Development of a Threat Assessment Algorithm for Intersection Collision Avoidance Systems

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ABSTRACT

Relative to other roadway segments, intersections occupy a small portion of the overall infrastructure; however, they represent the location for nearly 41% of the annual automotive crashes in the United States. Thus, intersections are an inherently dangerous roadway element and a prime location for vehicle conflicts. Traditional safety treatments are effective at addressing certain types of intersection safety deficiencies; however, cumulative traffic data suggests these treatments do not address a large portion of the crashes that occur each year.

Intersection Collision Avoidance Systems (ICAS) represent a new breed of countermeasures that focus on the types of crashes that have not been reduced with the application of traditional methods. Incursion systems, a subset of ICAS, are designed to specifically undertake crashes that are a result of the violation of a traffic control device. Intersection Collision Avoidance Systems to address Violations (ICAS-V) monitor traffic as it approaches the intersection through a network of in-vehicle sensors, infrastructure-mounted sensors, and communication equipment. A threat-assessment algorithm performs computations to predict the driver’s intended intersection maneuver, based on these sensor inputs. If the system predicts a violation, it delivers a timely warning to the driver with the aim of compelling the driver to stop. This warning helps the driver to avoid a potential crash with adjacent traffic.

The following dissertation describes an investigation of intersection approach behavior aimed at developing a threat assessment algorithm for stop-sign intersections. Data were collected at live intersections to gather infrastructure-based naturalistic vehicle approach trajectories. This data were compiled and analyzed with the goal of understanding how drivers approach intersections under various speeds and environmental conditions. Six stop-controlled intersection approaches across five intersections in the New River Valley, Virginia area were selected as the test sites. Data were collected from each site for at least two months, resulting in over sixteen total months of data.

A series of statistical analysis techniques were applied to construct a set of threat assessment algorithms for stop-controlled intersections. These analyses identified characteristics of intersection approaches that suggested driver intent at the stop sign. Models were constructed to predict driver stopping intent based on measured vehicle kinematics. These models were thoroughly tested using simulation and evaluated with signal detection theory. The overall output of this work is a set of algorithms that may be integrated into an ICAS-V for on-road testing.
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For My Family – Past, Present, and Future
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List of Acronyms and Abbreviations

AASHTO: American Association of State Highway and Transportation Officials
CICAS-V: Cooperative Intersection Collision Avoidance System for Violations
CP: Crossing path
DART: Data Analysis and Reduction Tool
DII: Driver infrastructure interface
DTS: Distance to stop
DVI: Diver vehicle interface
FHWA: Federal Highway Administration
GES: General Estimates System
ICAS: Intersection collision avoidance system
ICAS-V: Intersection collision avoidance system for violations
ICAV: Intersection collision avoidance for violations
IDS: Intersection decision support
LTAP/LD: Left turn across path – lateral direction
LTAP/OD: Left turn across path – opposite direction
LTIP: Left turn into path
NHTSA: National Highway Transportation Safety Administration
NDM: Naturalistic decision making
POV: Principal other vehicle
PRT: Perception reaction time
RDP: Required deceleration parameter
RLR: Red light running
RTIP: Right turn into path
SCP: Straight crossing path
SQL: Structure query language
SV: Subject vehicle
TCD: Traffic control device
TTI: Time to Intersection
TTS: Time to stop
VTTI: Virginia Tech Transportation Institute
CHAPTER 1 – INTRODUCTION

Intersections, where vehicles cross each other’s paths to proceed along their intended route, are prime areas for the occurrence of vehicle crashes. Of the 6.2 million police-reported crashes in 2005, 2.5 million (41%) occurred at intersections or were intersection related (NHTSA, 2006). Of these crashes, 8,655 were fatal and another 874,000 resulted in injuries. Given that intersections represent a very small portion of all roadways, they inherently carry a substantially higher crash risk than other street segments. Systems designed to prevent crashes at intersections could efficiently address a significant share of all traffic crashes. Thus, safety enhancements at such sites are a valuable investment (Ragland & Zabyshny, 2003).

Intersection Collision Avoidance Systems (ICAS) have recently attracted attention due to the potential to mitigate the intersection crash problem. ICAS were initially born out of the federal Intelligent Vehicle Initiative program and followed with the current federal Cooperative Intersection Collision Avoidance (CICAS) program. ICAS projects apply advanced technology solutions to reduce the intersection crash problem, which is beyond the capability of traditional methods. The envisioned ICAS systems employ a network of sensing equipment to monitor traffic as it approaches an intersection. Based on this information, the ICAS uses an algorithm(s) to predict future traffic conflicts and to initiate countermeasures as appropriate. The focus of this proposal is the development of threat assessment algorithms that will predict a conflict and initiate a countermeasure.

Two primary types of ICAS have emerged during the evolutionary process—gap acceptance and incursion. The first type of system, gap acceptance ICAS, addresses the conflicts typically caused when a driver selects a gap in traffic smaller then the gap required. This underestimation of gap may be caused by such factors as inattention, misjudgment, and visual occlusions. Gap conflicts tend to occur during right turn into path and left turn across path maneuvers. In these maneuvers, the driver must either pass through, or merge into, the available space between successive vehicles. The primary function of gap acceptance algorithms is to determine the appropriate safe gap size based on the intended maneuver, the conflicting traffic, vehicle type, and the driver’s capabilities. This type of ICAS has been envisioned as an advisory display that indicates when a gap entry maneuver is imprudent.

The second type of ICAS, and the focus of this research, addresses the incursion problem. It is referred to here as an Intersection Collision Avoidance System for Violations (ICAS-V). An incursion conflict occurs when a driver fails to relinquish the right-of-way at an intersection. These drivers act in direct violation of the Traffic Control Device (TCD), creating a situation where incompatible traffic may be simultaneously present in the intersection. For unsignalized intersections, this represents a driver who fails to recognize and/or respond appropriately to the stop sign. In a signalized approach, an incursion conflict occurs when a driver “runs the red light”.

Inattention, aggressive driving, and poor decision making are the primary reasons the current intersection system fails (Institute of Transportation Engineers, 2003). The present intersection system cannot fully compensate for these human limitations; however, ICAS-V can augment the decision process by warning the violating driver in an effort to overturn their decision to go. The ICAS-V would monitor traffic as it approaches the intersection, collecting data such as range, range-rate, acceleration, vehicle type, roadway conditions, signal phase, and signal timing. During the phase change, a threat assessment algorithm would calculate the probability of a violation based on the driver’s actions. The threat assessment would be made through an integration of dynamic vehicle data, signal state, and environmental variables. When a set of specified conditions is met, the algorithm will initiate the countermeasure.

Differentiating between inappropriate and compliant driver behaviors is difficult at the warning distance. Drivers must make quick assessments of speed, distance, TCD state, and also have time to decide if it is best to stop. Different drivers with differing levels of experience, judgment, risk tolerance, and mood/emotions will make different choices. As a result, the behavior of a compliant driver may overlap with that of a violating driver at locations where a countermeasure should be deployed. This could lead to cases in which a driver who did not need a warning receives one or vice versa. However, “each person that passes through an intersection should be accommodated at a reasonable level of safety and efficiency” (ITE, 2004, pg 5). Thus, engineers and designers must work to construct a violation threat assessment algorithm that enhances safety while avoiding unnecessary alarms.

