their contributions to my research, as well as my fellow graduate students SeHwan Kim and Ravi Lanka.

Finally, I would like to thank my family and friends who have supported me throughout my graduate studies and who keep me rooted in who I am: my parents Jiashun Jocelyn Li and Guochun Tom Lin; my cousin John, aunt Wei, and uncle Jiayu; my
roommate, fellow OU ME graduate, and friend Scott, and our cat Thor; my fellow Athletic Band Bass Trombones Bobby, Mitch, Rashad, Zach, Lukas, Diego, and Matt; Dr. Christopher Hoch; and the rest of my extended family and friends in The Ohio State University Marching and Athletic Bands and the Columbus Saints Drum and Bugle Corps.
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CHAPTER ONE

INTRODUCTION

1.1 Motivation

Statistics from the National Highway Traffic Safety Administration (NHTSA) show that approximately 1.7 million rear-end crashes occurred in 2012 in the United States, resulting in over 1,700 fatalities and 500,000 injuries [1]. These statistics could be significantly reduced if passenger vehicles were equipped with advanced safety technologies that can take partial control of a vehicle’s driving functions such as steering or braking in an emergency situation, reducing the severity of a crash or avoiding one altogether.

A follow-up NHTSA study in 2014 estimated that approximately 100 fatalities, 4,000 serious injuries, and 200,000 minor injuries could be avoided annually if technologies like Forward Collision Warning (FCW), Collision Imminent Braking (CIB), and Dynamic Brake Support (DBS) – collectively referred to as Automatic Emergency Braking (AEB) – were equipped on all light vehicles in the United States [1]. Another study of Volvo’s City Safety system conducted by the Highway Loss Data Institute (HLDI) [2] found that the Volvo XC60 midsized SUV equipped with City Safety substantially reduced
the frequency of insurance claims due to property damage, bodily injury, and collision compared to other vehicles in its class and among other Volvo vehicles without City Safety.

Fortunately, the availability of AEB and other advanced safety features has become more widespread across passenger vehicles sold in the U.S. in recent years. In 2011, 12% of vehicle models listed on safercar.gov offered FCW as optional equipment, while in 2014, 44% of listed models offered FCW [1]. These vehicles and systems cover a wide spectrum of sizes and classes, from luxury nameplates like Tesla, Lexus, and Mercedes-Benz to more mainstream models like Honda, Toyota, General Motors, and Ford. However, NHTSA and the Insurance Institute for Highway Safety (IIHS) announced in March 2016 a “historic commitment by 20 automakers representing more than 99 percent of the U.S. auto market to make automatic emergency braking a standard feature on virtually all new cars,” by 2022 and on trucks with a gross vehicle weight under 10,000 lb. by 2025. Research from the IIHS showed that this commitment would reduce rear-end crashes by 40% and prevent 28,000 crashes and 12,000 injuries in that timeframe [5].

With the advancement and widening availability of automated driving features, protocols and procedures for evaluating the performance and safety of vehicles with these features will need to be established. The IIHS began its front crash prevention rating program in 2013 for vehicles equipped with FCW and AEB systems, evaluating their warning systems and stopping capabilities in two tests at 12 and 25 mph and incorporating these ratings as part of their criteria for their Top Safety Pick and Top Safety Pick+ awards [3]. NHTSA has added both CIB and DBS to its list of recommended advanced safety features as part of its New Car Assessment Program in 2015 [4] and is presently in the
process of developing performance standards for these technologies. However, progress has been slow and NHTSA has yet to formally mandate AEB systems as required equipment on passenger vehicles.

One proposed method of evaluation consists of using automated Principle Other Vehicles (POVs) to create various driving scenarios and gaging the response of the AV system. This technique could be used in computer simulations or on a test track in real time. The motions of these POVs would need to accurately reflect normal, real-world driver behavior. One method to create this behavior is using naturalistic driver data to generate velocity profiles consistent with those from real drivers on real roads. However, this would require a large amount of data and a wide variety of driving scenarios in order to provide a strong enough foundation for the models.

The Second Strategic Highway Research Program (SHRP2), a naturalistic driving study conducted by the Transportation Research Board of The National Academies in association with the Virginia Tech Transportation Institute, is the largest study of its kind and contains a vast amount of driver data with over 3,000 participants and containing over 3,900 vehicle-years of data collected across the United States over a 4-year period between 2010 and 2013. The analysis of such a rich data set is sufficient to provide the necessary foundation for development of the model.
1.2 Objectives

The research in this thesis focuses on the development of a driver lead vehicle model that may be useful in the quantitative assessment of automation systems with longitudinal control, namely Adaptive Cruise Control (ACC) systems. In order to do that, an analysis of normal driver behavior will need to be conducted at different speed ranges in order to gain a basic understanding of driving patterns. From this foundation, new speed data can be stochastically generated in a way that reflects this behavior and is consistent and repeatable for a variety of tests, scenarios, and time periods. Finally, the speed data will be used to represent a lead POV driven by a normal driver under steady-state driving scenarios in order to gage the response of an ACC system with a given input of the rate of change in follow distance to the POV.

1.3 Thesis Overview

Chapter One contains a brief introduction to the thesis topic, objectives of the study, and an overview of the rest of the thesis. Chapter Two introduces background information on several noteworthy advanced safety features, research conducted with AVs, and an overview of the SHRP2 study. Chapter Three discusses the decomposition of the speed data from the SHRP2 database using the Fast Fourier Transform (FFT). Chapter Four discusses the use of that information and various methods to be used to stochastically generate the desired speed data. Chapter Five presents an example on how this data is used in experiments with ACC models and other things. Finally, Chapter Six discusses the contributions of this research and how it can be applied to future research.
Chapter 1 References


CHAPTER TWO

LITERATURE REVIEW

2.1 Research on Advanced Vehicle Safety Features

Before any type of models or procedures for testing AVs can be developed, it is imperative to first gain an understanding of the state-of-the-art. Various technologies and methods are used in advanced driver assistance systems available to consumers on many new passenger vehicles. The following sections discuss three types of these systems that have been publicly deployed on passenger vehicles as of this writing.

2.1.1 Automatic Emergency Braking

One of the most prominent advanced technologies available on new consumer vehicles is Autonomous, or Automatic, Emergency Braking (AEB). According to Consumer Reports, 182 vehicle models sold in the 2017 model year had AEB systems available as standard or optional equipment [1]. These systems use a variety of forward-looking sensors such as RADAR and cameras either standalone or in combination to establish range and movement of potential hazardous vehicles and pedestrians. If a potential collision is identified, these systems send auditory, visual, and/or haptic alerts to the driver and can apply the vehicle’s brakes to avoid or mitigate the severity of the crash.
if the driver does not take sufficient action. One study by the Highway Loss Data Institute (HLDI) showed reductions in insurance claims of up to 10.5% for Mercedes-Benz vehicles, 12.1% for Honda vehicles, and 12.8% for Volvo vehicles equipped with AEB systems \[2\]. Numerous evaluations by NHTSA \[3\], the National Transportation Safety Board \[4\], and Thatcham Research \[5\] among other organizations have examined the performance of different AEB systems under various test and real-world scenarios.

2.1.2 Lane Keeping and Lane Centering

While less common than AEB, lane keeping and lane centering systems were available on 119 vehicle models in the 2017 model year as either standard or optional equipment \[1\]. Both lane keeping and lane centering use forward-looking cameras to examine the lane markings on the road to determine the vehicle’s position in its lane. If the driver is not using the turn signals, these systems can assist the driver to prevent unintended drifting out of the lane. This is usually accompanied with an auditory, visual, and/or haptic alert to the driver. The goal of these systems is to prevent collisions with oncoming or neighboring vehicles as well as prevent the vehicle from drifting off the road altogether (like rumble strips do on long, open stretches of highways).

The key difference between lane keeping and lane centering systems is that lane keeping only intervenes if the driver does not stay within the marked lanes, while lane centering actively keeps the vehicle centered between the lane markings. One system, developed by Volvo \[6\] in 2007, is an example of a lane-keeping system that uses a motor, acting on the steering column, to generate an appropriate amount of torque to steer the
vehicle in order to avoid a lane departure. This system also incorporates a driver-distra c tio n
monitor and only intervenes if it detects the vehicle is departing the lane and the driver is
distracted from the task of driving. According to [6], while it did not generate any false
positive results (unnecessary alerts/interventions) during testing, it did have, “a large
number of interventions … missed owing to robustness and tracking envelope reasons.”

In contrast, a lane management system model developed at Michigan State
University [7] incorporates both a lane-keeping system and a lane-centering system that
allows the system to “take control and make steering adjustments to keep the car at a certain
predefined position within the lane,” set by the user in the driver interface. In addition to
controlling the steering, this system also controls the braking if the road is curving,
allowing the vehicle to adjust its speed in order to make the turn without crossing the lane
lines. However, results from testing this prototype model were not available. A more
detailed study by Banach and Butler [8] examined a lane centering system using mode state
and continuous control. However, their analysis oversimplified the model to a linear
feedback control. This caused uncertainty in maintaining the tolerance of the system’s
active state (using the difference in target and current steering angle and lane center
deviation) for extended periods of time.

There are other significant drawbacks to these systems. Lane keeping and lane
centering will not work if the cameras cannot see the lane markings. This can occur when
the lanes are covered by snow or mud, the camera’s vision is reduced or blocked by weather
or obstructions, or the lane markings simply do not exist. Additionally, IIHS researchers
found that only one-third of owners of Honda vehicles with lane departure warning had the
system turned on\cite{9}. The researchers concluded that the combination of the system being a nuisance to drivers and easy to turn off led to such a low utilization. Comparatively, 183 of the 184 vehicles in the survey had forward collision warning active. Further studies from the HLDI \cite{2} and the AAA Foundation for Traffic Safety \cite{10} suggest that lane departure mitigation systems (warning only or with active intervention) do not provide a benefit in reducing collisions.

2.1.3 Adaptive Cruise Control

Although typically intended for convenience over safety, adaptive cruise control (ACC) systems are more common than lane keeping/centering systems and typically coupled with AEB as part of an advanced technology options package. Using the same sensors as an AEB system to detect forward range, ACC systems automatically adjust the vehicle’s speed in order to maintain a safe following distance from vehicles ahead. ACC is most commonly used during highway cruising, although several systems can operate in city driving and can even bring the vehicle to a complete stop and accelerate when the vehicles ahead begin moving again.

Several types of control strategies have been tested and implemented in ACC systems in both laboratory settings and in consumer vehicles. Extensive developments using PI and PID controllers have been designed and tested by researchers. In a thesis by P. Berggren \cite{11}, the author found that PID controllers do not have the capacity to handle low frequency noise. However, the simulation environment produced very little to no such noise, thereby negating the issue in the thesis, but which may pose challenges when
applying such models in real-world scenarios. A paper by V. Sivaji and M. Sailaja \cite{12} used a simpler setup of two PID controllers monitoring both velocity and distance and found their system took four seconds to adjust to a sudden change in the velocity of the follow vehicle. This amount of lead time may not be enough in emergency situations where the magnitude of change in velocity in a very short time frame may be too much for their system to handle, slowing down the vehicle at an insufficient rate to avoid a potential collision.

Other research strategies using Linear Quadratic Regulator (LQR) controllers have also been investigated and evaluated. A thesis by B. Breimer \cite{13} used one such controller in conjunction with a Kalman observer to detect faults in an ACC system, but did not directly assess the system’s performance in vehicle driving simulators or in physical systems. An investigation comparing the performance of PI and LQ controllers in an ACC system by P. Shakouri et al. \cite{14} found one instance where the LQ controller had a slower response by about 15 seconds compared to the PI controller, but their overall performances were very similar across other tests. This could likely be caused by the greater amount of information received and processed by the LQ controller continuously monitoring each of the states of the system as opposed to the relatively simple proportional and integral components of the system.

Finally, the verification of existing ACC systems is just as important as developing new ones from scratch. This is especially critical to hold the designers of these systems accountable to their performance claims and verify that they do what they were intended to do without colliding with the lead vehicle. Tests conducted by students at the University
of Pennsylvania \textsuperscript{[15]} showed one ACC system accelerating to 60 mph to catch up to a lead vehicle, then rapidly decelerating down to 30 mph at nearly the same rate once it got too close. While a collision did not occur, this rapid deceleration almost seems like an emergency type of behavior for an ACC system, not exactly keeping the driver comfortable. In a different investigation conducted at The Ohio State University \textsuperscript{[16]}, one ACC system did not perform as well as it claimed to have advertised, resulting in a collision of the lead and follow vehicles under a particular set of braking conditions. With the lead vehicle braking softly and the following vehicle braking hard, the position profiles of both vehicles intersect at approximately 2 seconds after the initial acceleration, indicating a collision would have occurred under the specific test parameters. Both of these examples show the importance of verification testing of not just ACC, but any type of advanced driver assistance system so that they perform their intended functions without causing discomfort to their drivers.

2.2 Naturalistic Driving Studies (NDS)

In studying everyday driver behavior, there are two key components to consider: acquiring data that reflects real-world driving patterns in a variety of road types, locations, and conditions – and in sufficient quantities that, when processed, show a convergence to a general set of behaviors.

In regards to the first component, it is important that subject drivers are not changing anything about their normal driving habits. In an NDS, research subjects drive their vehicles as they normally would on a regular basis with minimal alteration to or influence
on their behavior. This is in contrast to Field Operational Tests (FOTs) where drivers may actively turn a particular vehicle system or multiple systems on or off for certain periods of time in order for researchers to study its effects on a driver’s behavior. For example, a study may want to examine how the use of ACC influences drivers’ braking patterns in highway cruising situations and may require that a test vehicle’s ACC system be turned on or off for specific periods of time while driving. While this may or may not require a deliberate intervention from the driver, it does actively change the conditions of the test, of which the driver will likely be aware. This could potentially influence their subsequent behaviors and response to the testing environment even if all other conditions are kept constant.

Driving simulators are another major test method for evaluating driver behavior. One major advantage they have over other driving research methods is the large degree of control over variables that may or may not affect driving behavior. This is very useful in presenting a wide variety of different, precisely tuned, and repeatable scenarios, such as varying ambient light levels, modifying road markers, changing density of vehicles, or altering how the simulated vehicle responds to driver inputs. However, they cannot fully replicate the combination of complex driving environments and the simultaneous array of driver behaviors that lead to multiple outcomes for a given scenario. Additionally, it may be impractical and too costly to run a driving simulator for hundreds or thousands of hours in order to obtain a sufficiently large data set. Therefore, while useful in their own right, driving simulators do not completely satisfy the purpose of this particular research either.
Naturalistic driving studies aim to provide data that satisfies both of these conditions in the hopes of offering insight into relationships between the driver, road, vehicle, weather, and traffic conditions under normal driving conditions as well as in crashes and near-crashes. In an NDS, drivers are given no special instructions, no experimenter is present for the duration of the data collection, and a data acquisition system (DAS) is unobtrusively installed into the vehicle. The DAS records vehicle maneuvers (such as speed, acceleration, and throttle/gear position), driver behavior (such as eye, head, and hand maneuvers, presence of alcohol, and use of vehicle controls), and external conditions (such as radar tracking of nearby vehicles, external weather/temperature, and GPS tracking) \[17\].

2.2.1 The 100-Car Study

Conducted by the Virginia Tech Transportation Institute (VTTI) and sponsored by NHTSA, the 100-Car Naturalistic Driving Study was the first large-scale instrumented naturalistic driving study conducted. It intended to generate detailed information about the factors that may play a role in the occurrence of crashes or near-crashes. Completed in 2006, the data set contains approximately 2 million vehicle miles and 43,000 hours of recorded vehicle and video data \[18\].

While 100 drivers were recruited as primary drivers for the study, the researchers note that a few drivers were replaced for various reasons (such as a move from the study area or repeated crashes in leased vehicles), and other family members and friends also occasionally drove the instrumented vehicles. In total, 109 primary drivers and 132
secondary drivers participated over the course of the study. Of the 100 vehicles used in the study, 22 were leased to participants with a DAS pre-installed, while 78 vehicles were privately-owned by the participants and had a DAS installed. Examples of the DAS used in the 100-Car study are in Figure 2.1. Each vehicle involved in the study collected data for 12 to 13 months. Participants were also asked to complete questionnaires about their demographics and driving history and skills before entering the study.

![Central Data Collection System](image1)
![In-Cabin Camera](image2)

<table>
<thead>
<tr>
<th>Central Data Collection System</th>
<th>In-Cabin Camera</th>
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<td><img src="image3" alt="Camera Views" /></td>
<td><img src="image4" alt="Forward Radar" /></td>
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Figure 2.1 DAS from the 100-Car Study [18]
Among the data set are numerous cases of extreme driving behavior and performance such as severe fatigue, impairment, aggressive driving, and traffic violations to name a few, indicating that the presence of the data collection instrumentation had little role in influencing the drivers’ behavior. 82 crashes were recorded over the duration of the study, with 69 of them containing sufficient data for analysis and 49 being low g events such as hitting a curb, median, parking blocks, or small animal. In addition, 761 near-crash events requiring an evasive braking maneuver of greater than 0.5 g or a steering input creating a lateral acceleration of greater than 0.4 g were recorded, as well as nearly 8,300 incidents consisting of evasive maneuvers of lesser severity as a near-crash event or proximity conflicts where the driver is unaware of and has a delayed response to a nearby hazard.

There are two demographic limitations in the 100-Car study. The primary one is that only one area of the country was sampled in the study – the Northern Virginia/Metro Washington D.C. area near the VTTI site, consisting of primarily urban and suburban driving environments, often in moderate to heavy traffic. Subsequently, rural driving and other demographics within the U.S. are not well represented and may show different behaviors, such as in the Midwest, California, Texas, or New York. A secondary limitation is in the array of vehicles that were chosen for the study, consisting of only five sedan models (Toyota Camry and Corolla, Chevrolet Cavalier and Malibu, and Ford Taurus) and one SUV model (Ford Explorer). This was done due to the complexity of the data collection hardware and custom mounting brackets used. While these models did represent common
body types found on passenger cars on the road, this meant that drivers that did not own or lease one of these vehicles were excluded from the study.

2.2.2 The Second Strategic Highway Research Program (SHRP2) NDS

SHRP2 was launched by the U.S. Congress in 2005 as a program of research into roadway safety and congestion. It is a national partnership of the Federal Highway Administration (FHWA), the American Association of State Highway and Transportation Officials (AASHTO), and the Transportation Research Board of the National Academies (TRB). According to the TRB’s research protocol [19], “The central goal of the SHRP2 Safety Research Plan is to address the role of driver performance in traffic safety,” including, “developing an understanding of how the driver interacts with and adapts to the vehicle, traffic environment, roadway characteristics, traffic control devices and other environmental features,” in order to, “support the development of new and improved safety countermeasures to prevent traffic collisions and injuries.”

A major component of SHRP2 was a large-scale NDS launched in 2007 in collaboration with VTTI as a successor to the 100-Car study, with data collected between 2011 and 2014. The SHRP2 NDS collected a myriad of driver data, including vehicle network information, GPS, accelerometers, forward radar, alcohol presence, turn signals, and video views of the forward roadway, driver’s face, instrument cluster, and rear of the vehicle. Figure 2.2 outlines a schematic of the DAS used in the SHRP2 NDS.
Figure 2.2 SHRP2 DAS Schematic [21]

The total data set amounts to approximately four petabytes in size containing driver data from over 3,000 drivers across 32,000 individual trips and 3,900 vehicle-years [21]. Unlike the 100-Car NDS, the SHRP2 NDS spanned across six different metro regions across the United States – Bloomington, IN; State College, PA; Tampa Bay, FL; Buffalo, NY; Durham, NC; and Seattle, WA – and selected participants regardless of the make or model of their personally-owned vehicle in which the DAS was installed, covering a wide spectrum of demographics. Participants were also asked to complete a wider variety of assessments than that of the 100-Car NDS, including information about medical conditions, behavior assessments, visual, physical, and cognitive tests, sleep habits, and an exit interview. Additionally, cell phone records of a subset of participant drivers were also collected and analyzed, as well as matching GPS records to an extensive roadway database that was in concurrent development [22]. This provides an extensive basis for analysis into driver behaviors and the factors that can lead to a potential crash.
As a result, multiple studies using the SHRP2 data set have found connections between the road curvature and lane departure behavior of drivers on two-lane highways, the design of offset left-turn lanes on crash rates in intersections that have them, and driver distraction on highway crashes and crash risk to name a few. From this, it is clear that a lot can be learned about driver behaviors and the internal and external factors that affect drivers in collision or near-collision scenarios, which may help guide the behaviors of automated vehicles. By understanding the factors that can lead to crashes or other non-desirable outcomes, AVs can be programmed to predict what a neighboring driver may do based on the current dynamics of the vehicles and surrounding conditions in order to avoid potential collisions and keep the occupants of all vehicles – both itself and neighboring vehicles – safe and out of harm’s way.

2.2.2.1 SHRP2 Dataset Used for Analysis

Since the SHRP2 NDS data contains personally-identifiable information on human subjects, it is imperative that the privacy of the participants is protected and approval is obtained from the Institutional Review Boards (IRBs) of the host and requesting institutions. The SHRP2 data obtained for and analyzed in this research strictly followed an approved data usage and sharing agreement between The Ohio State University and VTTI. No personally-identifiable information or data was used for this particular research.

The subset of data requested contains only the time series data set for 270 individual drive samples and was obtained in September 2016 with accompanying video footage from only the forward-facing camera following one month later. Of these samples, 191 were
considered for analysis in this research as they were categorized as non-conflict events (within the bounds of “normal driving”) or non-participant conflicts (crash, near-crash, or crash-relevant events that do not involve the participant driver) [22]. The particular set of time series data analyzed in this research are listed in Table 2.1. Each data series was sampled at a rate of 10 Hz, or 0.1 seconds per sample.

<table>
<thead>
<tr>
<th>Table 2.1 Description of Selected SHRP2 NDS Time Series Data [20]</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Variable</strong></td>
</tr>
<tr>
<td>Speed</td>
</tr>
<tr>
<td>Acceleration</td>
</tr>
<tr>
<td>Radar, Range</td>
</tr>
<tr>
<td>Radar, Range Rate</td>
</tr>
<tr>
<td>Cruise Control</td>
</tr>
</tbody>
</table>

2.3 Conclusion from Literature Review

In an ideal scenario, if all vehicles on the road were capable of full autonomy (SAE Level 5 – performing all driving tasks, under all conditions that a human driver can), there would be little cause to worry about collisions as the vehicles and vehicle networks would hold nearly all operational controls for every vehicle. Until such a time becomes a reality, if ever, automated vehicles will inevitably have to co-exist with human-driven vehicles. Therefore, studying the interactions between them will become extremely important as
vehicles capable of increasingly advanced levels of automation become more frequent. Fortunately, the SHRP2 NDS database can provide a very thorough insight into such driver behaviors with thousands of individual data sets available to analyze.
Chapter 2 References


CHAPTER THREE

FREQUENCY ANALYSIS OF DRIVER STEADY-STATE BEHAVIOR

3.1 Introduction

According to NHTSA, there were 3,477 fatal crashes in 2015 involving a distracted driver, an increase of 8.8% from 2014[1]. Many of these fatalities could be prevented with the use of a system monitoring road conditions that the driver may not be paying attention to and alert him or her to a potential collision. When analyzing the driver behaviors as they relate to AVs, the most basic type of interaction between them is having one vehicle follow another in steady state highway cruising. Therefore, gaining a fundamental understanding of how drivers normally behave at steady state will play a vital role in reducing the number and severity of these types of crashes.

One of the most basic metrics in analyzing driver behavior is the vehicle’s speed data. It can show what types of roads the vehicle is traveling on such as neighborhood streets, city roads, or major highways. Additionally, studying how the speed changes with time can offer some insight into the vehicle’s surrounding conditions. For example, if the speed is relatively constant for an extended period of time, then it may indicate that there is little traffic on the road the vehicle is traveling on; whereas rapid fluctuations in speed imply that there the driver is reacting to changes in the surrounding environment such as
congested stop-and-go traffic or multiple intersections in dense urban settings. Even on open highways with no traffic, assuming that cruise control is not active and in use, drivers will have small natural fluctuations in trying to maintain a constant speed because human drivers have difficulty maintaining precise control of the accelerator pedal.

Thus, the speed data can be seen as a signal input with some frequency content. The most common method for signal analysis and obtaining this frequency content is the use of the Discrete Fourier Transform, most frequently applied as the Fast Fourier Transform (FFT).

In this chapter, Section 3.1 introduces the purpose of analyzing speed data to understand driver behavior. Section 3.2 discusses the functionality of the FFT and its use in signal processing. Section 3.3 describes the methods used to decompose the speed data into its frequency contents, including selection of desired regions of the SHRP2 data for analysis, the procedures used to analyze the selected regions, the combination of analyses of multiple regions, and the implementation used in the final analysis. Finally, Section 3.4 summarizes the results of these methods.

### 3.2 The Fast Fourier Transform

The overarching premise of a Fourier analysis is to convert a signal in its original domain, usually in time or space, into a representation in the frequency domain and vice versa by computing its Discrete Fourier Transform (DFT) or its inverse. An FFT algorithm can rapidly compute these transformations by factorizing the DFT matrix into a product of sparse factors, most often zeros. MATLAB’s FFT and Inverse FFT (IFFT) functions
implement the transform and inverse transform for vectors of length N in Equations 3.1 and 3.2, respectively:

\[ X(k) = \sum_{j=1}^{N} x(j) \omega_N^{(j-1)(k-1)} \]

(3.1)

\[ x(j) = \frac{1}{N} \sum_{k=1}^{N} X(k) \omega_N^{-(j-1)(k-1)} \]

(3.2)

\[ \omega_N = e^{-\frac{2\pi}{N}} \]

(3.3)

where \( \omega_N \) is defined as an Nth root of unity.

When the FFT is computed, the resulting output is complex. Each output value corresponds to a particular frequency and has both magnitude and phase values. In order to obtain the resulting periodogram containing frequencies and amplitudes, the magnitude across the frequency spectrum in proportion to the sampling frequency and the transform length is multiplied by a factor of 2 to account for the reflection about the Nyquist frequency \( F_{\text{nyq}} \), and is defined as:

\[ F_{\text{nyq}} = \frac{F_s}{2} \]

(3.4)

where \( F_s \) is the sampling frequency. This is true with the exception at the zero and Nyquist frequencies, which only occur once. Equations 3.5 and 3.6 outline this in more detail.