Over the past three years, a significant volume of test-track research has been completed on ICAS-V (Lee, Perez et al., 2005; Neale, Perez, Doerzaph, & Stone, 2005). From this research, a substantial amount of knowledge has been acquired about driver response to various types of countermeasures. Countermeasures tested include in-vehicle visual, auditory, and haptic displays, as well as visual alerts located on the roadway infrastructure. The test track environment has worked well for making relative comparisons between countermeasure options and for determining at what point an inattentive driver must receive a warning in order to stop.

However, test track data is limited when applied to algorithm design. Test track data does not fully consider the complex dynamic nature of the real-world event and the interaction with driver motivations that cannot be re-created on the test track. These deficiencies resulted in a need to gather observational data at actual intersections across a variety of experimental conditions. From this observational data, an algorithm can be created to better represent the driver’s actual behavior as they approach an intersection. This algorithm can be combined with the previous and ongoing countermeasure work to determine if an ICAS-V is feasible (e.g., will a timely warning also result in an unacceptable number of nuisance alarms?).

Project Overview

The work described in this dissertation relates to the collection and analysis of naturalistic intersection observational data. These data were collected and analyzed with the goal of understanding how drivers approach intersections under various approach
speeds and environmental conditions. Six stop-controlled intersection sites in the New River Valley region in Virginia were selected for data collection. The sites were chosen based on their intersection characteristics and crash statistics. Data were collected from each site for at least two months, resulting in more than sixteen months worth of raw data.

To gather this data, arrays of sensing and collection equipment were installed at the test sites. These systems included radar, video cameras, data pre-processing and data storage. The parametric data and digital video were retrieved through a weekly manual storage drive swap at each test site.

Analysis of the data focused on the development of a working algorithm to predict driver stopping behavior at intersection approaches, for the purpose of providing a warning to a violating driver. From the raw data collected, driver approach behavior was dissected and analyzed for trends. Logistic regression and cluster analyses were performed to investigate the differences between various intended driver maneuvers. Algorithms designed to predict whether or not a driver will stop were developed. These threat assessment algorithms were evaluated in a pseudo real-time simulation using the raw data collected.

The performance of each potential algorithm was assessed. Performance metrics were based on the effectiveness of the potential algorithm to predict a pending violation while minimizing false detections. In addition, other measures, such as the distance at which a prediction was made (i.e., does the driver have sufficient time to react to a countermeasure), and the extent to which a warning would be perceived as annoying were also considered.

The best performing algorithms are recommended for future system-level research to validate their performance when integrated into prototype hardware and implemental warning interfaces. This research project will feed into a growing body of knowledge regarding intersection approach behavior and in particular intersection collision avoidance. Intersection collision avoidance has been identified by the major federal CICAS initiative as a key research area and will continue to receive a significant level of attention and funding over the next decade (RITI, 2007).

An ICAS-V is expected to be evaluated in a full-scale field operational test within the next few years. Prior to that field test, the algorithm must be identified and optimized. It is the purpose of this study to construct the first algorithm, based on a large sample of naturalistic data. While focusing on the development of an ICAS-V for stop sign intersections, the results, techniques, methods, and lessons learned are applicable to all ICAS (as well as many other) vehicular warning systems.

**Scope of this Project**

The work described in this dissertation will feed into the Cooperative Intersection Collision System for Violations (CICAS-V) federally-sponsored research program. As
part of the CICAS-V project, a threat assessment algorithm will be developed for both signalized and stop-sign controlled intersections. Stop-sign intersections represent a slightly simpler case and should be studied first. The lessons learned during the stop-sign algorithm development, perhaps even the algorithm itself, may be applied to the signalized case.

It is not the purpose of this project to develop the CICAS-V hardware, software, or the driver-vehicle warning interface. Although this research is being funding by CICAS-V, the scope has been broadened because much of the data analysis is applicable to other types of ICAS as well. Broadening the scope will provide data to the engineering and scientific communities currently developing other ICAS in parallel with the CICAS-V. Furthermore, data from this study may be used by additional researchers and stakeholders who desire to understand how drivers approach intersections for purposes other than collision avoidance.

The reader may notice that some components of the literature review and discussions are relevant to signalized intersections as well as to stop sign intersections. There are two reasons for this. First, the volume of past research on signalized intersections is far greater than unsignalized intersections. Much of the findings on signalized intersections are expected to be relevant to unsignalized intersections. Second, this dissertation is the first step in the development of a violation threat assessment algorithm.

As such, the focus of this research is limited to stop-controlled intersections. However, future efforts will use the techniques and results of this research to construct the signalized threat assessment algorithm as well. It is hoped that the work performed here will define the algorithm development procedure for signalized intersections as well. For this reason, some of the attributes of signalized intersections were considered such that the methods and results of this project will be compatible with future signalized intersection projects.
CHAPTER 2 - ICAS BACKGROUND

The timing of warnings will ultimately determine the effectiveness of an ICAS-V. Alarms that occur too early will likely deflate the safety benefits of collision avoidance systems because of annoyance and loss of user trust in the system (Dingus, Jahns, Horowitz, & Knipling, 1998). Warnings that happen too late will fail to prevent an intersection collision.

The ICAS-V work thus far has provided a substantial amount of preliminary knowledge regarding the appropriate warning timing. However, significant knowledge gaps preclude the design of a robust threat assessment algorithm. It is not yet known if violating drivers can be distinguished from compliant drivers by the time the warning should be issued; until this can be determined, there is a risk of producing an unacceptable number of nuisance alarms.

The following section introduces the ICAS work completed to date. This ICAS background provides a foundation for discussing the current limitations and knowledge gaps presented in the subsequent section. This discussion establishes the opportunity for the present research to fill in this knowledge gap.

ICAS State of Knowledge

The ICAS concept originated from the Intelligent Vehicle Initiative (IVI), which aspired to enhance safety and mobility by applying technological solutions to transportation problems. Upon completion of IVI in 2005, the United States Department of Transportation launched CICAS to continue the development of the ICAS concept. The two sequential ICAS-related initiatives have resulted in a substantial number of completed and ongoing ICAS research projects over the last decade. To provide the reader background on the state of ICAS knowledge, this section will briefly discuss these projects at a high level.

The infrastructure consortium was created to research and develop infrastructure-based ICAS solutions. The consortium, lead by the FHWA, consisted of three participating state DOTs and their university research institutions. Each state selected a problem area to be the focus of their ICAS research. Virginia, along with the Virginia Tech Transportation Institute, selected the straight crossing path (SCP) problem area. Minnesota and the University of Minnesota selected rural stop-controlled left turn across path – lateral direction (LTAP/LD) crashes as their focus. California, along with the University of California PATH, selected urban left turn across path – opposite direction (LTAP/OD) crashes.

The Virginia research effort was the only program directed specifically at mitigating intersection crashes that occur as a result of incursion. Both the Minnesota and California programs were directed at providing gap size information to a driver. The gap acceptance problem is substantially different than the incursion (or violation) problem.
As a result, little ICAS-V relevant information has been released from these two projects. The Virginia research effort, on the other hand, has produced most of the ICAS-V data directly relevant to the present research effort.