For \( X(k) \) not at \( F = 0 \) or \( F = F_{\text{nyq}} \):

\[ P = \frac{2|X(k)|}{F_s L} \]

(3.5)

For \( X(k) \) at \( F = 0 \) or \( F = F_{\text{nyq}} \):

\[ P = \frac{|X(k)|}{F_s L} \]

(3.6)
where $L$ is defined as the transform length and $P$ is the resulting amplitude of the frequency. While it is ideal to use a transform length of the next power of 2 greater than the sample size in order to optimize processing time, this example uses an $L$ as simply the number of data points or length of the signal.

It is important to note that at this stage, the phase component of the signal is not being taken into consideration. The subject of the phase will be examined in more detail in Chapter 4 as that will play an important role in the next part of the driver model. Figure 3.1 shows a graphical example of the decomposition of a simple 1 Hz sine wave signal input into its frequency and amplitude components.

Figure 3.1 FFT of $y(x) = 2\sin(2\pi x)$
In this example, the sine wave is sampled at a rate of 100 Hz, or 100 samples/second. When normalized to the Nyquist frequency, the peak is shown at 0.02% of $F_{\text{nyq}}$. This makes sense since $F_{\text{nyq}} = \frac{100 \text{ Hz}}{2} = 50 \text{ Hz}$ and when multiplied by 0.02 becomes 1 Hz, which matches the known frequency of the sine wave.

### 3.3 Decomposition of Speed Data

In using the FFT, it is imperative that the proper areas of speed data are analyzed. To recall from the beginning of this chapter, the goal of this research is to analyze driver behavior at steady state conditions, namely at near constant velocities. Naturally, there are periods of rapid acceleration and deceleration throughout each data set as the vehicles come to a complete stop and subsequently accelerate from rest. There may also be periods of abrupt deceleration and acceleration at highway speeds if a driver sees an obstacle or another vehicle and must apply the brakes, then proceeds to accelerate back to their desired speed. Simply applying one overarching FFT to the entire data set will show frequency content not only of steady state conditions, but also of these non-steady state conditions. Therefore, it is best to isolate the regions of data that are most desirable in this research in order to provide the best picture of the steady state behaviors.

In these initial experimental analyses, a small sample of four example data packets available for free public download from the SHRP2 database were used in the development of these analysis methods before they were implemented in the analysis of the full requested data set. The key difference between the two data sets are the different channels
by which the speed data was obtained. The sample data provides speed from the DAS’s GPS sensor sampled at 1 Hz, while the full SHRP2 data set contains data from both the vehicle’s onboard network data sampled at 10 Hz as well as the same GPS sensor data sampled at 1 Hz. The majority of the plots in this chapter are from the sample data packets, labeled Drives 3 through 6. Results using the detailed SHRP2 data are shown beginning in Section 3.3.4.

3.3.1 Selection of Desired Regions for Analysis

The basic premise of determining the validity of a section of data for analysis is by taking the mean speed of a selected region and examining whether or not any data points in that region are within a specific tolerance. If it is, then it proceeds to the next step; otherwise, the next region is analyzed and tested.

3.3.1.1 Filtering of Raw Speed

In order to identify these regions, the data must first be filtered of any high frequency content. While the actual speed data has a wide array of high frequency fluctuations, the driver may not be intentionally trying to achieve the speeds as indicated by the data, but rather attempting to maintain a constant set speed. These fluctuations may come from varying road grades, drag, rolling resistance from the tires, slight variations in power output from the engine, reactions to changing environmental conditions such as weather and obstacles, and inconsistent human control over the acceleration without the
use of cruise control. This is a key part of the data selection: identifying the driver’s intended behavior as opposed to how the vehicle actually behaves.

The type of filter used in this research analysis is the Butterworth filter, originally developed by Stephen Butterworth in 1930 \[^3\]. He claims that, “An ideal electrical filter should not only completely reject the unwanted frequencies but should also have uniform sensitivity for the wanted frequencies,” however, this is not possible in practice. Nonetheless, he showed that a low pass filter could be designed to approach this type of behavior with increasing numbers of filter elements. With the cutoff frequency normalized to 1 radians per second, the filter gain was:

\[
F(\omega) = \frac{1}{\sqrt{1 + \omega^{2n}}}
\]

(3.7)

where \(\omega\) is the angular frequency in radians per second and \(n\) is the number of poles in the filter, equal to the number of reactive elements in the filter. As \(n\) increases, the gain approaches 1 if \(\omega\) is less than 1 and approaches zero if \(\omega\) is greater than 1.

For this analysis, two 4-pole Butterworth filters of different frequency bands were examined: one at 0.1 Hz and another at 0.005 Hz. Figures 3.2 and 3.3 show an example comparison between the original speed data and the speed data with both filters applied.
Figure 3.2 Raw Speed Data with Filters

Figure 3.3 Zoomed In Section of Figure 3.2
As the filters decrease in frequency band, the velocity profile becomes smoother and the intended speed becomes more apparent as well. The 0.1 Hz filter does a good job of removing the higher frequency fluctuations while the 0.005 Hz filter indicates the speed at which the driver is attempting to maintain. While the actual speed in Figure 3.3 varies between 58 mph and 62 mph, the 0.005 Hz filter suggests that the driver is actually intending to hold a speed between 59 and 59.5 mph within this particular time frame.

The information provided by the 0.005 Hz filter is then used to guide the selection of regions based on a specified tolerance in the intended speed of the driver. In order to determine this, when a region is selected, the mean of the filtered speed within that region is calculated and the difference in magnitude between the mean and each data point of the filtered speed is compared against a given tolerance. If there are no points within this region that exceed the tolerance, then the 0.1 Hz filtered speed data is parsed to the next steps for analysis. Otherwise, that region is rejected and the analysis advanced to the next region. Figures 3.4, 3.5, and 3.6 compare how different regions are selected on the same data using different tolerances. The regions selected for analysis are denoted in black; the vertical bars represent the endpoints of the selected region, and the selected section of the speed filtered at 0.005 Hz is also highlighted in black. This example uses regions of fixed length and intervals of 120 seconds as outlined in Section 3.3.1.2.
Figure 3.4 Region Selection using Tolerance = ±1 mph

Figure 3.5 Region Selection using Tolerance = ±2 mph
From these plots, it is clear that as the tolerance increases, more regions along the run are selected. Using a tolerance of ±1 mph, only 12 regions were selected; at ±2 mph, 31 regions were selected; and at ±5 mph, 55 regions were selected. It is also clear that there needs to be a balance in the number of valid regions selected as using too small of a tolerance only yields a small fraction of data available to use, whereas using too great of a tolerance includes regions where there is a noticeable deliberate acceleration or deceleration. Of the examples tested, the tolerance of ±2 mph showed the best performance of covering appropriate regions of what appear to be steady state conditions for analysis. Therefore, this tolerance will be used in all future data analyses. It is important
to note that the filtered speeds are only used in identifying the desired regions; the original data is still used in the actual frequency analysis.

3.3.1.2 Determining Region Length and Location

Because the interest of this research is in studying steady-state conditions, it is imperative to isolate these specific regions in the speed data that are relatively constant and reject regions that have noticeable intended accelerations or decelerations. To do this, three different interval types were tested: fixed length with fixed timing, variable length with fixed timing, and fixed length with variable timing.

With intervals of fixed length and fixed timing, the entire speed run is divided up into equal sections of a specific length of time beginning at time equals 0. The example shown in Figure 3.7 shows a zoomed-in example of the run in Figure 3.5, using intervals 2 minutes in length occurring every 2 minutes. The primary advantage of this method is that each region is the same length, making comparisons between regions clear and easy, without the need to zero-pad any regions of different lengths.
Using a slight variation as above, intervals of variable length with fixed timing still divide the speed run into intervals of fixed length and timing as before. However, valid regions that are adjacent to one another may be combined into one single region using the same tolerance criteria described in Section 3.3.1.1 across all valid intervals. Doing this highlights regions of extended steady state conditions and compares broader sections of steady state behavior instead of dividing them up, which may not reflect the overall behavior. Figure 3.8 highlights an example of this method using the same run as in Figure 3.7. In order to obtain a higher precision in combining multiple regions together, this example uses regions 30 seconds in length occurring every 30 seconds, combining valid adjacent regions together into larger regions of varying lengths within the same tolerance.
From Figure 3.8, there are a few individual 30-second regions covering brief moments of acceleration and deceleration. However, the regions between 113 minutes and 118 minutes are all taken as one single region, showing an extended period of time of relatively steady velocity. There are also other regions of varying length, including one at 110 – 113 minutes, 120 – 122 minutes, and 124 – 125 minutes. Unfortunately, this method creates an issue where smaller regions that may appear valid, but actually indicate acceleration or deceleration, become included in the data analysis. Additionally, this method also requires any regions smaller than the largest region to be zero-padded, the consequences of which are discussed further in Section 3.3.3.
The last method tested uses intervals of fixed length but variable timing. Like the first method, each region is the same fixed length and adjacent valid regions are processed individually as opposed to being combined into one extended region. However, if a selected region is not valid, instead of rejecting the entire region and all the data points within it, the region simply advances to the next point in the run and repeats the validation process. The examples shown in Figure 3.9 illustrate this method more clearly, using the same sized regions of 2 minutes as in the first method.

Figure 3.9 Fixed Interval Length, Variable Timing

The main advantage of this method compared to the other two is that it actively finds valid regions within the speed data as opposed to predetermining what the regions
are and whether or not they are valid for analysis. For example, the region centered about 120 minutes is highlighted as valid, but the distance between this region and the next valid region one centered about 123 minutes is significantly less than the length of an individual region. The same is true for the regions centered about 123 minutes and 126 minutes; the distance between them is only a few data points, with the speed data between them showing a distinct acceleration. Additionally, this method also has the same advantage as the fixed length and timing method in that all regions are the same length and do not require zero-padding. Therefore, the fixed length region with variable timing method is the best one to use for analysis of the SHRP2 data.

3.3.2 Analysis of Individual Speed Regions

When a region is selected for analysis, it must first be parsed through a window before being processed. This is to ensure that the endpoints are evenly lined up with one another in order to minimize the amount of spectral leakage during analysis. One particular type of window most often used in spectral analysis using a Fourier Transform is the Hann or Hanning window. Named after Austrian meteorologist Jullus von Hann, the Hann window is a discrete cosine wave window function applied to a signal or section of a signal in the time domain as shown in Equation 3.7:

\[ w(n) = \frac{1}{2} \left( 1 - \cos \left( \frac{2\pi n}{N-1} \right) \right) \]  

(3.7)

where \( n \) is the particular point within a signal sample and \( N \) is the window length. Figure 3.10 shows a graphical example of a Hann window with \( N = 120 \), while Figure 3.11 shows the FFT of the Hann window.
Figure 3.10 Hann Window
Figure 3.11 FFT of 120 pt. Hann Window

The zero-frequency amplitude of the Hann window in Figure 3.11 is the mean value of the curve from Figure 3.10. Taking the integral of the Hann window results in the steady-state gain of 0.5. For future research, an examination of other types of windows and their effects on frequency attenuation is strongly recommended.

When the Hann window is applied to the signal, the FFT and resulting amplitudes are calculated as described in Section 3.2, using Equations 3.1, 3.3, 3.5, and 3.6. An example of the FFT for one individual region is shown in Figure 3.12.
It is important to note that the data used in this example run used the sample data available for free to the general public on the SHRP2 database, which was sampled at a rate of 1 Hz. Thus, across a two minute time interval, there were 120 data points available in the region. Rounding up the sample length to the next power of 2 results in a transform length of 128. Even though the transform length is greater than the number of samples, the resulting amplitude spectrum converges very rapidly, leveling off at around 0.35% of the Nyquist frequency with the peak amplitude at 0.0078%. The Nyquist frequency in this example is 0.5 Hz with the peak occurring at approximately 0.0039 Hz and leveling out
near 0.175 Hz. Since this research is focusing on steady-state conditions, having such low frequency content is expected to occur.

### 3.3.3 Combining Multiple FFTs

Determining how to process the selected speed regions into their frequency and power contents proved to be the most challenging aspect within this chapter. Throughout this process, three different approaches were considered: combining the raw FFTs together, averaging the powers of the FFTs, and considering the use of zero-padding with regions of varying length.

The first technique stores the raw FFTs containing both magnitude and phase into an array of uniform length with each row representing one region. Using the fixed region length with variable timing method, after all regions are selected and stored, each column is averaged together and the resulting array is then processed into amplitudes and normalized frequencies as shown in Figure 3.13.
Figure 3.13 Periodogram from using Averages of Raw FFTs

While the highest peak does line up with a single FFT example in Fig. 3.12, the main issue this method creates is additional noise from higher frequencies. There are distinct peaks at 0.05 Hz, 0.08 Hz, and just past 0.15 Hz, indicating that there is some amount of noise the driver or vehicle is inducing in the vehicle’s speed. In addition, the amplitudes generated from this method are nearly 1.5 orders of magnitude less than the single FFT from Fig. 3.11, the level at which most vehicles do not operate. The variations in speed are extremely low, barely peaking at 0.065 mph, while the peak amplitude in Fig. 3.12 is around 1.25 mph, nearly 20 times greater.