Virginia performed two studies for the infrastructure consortium that are directly applicable to the proposed work: (1) driver response to a changing traffic signal; and (2) an investigation of driver infrastructure interfaces. The first study investigated driver response to a changing traffic signal as a function of driver characteristics, phase change distance, approach speed, and behavioral state (Doerzaph, Perez, & Neale, 2004b). The studies aimed to better understand how drivers approach intersections during different mental states (“baseline”, “distracted”, and “willful”). These studies took place at the Virginia Smart Road test track facility. Because it was not feasible to manipulate the participant’s actual mental state, the researchers relied on simulation methods to motivate the “distracted” and “willful” driver behavior. Results from these studies provided preliminary information that was used to develop the data collection apparatus and initial threat assessment algorithm.

The second type of research investigated Driver Infrastructure Interfaces (DII) (Neale et al., 2005), which is a warning interface that lies entirely outside the vehicle. These studies used an occlusion technique to simulate a highly distracted driver. The driver’s vision was occluded at a key location from the intersection so the driver was unaware of a green-to-amber signal change. As the occlusion cleared, the driver was forced to make a last-second go/no-go decision.

The influence on that go/no-go decision was studied for a variety of DII types. For each warning type, an “optimal” onset location was found. This location represented the 100% compliance point (the position nearest to the intersection at which the entire sample [16 drivers] successfully stopped).

However, the test-track data were not collected for the purpose of determining nuisance alarm rates. It was limited in sample size and lacked many of the natural factors likely to contribute to the intersection approach. The authors recommended that additional naturalistic studies be completed to evaluate the implications of the warning timing. The proposed study fills this recommendation.

A parallel research project was also performed by VTTI under contract from NHTSA. This parallel research project investigated warning effectiveness for a variety of Driver Vehicle Interfaces (DVI). A DVI is located inside the vehicle where more salient and directed warnings may be provided through multiple modalities; these include auditory, visual, and haptic warning types. The results from this study identified later warning onset requirements than IDS. As with the infrastructure warnings, the full extent of the nuisance alarm problem will not be known until actual intersection approach behavior is gathered. The objective data from these studies will have utility in the algorithm development process. Measures such as perception reaction time and warning onset timing, discussed in the subsequent sections, may be used as inputs to the human component of the threat assessment model. Furthermore, the warning onset timing
determined by these studies will be overlaid on the data collected for the present study to help identify the best threat assessment algorithms.

Other research efforts have also been directed at ICAS development. Veridian Engineering performed much of the early technology ICAS work (Pierowicz, Jocoy, Lloyd, Bittner, & Pirson, 2000). This work was predominantly hardware-driven and under somewhat different ICAS framework than the present study. In particular, the Veridian system was not designed to address situations in which a violation occurred. Thus, little of the Veridian work is relevant to the current study.

The most complimentary research to date was performed by Bellomo-McGee Incorporated (2003) in support of ICAS-V. The relevant study placed an experimenter at a live intersection to record approaching vehicles using hand-held radar. A total of 110 approaches at three intersections locations were analyzed. The researchers collected data on both drivers who were stopping at the red and those drivers who were under a free-flow green. The researchers assumed a driver in the free flow condition was equivalent to a driver that violated the signal. Comparisons were made between the range-rate and acceleration of the two conditions in order to define basic threat assessment algorithms. The results of their study will be discussed further in existing algorithm section below. Overall, the research indicated that ICAS-V threat assessment was possible but would require an advanced algorithm.

There has also been some relevant work that was not originally intended for ICAS-V use. Perhaps the best example of this was performed by the TNO Institute for Perception (Horst, 1990). The TNO studies collected driver behavior at live intersections in the Netherlands. The researchers looked at a variety of time-based measures to quantify and describe the approach behaviors and decision points of drivers. Data were collected for three to four hours at each site using a video camera. The data from these studies suggests many potential algorithm inputs and provides some initial values for the threat assessment.

General intersection approach knowledge was required to design the study and analytical techniques employed during this dissertation. There are many general intersection and driver-related epidemiological investigations that are relevant to ICAS. These investigations were not aimed directly at ICAS; however, they provide background information regarding the intersection scenario. For instance, some of the studies provide data regarding environmental factors that lead to violations. Additional discussion of these general intersection studies will be provided as part of the literature review in the subsequent chapter.

**Limitations of Research to Date**

At the present time, there is an insufficient knowledgebase to develop the threat assessment algorithm for ICAS-V. The previous research provides a variety of risk factors that contribute to intersection crashes. This information is useful because it suggests measurements sensitive to violation behaviors (i.e., time of day, and traffic volume). However, it does not provide continuous approach data of the kind that is necessary for a threat assessment algorithm.
The ICAS-V studies performed by VTTI did collect continuous data that was needed for threat assessment. These studies were primarily aimed at determining which warning interfaces resulted in the highest compliance. Although one study was used to look at nuisance alarm issues, it was limited by a small sample size, experimental demand characteristics placed on the participants, and a test-track environment.

Bellomo-McGee did collect live intersection data. The results of this data collection demonstrated some potential methods for threat assessment that were investigated during this research. However, the sample size of this data were limited and some large assumptions were made. One primary assumption presumed the behavior of a violating driver is the same as a driver going through the green. Furthermore, these data were collected with low-fidelity equipment at rates too low for a threat assessment. These limitations are directly accounted for in the present research by collection of a large data sample, which included naturalistic violation behavior which can be measured with high-fidelity data collection equipment.

The TNO studies provided live data over several independent variables that do suggest some algorithm inputs. The main limitation of this research is the reduction-intensive video technique which forced researchers to collect data for relevantly short periods of time and at a low update rates. Recent work by Virginia has indicated that an update rate nearly three times higher than that used by TNO will be required to make an accurate and timely threat assessment (Lee, Perez et al., 2005).

The existing research provides many preliminary inputs to the ICAS-V algorithm development process. Basing a threat assessment algorithm on these values alone, however, would result in substantial assumptions regarding general intersection approach behavior. None of the data collection efforts up to this point have obtained continuous measures of actual violation behavior. The approach behavior of violating drivers should be well understood if an accurate algorithm is to be devised. Safety systems such as ICAS-V need to be thoroughly tested to ensure that unintended consequences are avoided. This means that large samples taken across a variety conditions (i.e. geometry, speed, weather, and time) are necessary. The ICAS-V directed data collection effort presented in this dissertation has filled this data gap.
CHAPTER 3 – LITERATURE REVIEW

Intersections are arguably the most complex roadway element that drivers regularly traverse. At any intersection the driver must perceive a dynamic environment and make a series of control maneuvers based their prediction of the future. The arrival of adjacent vehicles, traffic patterns, signal timings, and vehicle control are a few of the judgments made in the seconds leading up to an intersection crossing. With the complexity of the required decisions, it is a matter of when, not if, an error will occur.

During an intersection approach, there is a decision/response process that must be completed by the driver in order to minimize the opportunity for a collision. The stages of this process encompass: 1) Detection of the upcoming environment including the roadway, intersection, traffic control devices (TCD), pedestrians, adjacent vehicles, and other obstacles; 2) recognition of these environmental elements; 3) cognition, which should result in selection of a subsequent action; and 4) execution of the intended action. Depending on severity and timing, a breakdown in any stage of this process may result in a collision.