The primary flaw from averaging the raw FFTs together comes from the averaging of both magnitude and phase components together. From analyzing this data, it appears
that the phase of each region processed appears to be random. Attempting to find an average of a random signal just results in another random signal, as shown in Figure 3.14.

![Figure 3.14 Phase Profile](image)

**Figure 3.14 Phase Profile**

In theory, the two phase profiles should overlap each other fairly closely, and while there are points where they appear to overlap, the vast majority of the phases are nowhere near each other for most of the frequencies. In fact, the phase appears to be completely random in both cases, making it not very useful for this application. However, the importance of the fact that the phase appears to be random will play an important role in the second half of this analysis, which is discussed in Chapter 4.

A more appropriate means of combining the FFTs together is simply averaging the amplitudes together as opposed to the raw FFTs themselves. This removes the phase component of the FFT and focuses solely on the amplitude of each frequency band, as that is what is of key interest. It also disperses the vast majority of the noise that may be found from an individual FFT. This creates frequency curves that are much smoother and gradual in shape, as shown in Figure 3.15, with the same sharp peak early on. However, the
amplitudes of the remaining frequencies are much more consistent with one another and indicate a more gradual leveling off point at around 0.25 Hz.

Looking back at the second approach of using variable windowing discussed in Section 3.3.1.2, it requires zero padding at the end of the selected region to match the length of longest region, the result of which is shown in Figure 3.13. From the sample data, there is one region at the beginning of Drive 6 that stretches from 5.5 minutes to 31 minutes, spanning over 1,600 data points in length. The next highest power of 2 from 1,600 is 2,048, adding over 500 points worth of zero padding onto the end of the data set. This pales in comparison to a single one of the 30 second regions used in this method (See Figure 3.16)
as the length of a 300 data point region is zero padded up to 2048 points, creating a sharp spike early on and nothing afterward.

As a result of combining multiple regions zero padded in this way, the frequency content looks more like an impulse response than a steady curve of frequencies. The result of combining the average of the FFTs using the previous method is shown in Figure 3.17.
This creates negative amplitudes and an extremely noisy frequency profile. From this, it is clear that zero padding is a poor choice when trying to combine FFTs.

The final step in the entire process is to combine the FFT results of multiple runs together, using the same principle of averaging amplitudes from multiple regions of a single run. Fig. 3.18 shows the individual frequency spectrums from the four sample data packets and the average amplitudes of all four runs combined. Doing this rounds out the noise from each of the runs and creates a comprehensive image of average driver behavior.
3.3.4 Analyzing the SHRP2 Data

The collection of SHRP2 data obtained for this research contained 270 individual runs with sufficient speed data for analysis. The speed data in these packets is sampled at 10 Hz. Four different region sizes were examined to see if the region length had an effect on the frequency spectrum: 256 points (25.6 seconds), 512 points (51.2 seconds), 1,024 points (102.4 seconds), and 2,048 points (204.8 seconds). It is interesting to note that each of the periodograms converged to a steady curve within about 30-40 runs.

Figure 3.18 Amplitude Spectrums of Selected Sample Runs
Figure 3.19 Periodograms of Entire SHRP2 Data Set – 256 point regions

Figure 3.20 Periodograms of Entire SHRP2 Data Set – 512 point regions
Figure 3.21 Periodograms of Entire SHRP2 Data Set – 1,024 point regions

Figure 3.22 Periodograms of Entire SHRP2 Data Set – 2,048 point regions
For each region size, the frequency with the highest amplitude is equal to one cycle per the length of time of the region: 25.6 seconds for 256 points, 51.2 seconds for 512 points, 102.4 seconds for 1,024 points, and 204.8 seconds for 2,048 points. This is due to the effect of applying the Hann window to each region before processing the FFT, attenuating the ends of the signal so much that the signal appears to contain only one primary cycle. In addition, as the regions increase in length, the value of the highest amplitude and the amplitude at zero frequency gain decreases. This is a result of isolating longer periods of time of steady-state driving, where drivers are less likely to fluctuate their speeds. Under these conditions, it can be assumed that as the length of the region increases, the primary frequency of these regions is equal to one cycle per the region length.

However, as the region lengths become longer, fewer valid regions are processed because there is a higher chance of the driver’s intended speed exceeding the tolerance for a valid region over longer periods of time. This reduces the validity of the resulting frequency profile. Using a length of 256 points, 4,226 valid regions were processed; a length of 512 points processed 1362 valid regions; a length of 1,024 points processed 416 valid regions; and a length of 2,048 points processed only 131 valid regions. In order to strike a compromise between finding the most prominent frequency and the number of valid regions processed, the region length of 512 points with a peak frequency of 0.02 Hz offers the best balance between the length of time sampled and the number of valid samples being analyzed.

In addition to a comprehensive analysis of driver behavior, this research also examined different behaviors within different speed bins (0-10 mph, 10-20 mph, and so
on). Because the driving conditions at highway cruising speeds are different from urban city driving, which are different from rural highway and neighborhood driving conditions, drivers will respond differently at different speed ranges. A periodogram of the entire SHRP2 data set sorted by speed bins using regions of 512 points in length is shown in Figure 3.23.

![Periodogram by Speed](image)

Figure 3.23 SHRP2 Periodogram by Speed Bins – 512 point regions

From Figure 3.23, it is evident that there are very low amplitudes at under 10 mph in comparison to the other speed bins, indicating that there are not that many fluctuations at such low speeds. Drivers normally experience brief periods of intense acceleration or braking in these conditions, or they may be stopped at a red light for a minute.

However, the speed bin at 10-20 mph exhibits a wide variety of frequency content, with multiple peaks of amplitudes far exceeding those in the other speed bins. This range is where the majority of acceleration and braking occurs as these types of speeds are often experienced in neighborhoods, where the roads tend to curve around a lot and drivers need
to be aware of children and pets playing around the streets as well as other vehicles exiting driveways. In the remaining speed bins, the frequency behaviors are very consistent and nearly identical in behavior aside from the value of the peak amplitude.

3.4 Conclusions

This chapter discussed the use of the FFT in signal processing, the use of the FFT in decomposing a speed signal into its amplitude and frequency components, methods of refining the selection of specific regions of interest for analysis, methods of combining the results of multiple FFT analyses, and the application of these methods in analysis of the SHRP2 data. From these studies, it can be concluded that the best method for selecting particular regions of speed data for analysis is using regions of a fixed length and variable timing in order to find regions of semi-constant speed. The best method for combining multiple FFT results is by averaging the resulting amplitudes of the FFT as opposed to averaging the raw FFTs themselves as the latter introduces the phase component in the analysis, which was determined to be random. The use of regions of variable length requires the use of zero-padding in order to allow the FFTs to be compared to one another, but this creates undesired behaviors in the resulting analysis, thereby invalidating that method. Finally, these methods were used to process the full set of SHRP2 data, showing results that align with the expected driver behaviors at particular speed ranges. However, the influence of the window being used has a significant effect on the strongest frequency present in the signals and attenuating higher frequencies.
Chapter 3 References


CHAPTER FOUR

GENERATION OF STOCHASTIC SPEED PROFILES

4.1 Introduction

With an understanding of the driver frequency profiles developed in Chapter 3, the next step is to use that information to generate a stochastic set of driver speed data. Recall from Chapter 1, the objective of this research is to replicate the normal behaviors of drivers in a repeatable manner. Using actual samples of the SHRP2 speed data as the basis on which AVs are tested against is impractical because those data were created reflecting one individual driver under specific conditions and not as a general case. In addition, these speed profiles are of a finite length of time; in order to run longer tests, data must be recorded for longer periods of time. If speed data sets could be stochastically generated for infinitely long periods of time in a way that is reflective of the driver’s general behaviors, this would serve as a much stronger basis on which to test AVs against.

Section 4.1 presents an overview on the purpose of generating stochastic speed data. Sections 4.2 and 4.3 outline two different methods tested to achieve this: using a Finite Impulse Response (FIR) filter to filter uniform white noise to the particular response bands of the frequency profiles, and randomizing the phase of the frequency profiles and using the IFFT to convert the frequencies back into speed signals in the time domain with
the appearance of random data. Finally, Section 4.4 summarizes the results of these analysis methods.

4.2 FIR Filtering

For many applications, FIR filters are the primary type of filter used in digital signal processing as they are simple to implement and are often designed with linear phase to preserve the phase of the original signal. Unlike Infinite Impulse Response (IIR) filters, which use feedback to generate outputs indefinitely even after all of the inputs have ceased, FIR filters always have zero output once they reach a finite number of samples. This is important because many applications, including this one, have only a finite number of samples with which to work and it is inappropriate to assume what the response may be outside of the range of these samples.

4.2.1 FIR Filtering in MATLAB

MATLAB’s Signal Processing Toolbox has several different functions available to design linear phase FIR filters. The one used in this application is the fir2 function, which creates an n-th order FIR filter using a given set of frequency and magnitude characteristics. It performs a linear interpolation of the desired frequency response onto a dense grid and then uses the inverse Fourier transform and a Hann window to determine the filter coefficients. However, in order to achieve a desired level of performance, FIR filters often require a much higher filter order than comparable IIR filters. Figure 4.1 shows a
comparison between the zero-phase response of a 256-order FIR filter compared to the original frequency profile from the overall compilation of the SHRP2 data.

![Zero-phase response graph](image)

**Figure 4.1 Zero-Phase Response of 256-Order FIR Filter**

Overall, the FIR filter response matches very closely with that of the original frequency profile after approximately 0.01% of the Nyquist frequency. The primary area of concern is at the lowest frequencies, especially at zero. The FIR filter does not quite reach the same peak value as the original profile, nor does it occur at the same time. In fact, the peak amplitude of 2.25 in the FIR filter response is at a frequency of zero, three times the amplitude of the original profile.
4.2.2 Validation of FIR Filtering

The primary method of validation used to verify the performance of both the FIR filtering and phase randomization methods is a sanity check of the resulting speed profiles compared to the original SHRP2 data samples. Specifically, the metrics examined are the general behaviors of the speed signals themselves, the acceleration taken as the derivative of the speed and converted into G forces, and changes in velocity $\Delta V$ across each data set. Figures 4.2.1 and 4.2.2 show an example of the accelerations and $\Delta V$ across a segment of one of the SHRP2 data samples chosen that will be used as the control sample for comparison.

![Velocity Profile](image_url)

Figure 4.2 Velocity Profile of Selected Baseline Control Sample
This specific window of time was chosen as it is representative of the steady-state behavior being examined, avoiding most points of rapid acceleration/deceleration. Throughout most of this window, the acceleration tends to stay around $\pm 0.02$ g with one brief spike of $-0.04$ g of acceleration. Similarly, the $\Delta V$ tends to stay below 0.6 mph with a brief spike of 0.12 mph at the same time as the spike in acceleration.

For an initial comparison of the FIR filter, a signal of random uniform noise is generated and shown in Figure 4.4. This signal has an amplitude of 0.5 mph with a resolution of 10 Hz across 512 data points. Additionally, a 0.005 Hz Butterworth filter used in Chapter 3 is also applied to show the average intended velocity of the signal. Figure 4.5 shows the result of filtering the random speed signal through the FIR filter, with that signal
also being parsed through the same Butterworth filter to see how the intended velocity changes. The sanity check of the FIR filter is shown in Figure 4.6.

Figure 4.4 Uniform White Noise Signal
Upon initial observation, the FIR filtered speed data has very little resemblance to either the random noise or the original speed data. There appears to be virtually no change in relative speed for the first 10 seconds, then the speed begins to oscillate about 0.05 mph with very high frequency content throughout. Such high frequencies are not possible to achieve from normal human drivers, nor can a vehicle’s propulsion system be so precise in its velocity control. Additionally, the overall response of the vehicle appears to be unstable as the amplitude of the oscillations increases over time. Even though the original noise had an amplitude of only 0.5 mph, the rapid attenuation of the speed profile shows that there are concerns with the implementation and/or design of the FIR filter.
Further, the sanity check of the speed profile does not remotely come close to mimicking the behavior of the control. The magnitude of the acceleration profile is smaller by a factor of 5 and the ΔV profile is nearly 50 times smaller than the control profile. While it may be possible to achieve the desired characteristics with further refinement of the FIR filtering method, it is clear that pursuing an alternative method is also of worthwhile consideration.
4.3 Phase Randomization

The idea of phase randomization was explored in a paper by Michio Yamada and Koji Ohkitani [1] which examined the orthonormal wavelet expansion method in turbulence flows. Their methodology is very simple – they added a uniform random phase over the interval \([0, 2\pi]\) and took the inverse transform of the Fourier coefficients with the amplitudes unchanged. This distorts the signal in the time domain as the amplitudes are out of phase with one another. However, the frequency spectrum of the signal remains the same as the original by definition, creating a signal that has the appearance of randomly generated data, yet it retains the original frequency properties.

The reasoning Yamada and Ohkitani use for justifying the use of phase randomization is that the distribution of the phases in the original signals used to create the frequency profile is also of uniform distribution. Therefore, it does not matter whether or not the phase of the original signal is maintained because it is random either way. Thus, it must be determined if the phase shown in the decomposition of the SHRP2 data also exhibits this same behavior.

4.3.1 Distribution of Phase

From the plot of the phase in Figure 4.6, it seems evident that the phase does appear to be randomly distributed. However, a clearer indicator of phase distribution comes from looking at its Empirical Cumulative Distribution Function (eCDF), the plot of which is shown in Figure 4.7.
If the set \([x_1, x_2, \ldots, x_n]\) is the set of independent, identically distributed real random variables with a common cumulative distribution function \(F(t)\), then the eCDF is defined\(^{[2]}\) as:

\[
F_n^e(t) = \frac{1}{n + 1} \sum_{i=1}^{n} 1_{x_i \leq t}
\]

(4.1)

where \(1_A\) is the indicator of event \(A\). In this application, each event \(x_i\) is the individual phase at a given frequency \(i\) within the range of \(-\pi\) to \(\pi\) radians.

![Figure 4.7 Phase Profile](image)
From Figure 4.8, the distribution of the phase is practically linear, indicating that the phase is indeed uniformly distributed across the frequency bands and is thus random. Therefore, the application of a random phase to the frequency profile of the SHRP2 data can be seen as a valid method of generating random signals that still retain the original frequency properties.

4.3.2 Application of Randomized Phase

The methodology for applying the random phase to the frequency profiles generated from the SHRP2 data is fairly simple. First, a speed profile of the desired average speeds is generated. Then a portion of the speed profile in which noise is to be added is
manually selected and the average speed within that selection is determined. Recall from Chapter Three that each 10 mph speed range exhibited a different frequency spectrum. Thus, the average speed of the selection dictates what type of behavior the noise will have as each speed range will have its own set of behaviors associated with its particular frequency spectrum.

Next, a random phase profile ranging from zero to $2\pi$ radians is generated for each frequency from zero up to the Nyquist frequency. Since the original transform length used was 512 points long, the phase profile is 256 points long. The reasoning for doing this is because the frequency spectrum is mirrored about the Nyquist frequency, so a phase applied to one half of the spectrum must also be reflected about that same point. This reflected phase must also be the negative of the first because each pair of FFT vectors opposite of each other about the Nyquist frequency must be conjugate symmetric in order to optimize the speed of the IFFT computation and for the output to be real. The vectors of each frequency $Z(\omega)$ are computed as:

$$Z(\omega) = \frac{A(\omega)}{F_s} e^{i\phi(\omega)}$$

(4.2)

where $A(\omega)$ is the amplitude at a given frequency, $L$ is the transform length, and $\phi(\omega)$ is the randomly generated phase for a given frequency. However, due to small round-off errors in the amplitudes, $Z(\omega)$ is not perfectly conjugate symmetric, so MATLAB has an option to treat an IFFT computation as if it is so in order to force the output to be real and not imaginary. This resulting noise signal is then added to the average speed signal in order to mimic the fluctuations of a normal driver attempting to maintain that desired speed.
In most cases, the length of the selection is greater than the length of the original FFT, so this process is repeated and the IFFTs are combined with one another in order to cover the length of the highlighted selection. However, because the phases are randomly generated each time, this creates an issue where the boundaries between IFFTs are not continuous with one another and would create artificial spikes in speed and acceleration. To solve this issue, a Hann window is applied to the IFFTs which attenuates the end points to zero while still maintaining most of the amplitudes. An example of this process is shown in Figure 4.9 where noise was added to a 15 minute-long run of a constant speed of 75 mph, with a sanity check of the speed signal shown in Figure 4.10.

![Figure 4.9 Phase Randomized Speed Signal](image-url)

Figure 4.9 Phase Randomized Speed Signal
The acceleration in Figure 4.10 has an identical behavior as the control in Figure 4.3, with most accelerations staying within ±0.02 g and occasionally reaching ±0.04 g. Additionally, the ΔV behavior is also identical to the control, staying consistently below 0.06 mph with an occasional spike just under 0.1 mph. This verifies that the speed and acceleration of the generated velocity profile is identical in behavior to the human driver in the same speed bin.

4.4 Conclusion

This chapter discussed the application of the frequency profiles generated in Chapter 3 into the generation of velocity profiles with identical behaviors to the human-generated velocity profiles from the SHRP2 data set, studying the methods of FIR filtering and phase randomization. The FIR filters have the potential to replicate the frequency profile very accurately in theory, but the implementation of the filter to a set of uniform
random noise did not yield positive results. Future analysis in the refinement of FIR filtering techniques may be beneficial. On the other hand, the use of phase randomization is easily justified as the phase of the FFT is uniformly distributed among all the frequencies. It is very simple to implement because it uses the exact frequency profile and an IFFT with a randomized phase to recreate a similar signal in the time domain. The results from the sanity check show that this method is very effective in replicating the behaviors of a human driver at the same speed bin.
Chapter 4 References


CHAPTER FIVE

EXPERIMENTATION WITH ACC MODELS

5.1 Introduction

With a method to generate a following driver speed profile in hand, the next step—and the primary focus of this research—is to use these profiles to test the response of a vehicle equipped with an ACC system following behind it. Recall from Chapter 1 that the main objective of this research is to develop a driver lead vehicle model described in Chapters 3 and 4 in analyzing the performance of ACC systems. While there are many examples of simple to advanced ACC systems that rely on different methods and metrics, this chapter will analyze a second-order single degree-of-freedom (SDOF) model using concepts from classical vibrations theory in order to gain a fundamental understanding of how this driver model can be used in future research and testing. Additionally, an analysis of the radar range data from the SHRP2 database is discussed and an application of that analysis into the SDOF is examined.
5.2 Second-Order Single Degree-of-Freedom Modeling of an ACC System

Most, if not all, ACC systems depend on knowing the following parameters: the following distance $\Delta Y$ between the Subject Vehicle (SV) and the Principle Other Vehicle (POV), the velocities of the SV and POV ($\dot{x}$ and $\dot{y}$, respectively), and the accelerations of the SV and POV ($\ddot{x}$ and $\ddot{y}$, respectively). $\Delta Y$ is taken as the difference in the displacements between the SV and POV within the same frame of reference ($x$ and $y$, respectively). Figure 5.1 outlines these parameters with respect to the two vehicles.

It is important to note that this model and the following evaluations only consider the longitudinal displacement, velocity, and acceleration of the POV and SV. While incorporating the lateral motions may provide comprehensive insight into the true interaction between the two vehicles, the longitudinal components were isolated in order to simplify the evaluations and calculations.

![Figure 5.1 Car Following Diagram](image)

Even though these parameters are used in many ACC controllers, the methodology by which they are processed and the resulting acceleration or braking commands that are sent to the vehicle's driving systems vary between manufacturers and developers, as
exemplified in Chapter 2. Ultimately, it can be seen that the input of these parameters yields some type of output from the ACC that affects the motion of the SV. Therefore, the ACC controller can be represented as a black box system upon which another model can be applied and its parameters tuned using experimental data.

Because the SV is responding to the change in displacement of the POV, the model used to represent the ACC system is a second-order mass-spring-damper system with a base excitation as shown in Figure 5.2. The SV is treated as the body of interest with mass $m$ and the POV is treated as a base excitation with a random displacement, with a spring $k$ and damper $c$ connecting both bodies together. The motion of the base (POV) has a displacement $y(t)$, rate of change $\dot{y}(t)$, and acceleration $\ddot{y}(t)$, and the response of the ACC system on the SV has its own displacement $x(t)$, rate of change $\dot{x}(t)$, and acceleration $\ddot{x}(t)$. 
Using Newton’s Second Law of Motion (Equation 5.1), the motion of the SV can be determined. The forces acting on the SV come from the differences in the motion of the POV and SV through the simulated spring and damper.

\[ \sum F_x = m a_x \]  
\[ \sum F_x = k(y(t) - x(t)) + c(\dot{y}(t) - \dot{x}(t)) = m\ddot{x}(t) \]  
\[ ky(t) - kx(t) + c\dot{y}(t) - c\dot{x}(t) = m\ddot{x}(t) \]  
\[ m\ddot{x}(t) + c\dot{x}(t) + kx(t) = c\dot{y}(t) + ky(t) \]  

Since different vehicles have different masses, a general case of Equation 5.4 is derived by dividing the entire equation by the mass \( m \). The resulting coefficients are then substituted for two common terms used in the study of vibrations: the damping ratio \( \zeta \) and natural frequency \( \omega_n \):

\[ \ddot{x}(t) + \frac{c}{m}\dot{x}(t) + \frac{k}{m} x(t) = \frac{c}{m}\dot{y}(t) + \frac{k}{m} y(t) \]
\[
\omega_n = \sqrt{\frac{k}{m}} \quad (5.6)
\]

\[
\zeta = \frac{c}{2\sqrt{km}} \quad (5.7)
\]

Notice that \(\omega_n\) and \(\zeta\) are defined in terms of \(m, k,\) and \(c.\) Based on how this model is used, values for \(m, k,\) and \(c\) are not required for this research; rather, \(\omega_n\) and \(\zeta\) are tuned to reflect the performance of the model. Substituting Equations 5.6 and 5.7 into 5.5 yields:

\[
\ddot{x}(t) + 2\zeta \omega_n \dot{x}(t) + \omega_n^2 x(t) = 2\zeta \omega_n \dot{y}(t) + \omega_n^2 y(t) \quad (5.8)
\]

The transfer function of the system \(H(s)\) is derived by taking the Laplace transform of Equation 5.8 using initial conditions of \(x(0) = \dot{x}(0) = 0\) and \(y(0) = \dot{y}(0) = 0:\)

\[
\mathcal{L}(\ddot{x}(t) + 2\zeta \omega_n \dot{x}(t) + \omega_n^2 x(t)) = \mathcal{L}(2\zeta \omega_n \dot{y}(t) + \omega_n^2 y(t)) \quad (5.9)
\]

\[
X(s)[s^2 + 2\zeta \omega_n s + \omega_n^2] = Y(s)[2\zeta \omega_n s + \omega_n^2] \quad (5.10)
\]

\[
H(s) = \frac{X(s)}{Y(s)} = \frac{2\zeta \omega_n s + \omega_n^2}{s^2 + 2\zeta \omega_n s + \omega_n^2} \quad (5.11)
\]

Bode plots of \(H(s)\) are shown in Figures 5.3 and 5.4, examining how magnitude response changes with varying parameters of \(\zeta\) and \(\omega_n,\) respectively.
Figure 5.3 System Bode Diagram – Varying $\zeta$, $\omega_n = 0.02$ Hz
In this first Bode diagram, with zero damping, there is a very sharp spike in the magnitude response at the natural frequency. This is an indication of harmonic resonance, where if the forcing frequency $\omega$ is equal to $\omega_n$, the system’s response will be continuously amplified in a positive feedback loop and eventually reach a point where the system cannot physically handle the response, causing it to fail. In this application, this would mean that...
the SV would accelerate and decelerate at increasing magnitudes. Not only would this behavior be extremely undesirable to the driver, but this would also mean that the vehicle will eventually collide with the POV.

When damping is introduced, even a relatively small amount is enough to prevent a runaway harmonic resonance response. While the response is still at its peak at harmonic resonance, it is nowhere near the level without any damping. Additionally, introducing damping changes the end limit of both the magnitude and phase shift as the forcing frequency goes to infinity. For each difference in order between the forcing function and the system, the ending phase response is shifted 90 degrees or $\pi/2$ radians. In the case without damping ($\zeta = 0$), the transfer function in Equation 5.8 results in a zeroth-order forcing over a second-order system; therefore the ending phase shift is 180 degrees. However, the presence of damping changes the forcing to a first-order over a second-order system, resulting in an ending phase shift of only 90 degrees.