Crashes at intersections represent about 41% of all annual crashes (NHTSA, 2006). Most intersection crashes may be categorized as either rear-end or crossing path (CP) conflicts. Other crash types include single vehicle, pedestrian/cyclist, head-on and sideswipe. CP crashes cause an estimated 26.7% of all crash-caused delay, totaling approximately 120.3 million vehicle hours annually (Wang & Knipling, 1994). The envisioned ICAS-V will primarily address CP crashes resulting from a violation. Violation-related CP maneuvers account for 393,000 annual crashes, at a cost of $39 billion (Lee, Perez et al., 2005).

This dissertation addresses CP crashes at stop-sign intersections resulting from a violation of the TCD. Overall stop-sign CP crashes account for 374,000 (38%) of the annual intersection crashes, resulting in 3,994 fatalities. Crossing path crashes in which a violation was cited in the police report occur 184,000 times each year (Lee, Perez et al., 2005).

The next sections decompose the intersection CP crash problem. They begin with an introduction of terminology, followed by a review of the factors that influence intersection crashes. The intersection approach follows, addressing the required human decisions with respect to their capabilities and limitations. The purpose of this discussion is to understand and attempt to predict the factors leading to intersection CP crashes.
Intersection Crash Type Taxonomies

The necessity for vehicles to cross paths elevates the crash risk at intersections. Furthermore, the incidence rates and severity of intersection crashes depend on the relative positions and travel directions of the vehicles involved. To provide a means for analyzing these effects, several taxonomies for describing intersection conflict types have been used (Ferlis, 2001; Pierowicz et al., 2000; Wang & Knipling, 1994). These taxonomies describe the potential interactions of two vehicles that result in the primary collision.

The vehicle of interest (the violating vehicle) is defined as the subject vehicle (SV). The intended path of the SV is intersected by the principal other vehicle (POV) who always has the right-of-way. Thus, the SV is generally considered at fault in these crashes, as they have violated a traffic law by failing to surrender the right-of-way. The taxonomy presented by Ferlis (2001) provides a general classification system that is appropriate for use in both signalized and unsignalized intersection types. This taxonomy is described below and pictorially represented in Figure 1 through Figure 3.

**Straight Crossing Path (SCP):** The SV strikes, or is struck by, a POV while both vehicles are traveling through an intersection in straight paths perpendicular to each other (Figure 1).

**Left Turn Across Path – Lateral Direction (LTAP/LD):** The SV strikes, or is struck by, a POV while either the SV or POV is making a turn from the lateral direction (Figure 2).

**Left Turn Across Path – Opposite Direction (LTAP/OD):** The SV strikes, or is struck by the POV while either the SV or POV is attempting to make a left turn from the opposing traffic lanes (Figure 2).

**Right Turn Into Path: Merge (RTIP):** The SV or POV turns right into the path of the other vehicle so that both vehicles are traveling in the same direction at the time of collision. Both vehicles are initially traveling in perpendicular directions (Figure 3).

**Left Turn Into Path: Merge (LTIP):** The SV or POV turns left into the path of the other vehicle so that both vehicles are traveling in the same direction at the time of collision. Both vehicles are initially traveling in perpendicular directions (Figure 3).
Figure 1: Straight Crossing Path conflict (SCP).

Figure 2: Left Turn Across Path (LTAP): a) lateral direction (LTAP\LD), b) opposite direction (LTAP\OD)

Figure 3: Turn Into Path – Merge Conflict (TIP): a) Right – RTIP, b) Left – LTIP.
Delineating the Crash Problem

Intersection crashes appear to be influenced by a variety of infrastructure, environmental, and driver factors. Several researchers have studied the intersection crash problem in an effort to understand these influences. The purpose of this section is to review the relevant epidemiological findings in order to better understand the causes of intersection crashes. This information was used to design the naturalistic study and the subsequent algorithm development procedure of this dissertation. The end goal was, and is, to develop an algorithm that can be used to predict the occurrence of as many crash types as possible.

Crash Frequency by Location and Maneuver

A junction is the region formed by the connection of two or more roadways. Intersections are a type of junction that do not include driveway or alley access and that are contained within the boundary lines of the roadway (Ragland & Zabyshny, 2003). Nearly 60% of the U.S. crashes occur in the presence of a junction. Intersection crashes represent the largest contributor with 44% of the crash problem. Other junction crashes include: driveway/alley access (10.6%), entrance/exit ramp (2.6%), rail grade crossing (0.9%), and other (1.7%) (Ragland & Zabyshny, 2003).

Crash incidence data, segregated by classification, indicates the largest proportion of intersection crashes are classified as SCP (Ferlis, 1999). GES data from 1998 also indicated the prevalence of SCP crashes through the following distribution (Smith & Najm, 1999). These results are supported by Wang and Knipling (1994) as well as Ragland and Zabyshny (2003), who demonstrated similar distributions of ICP crashes.

- Straight crossing path (SCP) 36.6%
- Left turn across path/opposite dir. (LTAP/OD) 27.3%
- Left turn across path/lateral dir. (LTAP/LD) 15.9%
- Left turn in path (LTIP) 4.7%
- Right turn in path (RTIP) 4.7%

Driver Demographics

In general, older and younger drivers appear to have elevated crash risks during intersection crossings (Chovan, Tijerina, Pierowicz, & Hendricks, 1994; Tijerina, Chovan, Pierowicz, & Hendricks, 1994; Wang & Knipling, 1994). In particular, drivers in the 65 to 69 age group are involved in intersection CP crashes at nearly twice the rate of other crash environments. For drivers 85 and older, this likelihood increases to nearly three times the normal rate (Preusser, Williams, Ferguson, Ulmer, & Weinstein, 1998). Increased risk for older drivers may be a result of a higher probability for violating a TCD when they are required to yield to opposing traffic (Garber & Srinivasan, 1991; Wang & Knipling, 1994). The increased risk for younger drivers may be due to an increased probability of attempting an unsafe crossing (Sivak, Soler, & Trankle, 1989).

Gender does not appear to have a significant effect on intersection crash frequency. Wang and Knipling (1994) showed that intersection SCP collision rates (per 100 million vehicle miles traveled) are higher for females than males, but the likelihood (involvements per 1000 registered drivers) is higher for males than for females. Mixed
results appear across the literature indicating that gender is not a predominant factor in most intersection crashes (Chovan et al., 1994; Tijerina et al., 1994).

**Contributing Factors**

Many factors can contribute to an intersection crash (Figure 4; (data from Lee et al., 2004). Some of the most prevalent factors include obscured vision (10 %) and distraction/inattention (36 %). Both of these two causal factors may be directly addressed by the ICAS-V system. Additionally, depending on the ICAS-V architecture and performance, other casual factors such as roadway alignment, road surface, speeding, impairment, and even weather may be reduced.

![Figure 4: Percentage of Primary Contributing Factors for All CP Crash Types and Crash Severities for Light Vehicles Cited with Violations, 2000 GES data.](image)

**Time**

Most intersection crashes occur during daytime hours. Wang & Knipling (1994) found that 26 % of the ICP crashes occurred in the afternoon (15:31-18:30) compared about half that amount in the morning (6:31-9:30). Furthermore, ICP crashes occurred most frequently on Friday and least frequently on Sunday.

About 40 % more crashes occurred on an average weekday than on an average weekend day (Wang & Knipling, 1994). These results may indicate a role of fatigue or emotional motivation on intersection crash incidence rate (drivers heading home vs. to work).

**Vehicle Type**

Passenger vehicles comprise the majority of all crossing path crashes (96.7 %). Medium/heavy trucks are responsible for 1.8 % and motorcycles are involved in only 0.9
% (Wang & Knipling, 1994). In terms of overall crash rates, CP crashes constitute 30.2 % of the annual light vehicle crashes, 17.4 % of the truck crashes, and 31 % of motorcycle crashes.

**Intersection Attributes**

Wang and Knipling (1994) found that crashes occurred more often on one or two-lane roadways (48.7 %) than on three to four-lane (36.8 %) or on roadways with five or more lanes (25.9 %). Most crashes also occurred on straight and level roadways (76 %).

The type of control device installed at an intersection also appears to influence crash risk. Standard 3-phase traffic signals account for nearly half (46 %) of the ICP crashes, followed by stop-controlled intersections at 23 % (16% for two-way and 6 % for four-way stops). Un-controlled intersections are attributed with 26 % with the remaining five percent categorized as “other” (Ragland & Zabyshny, 2003). Violation crashes in which only one vehicle had a stop sign occur at six times the rate when both vehicles have signs (Lee et al., 2004).

Speed also impacts the rate of CP crashes. Data from Lee et al. (2004), show that CP crashes are most common at higher speeds where conflicts tend to result in the most injurious accidents with the highest levels of property damage (NHTSA, 2003). By focusing on high-speed intersections first, researchers hope to reduce the number of fatalities and life-altering injuries.

**Weather**

According to Wang and Knipling (1994), most intersection crashes occur in clear conditions (85.2%), followed by rain (12.2%) and finally sleet/snow/fog/other (2.6%). As expected, the road is most often dry (76.8%), followed by wet (19.6%), and finally, covered in snow/ice/sand/other (3.6%). Tijerina et al. (1994) reported that straight crossing path crashes at signalized intersections occur mainly on dry pavement, in good weather, and during daylight conditions.

**The Intersection Approach in the Context of Driver Decision Making**

This chapter has demonstrated that intersection crashes are primarily a result of a breakdown in the driver’s perception/decision process. To better understand where these breakdowns occur, a couple of models are introduced. The first model was developed by Bonneson while expanding on earlier work by Van der Horst (ITE, 2003). This model describes the intersection approach as a methodical comparison between the consequences of going vs. the consequences of stopping. The driver uses the perception of the vehicle’s dynamic characteristics and the intersection timing as inputs to this decision process.

<table>
<thead>
<tr>
<th>Components of the decision process</th>
<th>Decision factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimated consequences of Not stopping</td>
<td>Threat of right-angle crash and threat of citation</td>
</tr>
<tr>
<td>Estimated consequences of Not stopping</td>
<td>Threat of rear-end crash and expected delay</td>
</tr>
</tbody>
</table>
As is frequently the case in transportation research, this model views the human decision as an intellectual, information-driven process. Based on the information provided during this literature review, it is clear that this type of framework fails to describe all the emotional and experience-related attributes that guide human decision during the intersection approach.

A driver who has been forced to stop at a series of red lights may attempt to run the upcoming light out of frustration (Horst, 1990). Furthermore, naturalistic decision making appears to occur without carefully examining all of the potential alternatives (Zsambok & Klein, 1997). Thus, a driver approaching the intersection may come to a decision based on the success of a similar previous attempt, without considering all of the possible options on this particular approach. This explains how expertise makes people better decision makers. It also explains how people make decisions under extreme time pressure, which is often the case in the context of driving.

Recall the primary goal of this present research is to predict a violation before it occurs. The application of this prediction is an ICAS-V that will eventually provide a warning to a driver with the aim of altering their intended maneuver. An ICAS-V is limited in that it can only monitor the driver through changes in the vehicle’s physical state. The ICAS-V will not be able to monitor driver behaviors or physiological measurements directly. Thus, a simple model of the human must be selected for this research. The model below groups several stages of typical decision models (Figure 5). The next several sections will provide an overview of the existing knowledge in context of this simplified model.

![Figure 5: Simplified model of driver decision making](image)

**Sensation and Perception Related to Environmental Cues**

Intersections and intersection devices are engineered so a driver is not enticed to violate the TCD. This includes making the elements of the intersection as visible as possible so that the driver can prepare to stop. Improvements to the intersection geometry, pavement markings, advanced warning signs, rumble strips, and dedicated left turn pockets can reduce crashes (Bonneson, Zimmerman, & Brewer, 2002; ITE, 2003). In a recent review of intersection crashes, 40% of red-light runners claim they did not see the signal and another 12% apparently mistook the signal indication and claimed they had a green light (ITE, 2003). This indicates that in some cases the TCD themselves are not conspicuous enough. Conspicuity of stop signs is standardized in the Manual for Uniform Traffic Control Devices (MUTCD, 2004; USDOT, 2001). These standards are based on visibility research performed over the last three decades.
• Size: 750 cm for conventional up to 900 cm for expressways
• Color: Red with white lettering
• Reflectivity: Shall be reflective in the same color visible during daylight
• Placement:
  • On the side of the road to which the sign applies
  • When visibility is restricted, the stop sign shall be accompanied by a stop ahead sign
  • Located at the point where the road user should stop
  • Mounting height of 2.1 meters

Another important characteristic is the distance at which the TCD becomes visible. This value is known as the site distance. With increasing speed, more site distance is required to perceive the sign and safely stop the vehicle. The site distance is made up of two components: the distance consumed while the driver is reacting and the distance consumed while stopping the vehicle. The American Association of State Highway and Transportation Officials (AASHTO) recommend 2.5 seconds for a typical driver to react. In addition, the driver should also be provided with sufficient distance to stop the vehicle. AASHTO recommends that the driver be expected to stop at a rate of 11.2 ft/sec^2. Correcting for roadway grade the following equation is used by civil engineers to determine the stopping site distance for a sign:

\[
SD = 1.47 \cdot V t_{pr} + \frac{V^2}{30(2a + G)}
\]  
(Equation 1)

Where:
- SD = Stopping site distance (ft)
- V = Velocity (mi/hr)
- \( t_{pr} \) = Perception-reaction time (2.5 sec)
- a = Assumed deceleration rate (11.2 ft/sec^2)
- g = Gravitational force (32.2 ft/sec^2)
- G = Roadway gradient (ft/ft)

Response Selection
The driver’s response selection ultimately determines whether or not an unsafe intersection crossing will occur. The nature of an intersection requires the driver to make many decisions throughout the approach. These decisions range from the selected initial speed to the location for brake activation. The ICAS-V must predict the ultimate stop/pass decision of the driver by monitoring changes in vehicle attributes as a surrogate for the driver’s choices. The following subsections review the literature available to describe the decisions made by drivers during their intersection approach. When possible, the relationship between a given decision and the likelihood of an unsafe intersection crossing are identified.
Behavioral Influences of the Stop/Continue Decision

The following discussion identifies various intrinsic and extrinsic factors that appear to affect a driver’s choices during an intersection approach. It focuses on the influences that contribute to aggressive and inattentive behaviors, as these are believed to be the primary causes for violation. For signal controlled intersections, aggressive behavior refers to a driver that attempts a late crossing in an effort to “beat the light”. However, an aggressive driver may also stop at a high rate of deceleration should they decide not to go. In the case of stop-signs, an aggressive driver is one which approaches the TCD rapidly with the intention of braking late or running the sign. The term ‘inattentive’ describes drivers who exhibit abnormally long perception-reaction times due to internal or external distracters. The aggressive and inattentive behaviors do not necessary imply that a violation was made, only that the risk of violation was elevated.