From Figure 5.4, changing the natural frequency while maintaining the same damping coefficient only results in a lateral shift in the response and phase shift. That is, the overall response behavior is the same, but the frequencies at which those behaviors occur are shifted by the same order of magnitude as the differences in natural frequency. For example, the frequency at which the magnitude response is -20 dB is 0.3 rad/s for $\omega_n = 0.002$ Hz, 3 rad/s for $\omega_n = 0.02$ Hz, and 30 rad/s for $\omega_n = 0.2$ Hz. Likewise, the frequency at which the phase shift is equal to 45 degrees is approximately 0.9 rad/s for $\omega_n = 0.002$ Hz, 9 rad/s for $\omega_n = 0.02$ Hz, and 90 rad/s for $\omega_n = 0.2$ Hz.
5.3 Model Response to Sinusoidal Input

To verify the performance of this model, an examination of its response compared to known behaviors according to classical vibrations theory is necessary. This research focuses on responses based on continuous inputs, so a simple sinusoid input signal will be sufficient for validation. However, while the response of the system can be derived using a known input, the actual input signals that this model will use in future testing will be random. Therefore, the system response $x(t)$ must be derived from the general excitation case using the Convolution Integral:

$$x(t) = \int_0^t F(t - \tau) g(\tau) d\tau$$

(5.12)

where $F(t - \tau)$ is the time-delayed response of the forcing $F(t)$ and $g(\tau)$ is the unit impulse response of the system, which will vary depending on the value of the damping coefficient $\zeta$. From Equation 5.8, the forcing term comes from the motion of the POV:

$$F(t) = 2\zeta \omega_n \dot{y}(t) + \omega_n^2 y(t)$$

(5.13)

The following definitions of the second-order unit impulse response for each damping case are adapted from Robert Cannon’s text “Dynamics of Physical Systems.” [1]

For an underdamped system ($0 < \zeta < 1$), the unit impulse response $g(t)$ is defined as:

$$g(t) = \frac{1}{\omega_d} e^{-\zeta \omega_n t} \sin(\omega_d t)$$

(5.14)

$$\omega_d = \omega_n \sqrt{1 - \zeta^2}$$

(5.15)

where $\omega_d$ is the damping frequency of the system.
For a critically damped system ($\zeta = 1$), the response $g(t)$ is defined as:

$$g(t) = e^{-\omega_n t}$$

(5.16)

For an overdamped system ($\zeta > 1$), Cannon does not explicitly express the response $g(t)$ as a single equation. However, his definitions are used to derive the response into a single equation (see Appendix A):

$$g(t) = \frac{e^{-\zeta \omega_n t}}{2\omega_n \sqrt{\zeta^2 - 1}} \left( e^{\omega_n t \sqrt{\zeta^2 - 1}} - e^{-\omega_n t \sqrt{\zeta^2 - 1}} \right)$$

(5.17)

The next series of figures examine the system response of basic sine wave inputs of $y(t) = \sin \omega t$ and $\dot{y}(t) = \omega \cos \omega t$ into Equation 5.13 using different values of $\zeta$ and the ratio of the forcing frequency to the natural frequency $\frac{\omega}{\omega_n}$. The forcing frequency $\omega$ in each scenario is selected as 0.02 Hz or 0.1257 rad/s as that is the frequency that exhibited the highest amplitude from the periodogram in Figure 3.18. Figures 5.5, 5.6, and 5.7 show how variations in $\zeta$ with a constant frequency ratio $\frac{\omega}{\omega_n} = 1$ affect the SV response, while Figures 5.8 and 5.9 show the change in SV response with variations in the natural frequency – and subsequently the frequency ratio – with a constant $\zeta$. For the sake of demonstration, the initial displacement between the two vehicles is 10 meters and the initial speed of the POV is 65.25 mph.
Figure 5.5 System Response, $\zeta = 0$, $\frac{\omega}{\omega_n} = 1$
Figure 5.6 System Response, $\zeta = 0.1, \frac{\omega}{\omega_n} = 1$
Figure 5.7 System Response, $\zeta = 1, \frac{\omega}{\omega_n} = 1$
With zero damping and a frequency ratio of 1 in Figure 5.5, the SV is experiencing harmonic resonance, so the response amplifies out of control as expected with the vehicles colliding at around $t = 175$ seconds. Adding a damping of 0.1 does prevent a runaway response as shown in Figure 5.6, but the response still follows a phase-shifted sinusoidal response. Instead, the response is contained to an amplitude of 5 meters after 200 seconds and is shifted 90 degrees from the forcing. These align with the behaviors described in the Bode diagram in Figure 5.3, with a phase shift in the response by nearly 90 degrees and a magnitude amplification of 14 dB. Likewise, a damping of 1 shows virtually no amplitude gain from the forcing and a phase shift of approximately 30 degrees, which also match the predictions from the Bode diagram.
Figure 5.8 System Response, $\zeta = 1, \frac{\omega}{\omega_n} = 0.1$
Figure 5.9 System Response, $\zeta = 1, \frac{\omega}{\omega_n} = 10$
In using a very low frequency ratio in Figure 5.8, the SV exhibits nearly perfect tracking with the POV, maintaining a constant distance of 10 meters from the POV and virtual identical speed profile. This makes sense as the natural frequency directly correlates to the spring constant \( k \); as \( k \) increases toward infinity with stiffer springs, the two vehicles effectively become connected with a rigid rod, thereby making the motion of the POV and SV identical. Conversely, with a very high frequency ratio in Figure 5.9, the SV cannot respond with nearly the same magnitude as the POV. This correlates to an extreme softening of the spring with a very low \( k \); reducing the stiffness of the spring also reduces the forcing being applied to the SV, thereby reducing the magnitude of the response.

### 5.4 Calibration of the ACC Model

With the performance of the model verified according to the concepts of classical vibrations, the next step is to calibrate the model parameters \( \zeta \) and \( \omega_n \) using a set of real driver data. In an ideal scenario, this data would come from physical tests of a vehicle equipped with an ACC system following a lead vehicle as it accelerates to and decelerates from a given speed, recording the speeds and accelerations of both vehicles as well as the range and range rate between them. Because the goal of this research is to provide a method on which to evaluate the performance of ACC systems, a baseline performance of how a human driver would behave in a car-following scenario must first be established in order to provide a metric to which a real ACC’s performance can be compared. Fortunately, the SHRP2 database contains the aforementioned variables in order to satisfy this condition.
5.4.1 Multivariable Linear Regression of Range Data

Recall from Figure 5.2 and Equation 5.2 the forces acting on the SV. The range and range rate between the SV and POV are defined as \( r = x(t) - y(t) \) and \( \dot{r} = \dot{x}(t) - \dot{y}(t) \), respectively, and substituted into Equation 5.2 gives:

\[
\ddot{x} = 2\zeta\omega_n \dot{r} + \omega_n^2 (r - x_0)
\]  
(5.18)

where \( x_0 \) is the desired following distance between the SV and POV. Next, two beta coefficients are defined as \( b_1 = 2\zeta\omega_n \) and \( b_2 = \omega_n^2 \) and substituted into Equation 5.18:

\[
\ddot{x} = b_1 \dot{r} + b_2 (r - x_0)
\]  
(5.19)

\[
\ddot{x} = b_1 \dot{r} + b_2 r - b_2 x_0
\]  
(5.20)

A third beta coefficient is defined as \( b_3 = -b_2 x_0 \) and substituted into Equation 5.20:

\[
\ddot{x} = b_1 \dot{r} + b_2 r + b_3
\]  
(5.21)

MATLAB’s mvregress function is capable of performing a multivariate linear regression by using a given set of data for each input variable to be calibrated and fits the respective beta coefficients to a set of output data. The outputs of the function are the resulting beta coefficients it has determined fit the inputs to the output the best. In this application, the variables used as the inputs of the mvregress function are range rate \( \dot{r} \), range \( r \), and an array of ones to stand in as a constant, with all three variables being fitted to the longitudinal acceleration of the SV \( \ddot{x} \), and the outputs are the values for the respective beta coefficients \( b_1, b_2, \) and \( b_3 \). Once the beta coefficients are obtained, \( \omega_n, x_0, \) and \( \zeta \) can be determined by rearranging the definitions of \( b_1, b_2, \) and \( b_3 \) to solve for the respective variables:

\[
\omega_n = \sqrt{b_2}
\]  
(5.22)
\[ x_0 = -\frac{b_3}{b_2} \quad (5.23) \]

\[ \zeta = \frac{b_1}{2\omega_n} \quad (5.24) \]

In order to verify that the beta coefficients yield a good fit between the modeled acceleration and the actual acceleration, \( b_1, b_2, \) and \( b_3 \) are input into Equation 5.21 with the range and range rate data and the resulting behavior is compared to the actual acceleration data. The quantitative measure used to evaluate the fit of these two behaviors to one another is the Coefficient of Determination \( R^2 \), a common metric used in statistical analysis for evaluating the strength of a predicted fit to a set of known data. \( R^2 \) is calculated using the observed SV acceleration from the SHRP2 data \( \ddot{y} \), its mean value \( \ddot{\bar{y}} \), and the predicted acceleration from the model \( \ddot{x} \) using the obtained beta coefficients and the range and range rate data:

\[ S_{Stot} = \sum_{i=1}^{n} (\ddot{y}_i - \ddot{\bar{y}})^2 \quad (5.25) \]

\[ S_{Sres} = \sum_{i=1}^{n} (\ddot{y}_i - \ddot{x}_i)^2 \quad (5.26) \]

\[ R^2 = 1 - \frac{S_{Sres}}{S_{Stot}} \quad (5.27) \]

where \( S_{Stot} \) is the total sum of squares proportional to the variance of the data, \( S_{Sres} \) is the residual sum of squares, and \( n \) is the total number of data points in the set. By this
definition, \( R^2 \) ranges from 0 to 1; the higher the value of \( R^2 \), the better the predicted fit is to the data and vice versa. While the basis for determining what is considered a good fit and a bad fit is subjective to the particular study being performed and the variability of the data collected, in most cases an \( R^2 \) value of at least 0.9 is considered to be a very good fit, accounting for 90% of the variability between variables. Given the wide variety of drivers, behaviors, and environments that comprise the SHRP2 data set, the \( R^2 \) value used in this research as the threshold for an acceptable fit is defined as 0.5. The proposed reasoning for using this value is that the SHRP2 data is from real-time driving scenarios and the driver may output a response that is entirely random without any stimulus. Thus, it is reasonable to assume that 50% of the variability in the drivers’ behavior can be accounted with this model and the remaining 50% is due to random behavior on the part of the driver.

5.4.2 Processing the SHRP2 Range Data

The methodology in collecting and analyzing the radar range data shares a few of the same principles used in the analysis of the speed data described in Chapter 3. Only specific selections of the radar data will be used in the analysis portion of the data processing that best reflect the desired behavior to be analyzed. Instead of isolating regions of near steady-state velocity, this analysis will focus on finding regions that yield a strong correlation between the observed SV acceleration and the acceleration determined from the multivariate linear regression discussed in Section 5.3. In fact, regions of steady-state velocity may not be as desirable as regions where the SV’s velocity (and subsequently the range, range rate, and acceleration) is changing, namely in response to the behavior of a
lead vehicle. The goal of the ACC model is to replicate the dynamic response of the system to an input; if it is calibrated using an input of zero or near zero, there is not much that can be learned about the dynamics of the system. Therefore, this analysis will focus on finding regions of data that show a strong correlation between changes in the range and range rate with the acceleration of the SV.

Once a valid region is identified, the selected data is concatenated in sequence to create individual arrays of range, range rate, and acceleration. While this does create discontinuities in the data when two nonadjacent regions are concatenated together, the multivariate linear regression method does not consider the time dependence of the range and range rate on the acceleration response, so that is not a concern for this research.

The primary focus of this analysis is obtaining an overall view of driver behavior irrespective of the individual drivers, vehicles, speeds, and environments. As such, the average speeds of the SV and POV are not initially taken into consideration, but this will be explored in Section 5.6.

5.4.2.1 Initial Variable Processing

Before any analysis of the SHRP2 data can be performed, it must first be refined to ensure that the units are compatible with one another, there are no gaps in the data, and any significant outliers are removed. To address the first issue, the units for the radar range and range rate were measured in m and m/s, respectively; however, the acceleration was measured in G forces. This was converted to m/s\(^2\) by multiplying the acceleration data by 9.807 m/s\(^2\), the acceleration due to Earth’s gravity.
In regards to the second issue, there are periods of time within each of the SHRP2 data samples where no radar data is recorded and appears as NaN (Not a Number) values. In many cases, prolonged periods of NaN values that may be several thousand data points long may indicate that there is simply no lead vehicle present at all or the lead vehicle is outside of the radar’s 200 m range of detection. However, this cannot explain other instances where radar data was not recorded or was only recorded for a few data points at a time.

In several cases, there are a few times where radar data is recorded for around 10 data points or less at a time, corresponding to periods of around 1 second or less. There are also occasional gaps of 1 or 2 data points within a set of otherwise continuous radar data of several hundred data points in total length that have been recorded as NaNs. The first problem may be explained by what the SHRP2 researchers describe as “ghost targets,” [2] when the radar identifies targets that are not physically present or are not part of the primary target, such as a road sign or the road itself. The second problem may be caused when the radar system identifies multiple targets and corrects itself back to the primary target due to a large deviation in range between the two targets, creating a small gap in the data as a result. Additionally, the researchers note that the tracking algorithm used to identify the radar targets has relatively poor accuracy at low speeds and some systems that depend on the GPS speed instead of the vehicle network speed have more problems with the radar data due to the difference in sampling rate. (The GPS speed is sampled at 1 Hz while network speed is sampled at 10 Hz)
There are also moments where the video footage from the forward-facing camera of a given run shows the presence of a lead vehicle within the radar’s range at a given time stamp shown in the video. However, when crosschecked with its corresponding data file, no radar data appears to have been recorded at that time stamp. Recall the DAS schematic from Figure 2.1 shows that the data collected by the radar unit is transmitted to the head unit wirelessly via Bluetooth before being transmitted by wire to the main DAS unit. The SHRP2 researchers explain how they corrected for this delay in addition to other corrections they made to the radar data after collection [2]. Nonetheless, there may have been interference or a loss of signal in the transmission of the radar data during these times or the radar unit may have had its power supply interrupted, which would not affect the other data collection units in the vehicle’s cabin.

Regardless of the cause, all of the NaN values from the radar data were removed to avoid having any gaps at all, as well as the acceleration data corresponding to those NaNs. This creates numerous discontinuities in the data set. However, as long as the relationship between the range and range rate with the SV acceleration is strong, these discontinuities are irrelevant to the analysis.