The behavioral influences discussed in this section are based on a handful of studies, the first of which was an observational study performed by Hicks et al. (2005). The researchers watched and recorded driver behavior in response to the amber at nine intersections. Observers recorded information about the driver, vehicle, and the environment. Manually reduced video from cameras setup at the intersection was used to determine approach speed, distance, and acceleration for 665 data samples.

In another study, a test-track was used to look at the differences in baseline, aggressive, and distracted drivers (Doerzaph, Perez, & Neale, 2004a). To avoid the difficulties associated with distracting a driver at a pre-defined location and duration, a simulated distraction method was used. The amber phase was occasionally shorted to simulate a driver who was distracted for the first part of the phase change. The study also motivated drivers to take aggressive actions by applying monetary incentives for crossing the intersection prior to red (penalties for violations were also applied).

Finally, an observational study of general aggressive behaviors over a variety of intersection locations was performed by Shiner and Compton (2004). For this study, 2177 aggressive maneuvers (honking, passing on shoulder, cutting across lane) were collected. For the purpose of this review, it is assumed that drivers performing an aggressive act, as defined for Shiner’s study, are also more likely to perform an aggressive intersection approach. This assumption is made because little public data with regard to aggression at intersections exists.

From the three studies identified above, a series of factors that affect behavior have been identified. These factors were used to determine the dependent measures and to help formulate threat assessment algorithms.

Intersection geometrics: Aggressive behaviors tend to occur more frequently as the number of through lanes decreases (Hicks et al., 2005). This may indicate that drivers are more cautious at more complex intersections.

Driver demographic characteristics: Females tend to exhibit less aggressive behaviors in response to yellow than men. Shinar and Compton (2004) found that in general males are 2 times more likely to drive aggressively than females. Senior drivers exhibited...
conservative intersection behaviors; whereas young drivers appeared more likely to exhibit aggressive behaviors (Hicks et al., 2005).

**Passengers:** Drivers with passengers are less likely to commit an aggressive action (Shinar & Compton, 2004)

**Distracters:** Doerzaph (2004a) found that drivers under the simulated distraction condition chose to continue more often than baseline drivers. Hicks (2005) found that drivers operating a cell phone were more likely to choose to stop when faced with a yellow-light indication. Those who did choose to go were more likely to do so aggressively.

**Traffic volume:** Drivers are more likely to proceed through an intersection in high traffic volume unless prevented to do so by vehicles ahead (Hicks et al., 2005).

**Vehicle type:** Drivers in pickups are more likely than drivers of sports cars to be classified as aggressive (13.33% vs. 7.22%). Sports car drivers also had the most normal stops (53.55% vs. 38.33% pickups vs. 41.8% all others) (Hicks et al., 2005). Shinar and Compton (2004) found that drivers of commercial vehicles are more likely to commit aggressive actions than passenger vehicles

**Amber light duration:** A study by Olsen and Rothery (1961) found that drivers tend to take advantage of long yellow phases to use it as an extension of the green phase. However, Hicks et al (2005) were unable to draw any conclusive differences in aggressive tendencies across the amber light durations at the selected intersection sites (between 4 and 5 seconds of amber).

**Time of day:** Independent of congestion, drivers are more likely (1.5x) to commit aggressive acts during rush hours than on weekends (Shinar & Compton, 2004). The authors suggest this effect is a result of the driver’s value on their time (feeling pressured to get to a location) rather than the actual day of the week.

**Motivation:** The study by Doerzaph et al. (2004a) demonstrated that motivation does have an influence on the decision made at intersections. Drivers that were monetarily compensated for beating the light tended to act in a more aggressive manor than baseline or distracted driving groups. It was hypothesized, but unknown if intrinsic motivations will have similar effects.

**Congestion:** Although aggressive actions are more likely with congestion, it appears this is due to the increased number of vehicles on the road and does not increase the likelihood of an aggressive behavior for any one driver (Shinar & Compton, 2004).

**Speed vs. approach type:** All non-aggressive drivers that chose to go showed speed decreases as the intersection was traversed. Drivers in the aggressive class exhibited the highest initial speed and accelerated at presentation of amber; but slowed after entering intersection (Hicks et al., 2005).
Traffic flow speed: Vehicles with speed higher than surrounding traffic are more likely to demonstrate sharp stops or aggressive passes. Those driving below the traffic flow tended to respond to yellow light cautiously (Hicks et al., 2005).

Deciding when to initiate braking

For the driver who does decide to stop, a secondary decision of when to initiate braking is also required. The point at which drivers initiate braking will help differentiate the behavior of a compliant driver from a potential violator by determining the distance-to-stopbar (DTS), or time-to-intersection (TTI) in which the two groups behave differently.

During a set of experiments at signalized intersections, Horst (1990) collected human approach behavior in the Netherlands. The sample consisted of 23 signalized intersections with 36 hours of data collection at each site. To determine when people make a go/no-go decision, the probability of stopping as a function of stimulus presentation were considered for a set of 50km/hr (31 mph) intersection approaches. The distributions were created for signalized intersections where the stimulus is a changing light. Although stop signs do not move as presentation of the amber does, it may be reasonable to assume that as drivers perceive the stop-sign at different distances their probability of stopping may take a similar shape.

As expected, an increasing proportion of drivers in the Horst study decided to stop as their DTS at stimulus onset increased. The authors preferred the TTI measure to DTS because it produced a more consistent description of the driver’s choice. A TTI of 4s was determined to have an equal probability of stopping or not-stopping which indicates the median decision point (Horst, 1990). This 4s rule remained consistent independent of speed, maneuver, road type, and traffic.

In their report Horst (1990) also presented the results of a data collection effort at non-signalized and unprotected intersections. The non-signalized intersections in the Netherlands differ from those in the United States. Yield intersections are the nearest match to stop-controlled intersections in the United States. However, yield intersections do not require the driver to come to a complete stop so generalizations of this data will be made cautiously. To understand the decision process of drivers approaching these intersections, Horst (1990) looked at when drivers started to brake by maneuver type (Table 1).
Table 1 Mean and standard deviation for the time-to-intersection (TTI), distance to main road, and velocity at the moment of braking.