5.4.2.2 Consideration of Time Delay

It is important to note that there is a certain amount of time delay between when the system of the human driver and vehicle receives the data inputs and when the vehicle actually responds. This delay is caused by the reaction time from when the driver sees an incoming vehicle, decides on a course of action, and then engages the vehicle’s brake,
throttle, and/or steering wheel, as well as the slight delay from when the vehicle’s propulsion and braking systems receive the driver inputs and then translates them into mechanical responses. Without considering a time delay, this analysis assumes that the ACC model is able to respond instantaneously or nearly so, creating a positive phase shift of the model’s predicted response compared to the human driver’s response. Without a time delay, the $R^2$ fit of the predicted response to the human response is worse than if they were aligned in the same phase.

5.4.2.3 Selection and Concatenation of Valid Regions of Radar Data

In order to account for the time delay, a linear regression and $R^2$ evaluation was performed using intervals of acceleration data fixed at 40 seconds in length and range and range rate data also sampled at the same interval. This was done for each time delay step between 0 and 10 seconds in increments of 0.1 seconds. Then within the set of $R^2$ values, the maximum $R^2$ value was determined and if that maximum was greater than or equal to 0.5, the set of radar data and accelerations was concatenated into the full set of data. If not, then the set of data was rejected and the next region of 400 data points was selected and analyzed. An example of this procedure is shown in Figures 5.10, 5.11, and 5.12, highlighting examples of a region with strong $R^2$ correlation and one with a weak $R^2$ correlation.
Figure 5.10 Example Radar Data Set
Figure 5.11 Region with Strong $R^2$ Correlation (green selection)
Figure 5.12 Region with Weak $R^2$ Correlation (red selection)
It can be seen from Figure 5.11 that the region with the rapid deceleration and subsequent acceleration yielded a very high $R^2$ correlation of 0.812 with a time delay of 0.6 seconds. The modeled acceleration very closely matches the behavior seen in the observed acceleration. Conversely, the region in Figure 5.12 with very little fluctuations in the acceleration yielded a low $R^2$ correlation of 0.542 with a time delay of 5.7 seconds. The model in this case does a poor job of predicting the acceleration seen from the observed data, especially within the first 25 seconds of the region. These results align with the conjecture from Section 5.4.2 that regions of relatively low acceleration will not produce very strong correlations with the range and range rate, while the region with a high acceleration produced a much stronger fit. In most of the observed cases, the time delay that yielded the maximum $R^2$ value was around or less than 1 second with numerous regions having a maximum $R^2$ value just barely above 0.5.

This process was repeated for each of the 191 data files, of which 131 contained at least one region of data meeting the $R^2$ threshold. After the entire data set was concatenated together end to end, another regression and time delay analysis was performed on the full concatenated data set to determine an overall time delay and $R^2$ fit. The entire concatenated data set shown in Figures 5.13 and 5.14 is nearly 650,000 data points long corresponding to approximately 18 hours of driver data. Results from the $R^2$ fit of this data is shown in Figure 5.15; with a sampling rate of 10 Hz.
Figure 5.13 Full Concatenated Data Set with Model Fit

Figure 5.14 Zoomed-in Section of Figure 5.13
While the time delay of the maximum $R^2$ is a reasonable 1 second in duration, the actual value of $R^2$ is significantly lower than the tolerance used to select regions for concatenation. This is because different regions selected for concatenation may have drastically different time delays associated with their maximum $R^2$ fit. As can be seen in Figures 5.11 and 5.12, the difference in the time delay for each region is over 5 seconds. Thus, it is reasonable to assume that the modeled fit of the two sets concatenated one after the other will be significantly worse than that of the individual sets because it is trying to find a common time delay between the two sets. This problem is amplified when
determining a modeled fit with hundreds of data sets concatenated one after the other, each with their own time delay.

5.4.2.4 Refinement of Analysis

In an effort to improve $R^2$ for the full concatenated data set, two measures were taken. First, all data with ranges greater than 100 meters were removed, as it is difficult to justify that a driver will respond to a lead vehicle at ranges greater than 100 meters. Additionally, several of the “ghost targets” within the data set recorded ranges far greater than 100 meters; removing these ranges also helps in part to remove some of these ghost targets. Second, a Butterworth filter was applied to the acceleration data in order to eliminate some high frequency noise. The filter cutoff frequency was determined by inputting the values of $\omega_n$ and $\zeta$ obtained from the beta coefficients into the transfer function described in Equation 5.11 and examining the resulting Bode diagram shown in Figure 5.16.
Figure 5.16 Bode Diagram from Best Fit of Concatenated Data

From Figure 5.16, the point of attenuation where the magnitude begins to change at a logarithmic rate with frequency was estimated at 0.6637 rad/s, or approximately 0.1 Hz. This guided the cutoff frequency of the Butterworth filter to 0.1 Hz, which was then applied to the acceleration data and the range and range rates were refitted to the filtered acceleration. The results of these changes are shown in Table 5.1.
Table 5.1 Results from Concatenated Data Sets

<table>
<thead>
<tr>
<th></th>
<th>Full Set</th>
<th>Range &lt; 100 m</th>
<th>Range &lt; 100 m, 0.1 Hz Filtered Acceleration</th>
</tr>
</thead>
<tbody>
<tr>
<td>Highest $R^2$</td>
<td>0.307</td>
<td>0.331</td>
<td>0.343</td>
</tr>
<tr>
<td>Time Delay (s)</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
</tr>
<tr>
<td>$b_1$</td>
<td>0.233</td>
<td>0.233</td>
<td>0.252</td>
</tr>
<tr>
<td>$b_2$</td>
<td>-8.62*10^{-4}</td>
<td>3.07*10^{-4}</td>
<td>3.08*10^{-4}</td>
</tr>
<tr>
<td>$b_3$</td>
<td>0.0356</td>
<td>0.0139</td>
<td>0.0139</td>
</tr>
<tr>
<td>$\omega_n$ (Hz)</td>
<td>0.0294</td>
<td>0.0175</td>
<td>0.0176</td>
</tr>
<tr>
<td>$x_0$ (m)</td>
<td>41.3</td>
<td>41.3</td>
<td>45.0</td>
</tr>
<tr>
<td>$\zeta$</td>
<td>3.97</td>
<td>6.67</td>
<td>7.17</td>
</tr>
</tbody>
</table>

5.4.2.5 Discussion of Results from Range Data Analysis

Eliminating the ranges greater than 100 meters yielded an 8% improvement in the highest $R^2$ from the full data set, while filtering the acceleration resulted in an improvement of 11.6% in the highest $R^2$ from the full data set. Removing the higher ranges also significantly changed the resulting values of $\omega_n$ and $\zeta$, but not $x_0$; $\omega_n$ saw a 61% change from the full data set regression and $\zeta$ saw a 68% change, while $x_0$ did not significantly change at all. This shows that the elimination of the outlying radar data had a significant effect on the behavior of the model, but not the steady-state following distance. However, once the acceleration was filtered, $x_0$ saw a change of 9% from the unfiltered acceleration fit, $\zeta$ saw a 7.5% change, and $\omega_n$ did not significantly change. This indicates that the refinement of the acceleration data affected the following distance and damping, albeit to a substantially lesser degree than the previous changes, but not the natural frequency.
In each case, the time delay that yielded the highest $R^2$ value was 1 second, which is a reasonable amount of time for the driver to respond to an oncoming lead vehicle. The steady-state following distance fell between 41 and 45 meters. Assuming the average length of a passenger car is 4.5 meters, this is approximately equal to 10 car-lengths. At a speed of 70 mph, this translates to approximate lead times of 1.3 and 1.44 seconds, respectively, also within reason.

The values of the natural frequency $\omega_n$ are not that much lower than the POV frequency found in Chapter 3. Compared to the POV frequency of 0.02 Hz, the $\omega_n$ from the full data set is approximately 50% greater than that value, resulting in a forcing frequency to natural frequency ratio $\omega/\omega_n$ of 0.66; after refinements, the frequency ratio becomes 1.11. In addition, $\zeta$ for each data set is greater than one, indicating the model is an overdamped system. While not quite the same, the natural frequency of the SV in response to the behavior of the lead vehicle is very close to that of a normal driver at steady-state. If the system had little to no damping, the SV would likely experience a response close to that shown in Figure 5.6 at harmonic resonance, creating a continuously amplifying response over time. Because the system is overdamped, it can be expected that the POV and SV would have similar behaviors as both are driven by human drivers prone to similar types of natural frequency.

Nonetheless, the lack of agreement of the modeling fit suggest that there is a higher variability in driver behavior than what was originally hypothesized. To improve the fit for future research, a higher $R^2$ threshold for selecting regions may be examined such as 0.7 or 0.9, where the driver is clearly reacting in response to the behavior of a lead vehicle and
reducing the likelihood that the response is random. This will likely yield a higher overall \( R^2 \) fit in the concatenated data set as a result. Additionally, a more detailed method of removing the ghost targets in the radar data may also improve the \( R^2 \) fit as the data will be based on real targets in front of the vehicle as opposed to non-real targets. In the meantime, the values of \( \omega_n, \zeta, \) and \( x_0 \) can still be useful for testing the response of the ACC model calibrated to those values.

5.5 Testing Response of the ACC Model

With a functioning model in hand and the parameters calibrated, the next step is to examine its response using a variety of different inputs. Each input utilizes the known displacement \( y(t) \), in meters, and speed \( \dot{y}(t) \), in meters per second, of the lead POV for each case as well as the \( \omega_n \) and \( \zeta \) values previously determined as the forcing input described in Equation 5.13. The model's response in displacement, speed, and acceleration is then compared to the displacement \( y(t) \), speed \( \dot{y}(t) \), and acceleration \( \ddot{y}(t) \) of the POV, the latter taken as the derivative of the POV speed. The parameters used for the model are the system natural frequency \( \omega_n = 0.0176 \text{ rad/s} \), initial offset displacement \( x_0 = 45 \text{ m} \), and damping value \( \zeta = 7.17 \). Additionally, the model's response includes a time delay of 1 second.

The first input signal examined is a simple sine wave signal consisting of displacement \( y(t) = \sin \omega t \), relative velocity \( \dot{y}(t) = \omega \cos \omega t \), and acceleration \( \ddot{y}(t) = -\omega^2 \sin \omega t \) with \( \omega = 10 \omega_n \), shown in Figure 5.17. Note that the relative velocity is the
derivative of displacement and acceleration is the derivative of velocity. The initial velocities of both vehicles is set at 100 km/h.

Next, a selected sample of the SHRP2 data is examined in order to compare the response of the ACC model to the response of the human driver, using the radar range, range rate, and SV speed and acceleration, shown in Figure 5.18. The SV speed and range can be used to determine the POV displacement \( y(t) \). First, the radar range \( z(t) \) is defined as the difference in displacement of the POV \( y(t) \) and the SV \( x(t) \):

\[
z(t) = y(t) - x(t)
\]

(5.28)

While \( x(t) \) cannot be directly measured, it can be derived as the integral of the speed \( \dot{x}(t) \):

\[
x(t) = \int \dot{x}(t) dt
\]

(5.29)

Substituting Equation 5.29 into Equation 5.28 and solving for \( y(t) \) yields:

\[
y(t) = z(t) + \int \dot{x}(t) dt
\]

(5.30)

In a similar fashion, the radar range rate \( \dot{z}(t) \) is defined as the difference in velocity of the POV \( \dot{y}(t) \) and the SV \( \dot{x}(t) \):

\[
\dot{z}(t) = \dot{y}(t) - \dot{x}(t)
\]

(5.31)

However, in this case, both \( \dot{z}(t) \) and \( \dot{x}(t) \) are known variables, so Equation 5.31 can simply be rearranged to solve for \( \dot{y}(t) \):

\[
\dot{y}(t) = \dot{z}(t) + \dot{x}(t)
\]

(5.32)
Finally, recall the generated stochastic velocity profile from Figure 4.8; the speed, displacement, and acceleration from this data are used as the properties of the POV to measure the response of the ACC, shown in Figure 5.19. While the speed $\dot{y}(t)$ is known, the displacement is simply taken as the integral of speed while the acceleration is taken as the derivative of speed.

![Figure 5.17 ACC Response to Sine Wave Input](image)

From the sine wave input in Figure 5.17, the model’s displacement, velocity, and acceleration responses each have a slight time delay response of 1 second as was originally defined. Even though the following distance seems to fluctuate at the same frequency as the POV and model, it is a stable motion. Likewise, in velocity, the magnitude response of the model is slightly less than the magnitude of the POV’s velocity, it still tracks it very
well; the same is also true for the accelerations. The ACC model does a good job of tracking a sine wave input.

Figure 5.18 ACC Response to Sample of SHRP2 Data Input

The model responses from this set of inputs show strong resemblances to the lead POV as opposed to the human-driven SV. It can be seen that the model’s range to the POV is nearly constant, while the measured radar range slowly increases with time. On the other hand, the model’s speed pattern is very similar in behavior to the POV speed with approximately a 1 second time delay as designed. In comparison, the measured SV lags behind the speed of the POV by about 3 seconds; this shows that the model can respond quicker to changes in the POV behavior than a human driver typically does. In addition,
the accelerations of both the SV and the model are within the same bounds of one another and follow one another with a slight time delay.

Figure 5.19 ACC Response to Generated Stochastic Data Input from Figure 4.9

In this last example, the model once again mirrors the behavior of the lead vehicle quite closely. Once again, the model does a very good job in maintaining a constant distance with the lead vehicle, as well as mirroring the velocity and acceleration profiles. The primary difference between the two behaviors is that the model has less noise in its speed than from the generated stochastic velocity profile, which is also reflected in a smoother acceleration profile with less noise.
5.6 Additional Explored Analyses

One set of data that was also explored in correlation with the SV acceleration was cruise control. The goal of studying this set of data was to examine if the activation and use of cruise control reduced the accelerations of the SV as the system attempts to maintain a determined speed set by the driver. However, there were very few data samples that actually contained any information on the cruise control – the vast majority of samples had an empty cell array for this set of data. Meanwhile, the small amount of data that was present did not seem to show any significant changes to the behavior of the acceleration when cruise control was active versus not active.

In addition to examining the overall fit between the modeled acceleration and the observed acceleration, the fit within each speed bin was also examined, much like examining the frequency content. If a region was determined to be valid for concatenation in the full data set analysis, its mean velocity was also determined and the region was also concatenated into a second data set for the particular speed bin. Once all the valid regions were identified and concatenated, a linear regression with time delay was performed for each speed bin in the same way as the full concatenated data set. The results from these analyses are shown in Table 5.2.

<table>
<thead>
<tr>
<th>Speed Bin</th>
<th>0-10</th>
<th>10-20</th>
<th>20-30</th>
<th>30-40</th>
<th>40-50</th>
<th>50-60</th>
<th>60-70</th>
<th>70+</th>
</tr>
</thead>
<tbody>
<tr>
<td>Highest $R^2$</td>
<td>0.1851</td>
<td>0.3599</td>
<td>0.3616</td>
<td>0.3463</td>
<td>0.3617</td>
<td>0.3314</td>
<td>0.2259</td>
<td>0.3172</td>
</tr>
<tr>
<td>Time Delay (s)</td>
<td>0.9</td>
<td>0.9</td>
<td>1.0</td>
<td>0.9</td>
<td>1.1</td>
<td>1.0</td>
<td>1.1</td>
<td>1.0</td>
</tr>
</tbody>
</table>
At highway speeds, the $R^2$ is less than the concatenated average with the range of
0-10 mph exhibiting the worst fit out of all the speed bins. One possible explanation is that
at highway speeds, drivers have less time to react to behaviors from any leading POVs than
at slower speeds, especially when vehicles are within close proximity to one another.
However, at speeds under 10 mph, such a low $R^2$ value indicates the driving behavior at
those speeds is mostly random. This hypothesis makes sense since the only times drivers
are driving at those speeds is usually when they are accelerating from a stop or slowing
down to a stop, with extended periods of time being stationary at a traffic signal, waiting
to merge into an intersection, or driving in highly congested traffic conditions. The
correlation is slightly better at lower bins as these speeds are normally experienced in urban
or suburban driving environments within nearby proximity to other vehicles on the road.
Additional insights into differences between the speed regions could be explored in more
depth, but for the purposes of this research, were outside of the scope of the underlying
goal.

5.7 Conclusion

This chapter explored the development and verification of a second-order SDOF
modeling approach to simulate the response of an ACC system. The calibration of this
model was also explored using vehicle radar range, range rate, and SV acceleration to
examine the relationship between the behavior of a lead POV and its effects on the response
of the SV. Due to the wide variety of drivers, vehicles, and driving scenarios being
processed, a strong affirmative relationship was not discovered and instead, exemplified
the wide variability of driver responses to lead vehicle behavior. However, appropriate values of $\omega_n, \zeta,$ and $x_0$ for the model were able to be obtained from this analysis, allowing the response of the ACC model to various input signals to be simulated with extremely affirmative results.
Chapter 5 References


CHAPTER SIX

CONTRIBUTIONS AND CONTINUING WORK

6.1 Contributions

Based on the work presented in this thesis, the following contributions to the engineering community have been made.

1) A frequency-based analysis of naturalistic driving behavior under steady-state conditions has been presented.

This analysis contributes an initial understanding on the natural frequencies at which drivers operate under steady-state conditions. While the actual values and amplitudes of these frequencies vary depending on the length of time being sampled and the window applied to the sample, the overarching behaviors are identical in that the lowest frequencies are the most prominent. This aligns with the initial conjecture that at steady-state conditions, only small fluctuations over prolonged periods of time will be present in the speed of the human-driven vehicle. Further study into the effects of different windows on the frequency and amplitude content of these data is strongly recommended as additional frequency content may have been suppressed by using a Hann window as opposed to other window types.
2) **A method to replicate the stochastic steady-state behaviors of human driving using a frequency-based approach has been applied.**

   This method is capable of generating speed profiles for infinitely long periods of time for a variety of speed ranges. The development of this method is essentially the reverse of the frequency-content based analysis previously described, applying a stochastic phase to recreate a speed signal in the time domain. By definition, the frequency content of this stochastic speed profile is exactly the same as the frequency content discovered above and sanity checks of the speed contribute additional confirmation of this method.

3) **An initial analysis of naturalistic driving behavior as it relates to a second-order single degree-of-freedom model was presented.**

   This initial analysis contributes valuable information to the understanding of the relationship between the behavior of a lead vehicle and the acceleration response of the subject vehicle. Upon first glance, it appears that there is a higher degree of variability in the drivers’ response than what was originally expected, resulting in a poor correlation between the predicted driver acceleration and the measured acceleration. However, this wide variability can be explained due to the extremely varied nature of the data with different drivers, vehicles, and environments. A proposed recommendation for future study is to sample regions of range and range rate data using higher thresholds for a valid fit and examining if the relationship between the lead vehicle behavior and driver response improves.
4) **An application in the development of a baseline performance model of an adaptive cruise control system.**

The results from studying the behavior of an ACC model based off naturalistic driving behavior establish an initial point of reference on which to guide the tuning of future ACC systems. This relatively basic model is able to respond quicker and smoother than regular human drivers using a variety of different input signals. Ideally, a more sophisticated and complex ACC system should perform within the same metrics as the model demonstrated in this research, if not better; following distances may be better maintained and responses should involve very low levels of acceleration that the driver may not even notice.

**6.2 Continuing Work**

The basis of the work presented – using naturalistic driver data to investigate driver behavior – has yielded valuable information in guiding the development of automated vehicles; from understanding drivers’ natural frequency behaviors under steady-state conditions and being able to replicate these behaviors; to the realization that drivers are more unpredictable than expected in their responses to lead-vehicle behavior. This investigation is only one facet of a vast array of other investigations into understanding how automated vehicles may respond to human drivers. The following realms of continuing work are presented, as they will offer other insights into the study and behaviors of a rapidly evolving technology.
6.2.1 Use of Stochastic Velocity Generation in Semi-Autonomous Systems

The current evaluation of ACC systems uses human drivers operating the lead POV while a vehicle equipped with an ACC system follows. The primary challenge in using human drivers, as shown in the work presented in this research, is that human drivers are unpredictable and not consistent in their normal driving behaviors. This makes it very difficult to repeat the results of one test to another, or even maintain a consistent behavior over the course of a single test. Additionally, human drivers cannot operate a vehicle for indefinite periods of time as they get fatigued from driving after a few hours and must take periodic breaks. The primary data point of reference against which these vehicle-following tests are based is the velocity profile of the lead vehicle; by being able to generate indefinitely long periods of velocity data with human driver-induced noise, these tests can be conducted for extended periods of time and long-term patterns of ACC behavior may be discovered as a result. This also allows tests to be repeated using the same velocity profiles, adding to the strength of their results.

6.2.2 Analyzing Human Driver Behavior in Lane-Merging Scenarios

As automated vehicles become more prominent on public roads, an analysis on the predicted driver behaviors under certain scenarios will provide valuable insight into how to guide the decisions being made in an AV. One particular driving situation that both human-driven and automated vehicles may encounter is a lane-merging or cut-in scenario, where a lead vehicle suddenly cuts in front of the SV and the driver must respond appropriately in order to avoid a collision. The research conducted by SeHwan Kim at The
Ohio State University\textsuperscript{[1]} identified a number of different types of potential cut-in scenarios, simulated them in driving simulators with human drivers, and analyzed their responses using a range-range plot of potential conflict zones. In addition to the findings from the simulator investigations, it is also worthwhile to analyze a number of events recorded in the SHRP2 NDS data sets that resemble the cut-in scenarios he identifies. With the wider array of data on which to base the analysis, the findings from this research have a very strong backing and may provide additional insights that may be unavailable from a driving simulator.

6.2.3 Analyzing Human Driver Behavior in the Probabilistic Estimation of Instantaneous Acceleration

For any given point in time under a particular set of circumstances and possible outcomes, the Instantaneous Safety Metric (ISM)\textsuperscript{[2]} can be used to determine the probability of an unavoidable collision. The ISM factors in the effects on the SV due to the actions of surrounding vehicles or obstacles, the resulting range of positions and orientations of those surrounding vehicles, and the requirement of any severe maneuvers in order to avoid conflicts due to the actions of other vehicles. One proposed way to supplement this model could be the development of a map of regions of different potential outcomes and categorize them based on the likelihood of a potential interaction. The goal of this research would be to develop an ISM using a map of longitudinal and lateral accelerations, which may be possible using the acceleration data from the SHRP2 NDS.
database. This map may then be incorporated into the ISM model to improve the accuracy in predicting potential outcomes of various scenarios.
Chapter 6 References


REFERENCES


Derivation of the Unit Impulse Response for an Overdamped Second-Order System

The unit impulse response $y(t)$ for an overdamped second order system is defined as (see Section 5.3 for further discussion):

$$y(t) = \frac{e^{-\sigma_1 t} - e^{-\sigma_2 t}}{\sigma_2 - \sigma_1}$$  \hspace{1cm} (A.1)

$$\sigma_1 = \sigma \left(1 - \sqrt{1 - \frac{1}{\zeta^2}}\right)$$  \hspace{1cm} (A.2)

$$\sigma_2 = \sigma \left(1 + \sqrt{1 - \frac{1}{\zeta^2}}\right)$$  \hspace{1cm} (A.3)

$$\sigma = \zeta \omega_n$$  \hspace{1cm} (A.4)

where $\zeta$ is the damping ratio and $\omega_n$ is the natural frequency of the system. The term underneath the radical sign in Equations A.2 and A.3 can be rewritten as:

$$\sqrt{1 - \frac{1}{\zeta^2}} = \sqrt{\frac{\zeta^2 - 1}{\zeta^2}}$$

$$= \sqrt{\frac{\zeta^2 - 1}{\zeta^2}}$$

$$= \frac{\sqrt{\zeta^2 - 1}}{\zeta}$$  \hspace{1cm} (A.5)
Substituting Equations A.4 and A.5 into Equation A.2 yields:

\[
\sigma_1 = \zeta \omega_n \left( 1 - \frac{\sqrt{\zeta^2 - 1}}{\zeta} \right) \\
= \zeta \omega_n - \zeta \omega_n \frac{\sqrt{\zeta^2 - 1}}{\zeta} \\
= \zeta \omega_n - \omega_n \sqrt{\zeta^2 - 1} \tag{A.6}
\]

In the same respect, Equation A.3 becomes:

\[
\sigma_2 = \zeta \omega_n + \omega_n \sqrt{\zeta^2 - 1} \tag{A.7}
\]

Using these new definitions of \(\sigma_1\) and \(\sigma_2\), the denominator in Equation A.1 can be written as:

\[
\sigma_2 - \sigma_1 = \left( \zeta \omega_n + \omega_n \sqrt{\zeta^2 - 1} \right) - \left( \zeta \omega_n - \omega_n \sqrt{\zeta^2 - 1} \right) \\
= \zeta \omega_n + \omega_n \sqrt{\zeta^2 - 1} - \zeta \omega_n + \omega_n \sqrt{\zeta^2 - 1} \\
= 2 \omega_n \sqrt{\zeta^2 - 1} \tag{A.8}
\]

Likewise, \(\sigma_1\) and \(\sigma_2\) can be substituted into the numerator of Equation A.1:

\[
e^{-\sigma_1 t} - e^{-\sigma_2 t} = e^{-\left( \zeta \omega_n - \omega_n \sqrt{\zeta^2 - 1} \right) t} - e^{-\left( \zeta \omega_n + \omega_n \sqrt{\zeta^2 - 1} \right) t} \\
= e^{-\zeta \omega_n t + \omega_n t \sqrt{\zeta^2 - 1}} - e^{-\zeta \omega_n t - \omega_n t \sqrt{\zeta^2 - 1}} \\
= e^{-\zeta \omega_n t} \ast e^{\omega_n t \sqrt{\zeta^2 - 1}} - e^{-\zeta \omega_n t} \ast e^{-\omega_n t \sqrt{\zeta^2 - 1}} \\
= e^{-\zeta \omega_n t} \left( e^{\omega_n t \sqrt{\zeta^2 - 1}} - e^{-\omega_n t \sqrt{\zeta^2 - 1}} \right) \tag{A.9}
\]

Finally, combining Equations A.8 and A.9 into Equation A.1 yields:

\[
y(t) = \frac{e^{-\zeta \omega_n t}}{2 \omega_n \sqrt{\zeta^2 - 1}} \left( e^{\omega_n t \sqrt{\zeta^2 - 1}} - e^{-\omega_n t \sqrt{\zeta^2 - 1}} \right) \tag{A.10}
\]