<table>
<thead>
<tr>
<th>Measure</th>
<th>Left Turn (n = 15)</th>
<th>Straight (n = 27)</th>
<th>Right Turn (n = 22)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Std</td>
<td>Mean</td>
</tr>
<tr>
<td>TTIbr (s)</td>
<td>2.95</td>
<td>0.44</td>
<td>2.92</td>
</tr>
<tr>
<td>DISTbr (m)</td>
<td>26.25</td>
<td>6.30</td>
<td>28.81</td>
</tr>
<tr>
<td>Velbr (m/s)</td>
<td>8.87</td>
<td>1.57</td>
<td>9.85</td>
</tr>
</tbody>
</table>

The study also looked at TTI inflection point values during an intersection approach. The values were thought to indicate the point at which a driver had determined that braking was sufficient to stop the vehicle if needed. It may be that this is a measure of the driver’s willingness to come to a complete stop. For drivers that exhibited this inflection, it almost always occurred at TTI greater than 1.5s (Horst, 1990). An algorithm may use an inflection point such as this to filter out drivers who are likely to stop.

**Driver decision in Response to an ICAS-V Warning**

One final key piece of information on driver decision-making pertains to the effectiveness of a violation warning countermeasure. If the warning is deployed too late in the approach, a distracted driver will not have sufficient time to react and stop the vehicle. On the other hand, if the warning is initiated too early in the approach, a nuisance alarm problem may arise. Thus, the goal is to present the warning at the last possible instant, providing a high hit rate while avoiding false alarms.

The countermeasure studies performed at VTTI located distances from the intersections at which 100% of the sample (8 drivers) stopped in response to a warning (Lee, Perez et al., 2005; Neale et al., 2005). The location at which this “favorable” point was located depended on the countermeasure presented. Only the countermeasures with the highest performance are included in the Table (Table 2). Note that the TTI for the warning was different for the two initial approach speeds, indicating that drivers react differently to a warning depending on the speed.
Table 2: Location at which 100 % of the driver sample stopped in response to the warning

<table>
<thead>
<tr>
<th>TTI of warning (sec)</th>
<th>Distance of warning (ft)</th>
<th>Nominal Approach Speed (mph)</th>
<th>Warning</th>
<th>Compliance</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.03</td>
<td>105</td>
<td>35</td>
<td>Baseline - no warn</td>
<td>0 %</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.3g brake pulse with “red light” auditory</td>
<td>100 %</td>
</tr>
<tr>
<td>2.65</td>
<td>135</td>
<td>35</td>
<td>Baseline - no warn</td>
<td>18.8 %</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Auditory “stop”</td>
<td>100 %</td>
</tr>
<tr>
<td>3.32</td>
<td>220</td>
<td>45</td>
<td>Baseline - no warn</td>
<td>50 %</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Auditory “stop”</td>
<td>100 %</td>
</tr>
</tbody>
</table>

Response Execution

If a decision is made by the driver to alter the current trajectory, a response is next executed on one of the vehicle controls. This response is the first opportunity for an ICAS-V to recognize that the driver has made a choice and to monitor that choice over time.

Once a countermeasure stimulus is presented, there are subsequent activities that must be performed by the driver. Traditional models of human information processing incorporate incremental stages such as sensation, perception and cognition (Sanders & McCormick, 1993; Wickens & Hollands, 2000). However, because these are difficult to measure in applied settings, transportation research typically relies on reaction time measures that encompass several components of the information processing sequence.

Perception reaction time (PRT) of drivers has been measured for a variety of scenarios (Green, 2000). It is important to consider the driving circumstances in which the PRT was measured because this can have a large influence on its value (Green, 2000). For the purpose of an ICAS-V algorithm there are two PRT measures of interest. The first is the PRT of a driver in response to a stop sign. This measure will be used to identify those drivers who are attentive and responsive to the sign. The second PRT measure needs to represent a driver’s performance in response to an ICAS-V countermeasure. This measure will be used to determine the last instant at which a warning can be issued while providing sufficient time for the driver to stop the car. When combined with dynamic equations these two PRT measures constrain the algorithm by determining the earliest and latest a warning can be initiated.

Although there are many sources for obtaining PRT (Dingus et al., 2004; Green, 2000; Schweitzer, Apter, G. Ben-David, Lieberman, & Parush, 1995; Sohn & Stepleman, 1998), few of them are representative of the two measures required for ICAS-V. The best source for PRT measures is from ICAS-V studies recently completed at the Virginia Tech Transportation Institute (VTTI). As part of the IDS and ICAS-V efforts, VTTI has run a series of studies that analyzed driver behavior during intersection approaches (Doerzaph, 2004; Neale, Perez, Doerzaph, Lee, & Stone, 2004; Neale et al., 2005).
During the ICAS studies, PRT was measured from stimulus presentation (yellow signal) to both the beginning of the accelerator release and to the beginning of brake pedal motion. The first measure reflects the time needed for decision making, whereas the second measure includes locomotion time (Table 3). Note the large variance associated with these measures, thus indicating that PRT depends on individual choice. Interestingly, the reaction times were not dependent upon speed.

Determining the PRT for a driver approaching a stop-sign is not as straightforward. While the traffic signal provides an obvious stimulus (green to yellow transition), the point of stimulus presentation is not as clear for stop signs. The stimulus presentation will depend largely on intersection attributes such as site distance. To control the presentation, VTTI created an apparatus that rapidly placed a stop sign on the road while the driver’s vision was occluded for two seconds, simulating a distracted driver. When the occlusion was lifted, the driver could see the stop sign and the subsequent response was measured (Table 3).

The caveat is that drivers were relatively close to the intersection when the occlusion was lifted. Thus, the PRTs reported in the Table may be substantially quicker than the PRT for a driver approaching a static stop sign. In general, thinking of a typical driver’s response to a stop sign in terms of reaction time may not be appropriate. It may be better to focus on the distance at which the driver responds, as discussed in a previous section.

VTTI also performed experiments to determine a distracted driver’s response to various vehicle DVI and infrastructure-based DII ICAS-V countermeasures (Lee, Perez et al., 2005; Neale et al., 2005). The PRT from these studies will help determine how late a countermeasure can be deployed and still have a safety benefit. In general, the infrastructure warnings were not found to be very effective relative to their in-vehicle counterparts. The five applicable test conditions are displayed in Table 3. The first in-vehicle version is displayed on a high-heads-down display and uses a speech-based “stop” auditory warning. This was the most effective non-haptic warning tested in the vehicle. A 0.3g brake pulse paired with a speech-based auditory warning exclaiming “red light” was also tested. The brake pulse produced the best response times but is less likely to be implemented in a deployed vehicle. The infrastructure version is a dynamic stop sign built from high-intensity LED array. It is mounted on the mast-arm between signal heads and includes both strobe lights and traffic clearing lights for increased detection.

Finally, the only warning tested for stop controlled intersections was an infrastructure-based static stop sign augmented with flashing LEDs around the perimeter. Unfortunately, an in-vehicle warning for stop signs was not tested. From the CICAS-V work, it appears that an in-vehicle warning is the most likely candidate for deployment. Thus, it may be necessary to assume that drivers will respond to the in-vehicle warning in a similar fashion for both signalized and stop controlled intersections. Notice the PRT to a countermeasure is longer than the baseline conditions. This is because drivers receiving the warning were distracted by the visual occlusion, whereas the baseline drivers were not. For all the countermeasures, more drivers were convinced to stop than when no warning was provided.
Table 3: PRT for typical drivers approaching a changing signal and for distracted drivers in response to a countermeasure for four warning types. PRT is shown as both the time-to-accelerator release (TAR) and the time-to-brake (TB).

<table>
<thead>
<tr>
<th>Driver behavioral state</th>
<th>Stimulus</th>
<th>TAR (sec)</th>
<th></th>
<th>TB (sec)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Avg</td>
<td>Std</td>
<td>Avg</td>
<td>Std</td>
</tr>
<tr>
<td>Typical driver approach</td>
<td>Amber Signal Phase</td>
<td>0.38</td>
<td>0.18</td>
<td>0.82</td>
<td>0.19</td>
</tr>
<tr>
<td></td>
<td>Standard Stop Sign</td>
<td>0.33</td>
<td>0.15</td>
<td>0.67</td>
<td>0.17</td>
</tr>
<tr>
<td>Occluded during approach to simulate distraction</td>
<td>In-vehicle no-haptic warning</td>
<td>0.41</td>
<td>0.12</td>
<td>0.63</td>
<td>0.11</td>
</tr>
<tr>
<td></td>
<td>In-vehicle w/haptic warning</td>
<td>0.27</td>
<td>0.13</td>
<td>0.69</td>
<td>0.16</td>
</tr>
<tr>
<td></td>
<td>Infrastructure signal warning</td>
<td>0.46</td>
<td>0.29</td>
<td>0.90</td>
<td>0.28</td>
</tr>
<tr>
<td></td>
<td>Infrastructure stop-sign warning</td>
<td>0.39</td>
<td>0.16</td>
<td>0.76</td>
<td>0.13</td>
</tr>
</tbody>
</table>

**Vehicle Control**

Within the paradigm introduced earlier (Figure 5), there is a secondary level of continuous decision occurring to support vehicle control. Often referred to as tracking, this process describes how a driver monitors changes in the environment and makes control inputs to the vehicle in order to arrive at a desired future state (Figure 6).

Consider a driver approaching an intersection from a distance. Initially the driver does not perceive the intersection and operates in the tracking loop to maintain the desired speed and lane position. At some point the intersection and/or TCD is perceived and a decision is made to stop. This decision results in a new desired future state \( i(t) \), slowing the vehicle with the intent of completing a stop at the TCD. When \( i(t) \) is compared to the roadway display, an error \( e(t) \) results between the current and desired state of the vehicle.

This error between the actual and desired speed is perceived by the driver who then applies a force \( f(t) \) to the brake which transfers through the control to a vehicle input \( u(t) \). The system response \( o(t) \) changes the roadway display and re-starts the control loop.

![Driver manual control tracking loop](image)

**Figure 6: Driver manual control tracking loop**

The control loop framework is useful for describing the vehicle-driver system continuously through the stop. Depending on the driver’s higher level decisions, \( i(t) \) may change over time during the approach as their strategy updates. For instance, a driver may initially intend to stop at the sign and later change that strategy to roll through the intersection. This change in strategy will affect the system and may be measured through the vehicle response. The goal of this research project is to predict \( i(t) \) through measuring \( o(t) \).
This framework is discussed for several reasons. First, it provides background on how the driver controls the vehicle system, which identifies how system components interact during an intersection approach. Second, the tracking loop paradigm emphasizes the continuous nature of the intersection approach. A successful algorithm will need to monitor the output \( o(t) \) of the continuous loop throughout the entire intersection approach to predict an ever changing \( i(t) \). Third, the framework demonstrates how the driver is involved in the control loop. The driver will have certain preferences that determine how the vehicle state \( o(t) \) will change over time. Once the driver makes a decision and responds, they must modulate their brake/throttle position to meet the set goal. Similar to the discussion on PRT, the acceleration rate assumed by drivers is dependent on the situation.

For the ICAS-V scenario, there are two primary acceleration values of interest. The first is the average negative acceleration that a baseline driver is willing to assume once they have decided to stop. This value may be used to help determine when an approaching vehicle is not representative of the typical driver, and so more likely to violate. A recent experiment at VTTI was used to determine this parameter (Lee et al., 2004). Drivers were asked to brake at the last moment possible in order to come to a comfortable stop. The trials were completed at both signalized intersections in the red phase, and stop-controlled intersections. Results indicated that the traffic control type (signal vs. sign) was not significant and that the maximum deceleration rate drivers were comfortable with was \(-0.24g\) (stdev=0.08). Furthermore, in the set of baseline VTTI experiments performed at stop-controlled intersections, the deceleration rate assumed by a baseline driver approaching a stop sign was measured. Unlike the previous scenario, drivers in this study were not asked to brake at the last moment, but rather were allowed to brake where they thought they normally would. The typical driver stopped at an average deceleration rate of \(-0.14g\) (stdev=0.04) (Neale et al., 2005). Thus, drivers who perceive the sign early may demonstrate a mild level of deceleration.

The second acceleration measure is the absolute hardest a baseline driver is willing to brake. This value indicates the range in which an aggressive compliant driver may be willing to brake. Providing false alarms to these drivers should try to be avoided; however, if a warning is provided, it may not be considered nuisance even though it was not necessary to make the driver stop. The same study described in the preceding paragraph was used with drivers instructed to brake at the last moment possible to make a hard stop. Drivers from this group stopped at a \(-0.39g\) (stdev =0.11) rate.

The third acceleration measurement of interest is the average negative acceleration that a driver is willing to assume in order to avoid violating the TCD intersection after receiving a DII or DVI. Results from the countermeasure study at VTTI suggest that a driver is willing to stop at \(-0.43g\) (stdev=0.03) for an infrastructure countermeasure and \(-0.46g\) (stdev=0.05) for an in-vehicle countermeasure (Lee, Neale et al., 2005; Lee, Perez et al., 2005; Neale et al., 2005).

**Driver Behavior Classification During the Intersection Approach**

To describe drivers as they approach the intersection, researchers have defined groupings based on the mental state of drivers during their approach (Doerzaph et al., 2004a;
The difficulty with applying these classifications schemes is their subjective nature, requiring information directly from the driver. This dissertation study did not have direct access to driver’s internal thoughts. Thus, it is important to review objective surrogates for driver behavior. The objective schemes do not measure behavior directly; rather, they look at the vehicle maneuvers as a representation for behavior.

In a study of 665 yellow light approaches, Hicks (2005) developed a four-level classification system. Two variables were used to determine which class was appropriate for an intersection approach. The first variable determined whether or not the driver elected to stop. The term “pass” was intended to represent drivers who decided to continue through the light; whereas “stop” represented drivers who decided to stop. The second variable used in the classification was the time-to-intersection (TTI) at which the driver received the amber (TTI). Based on the combination of these two variables, drivers were classified as follow:

*Conservative Stop* — the driver who decided to stop even though he/she had a TTI less than the yellow-light duration.

*Normal Stop* — the driver who had a TTI equal to or greater than the yellow-light duration and decided to stop.

*Normal Pass* — the driver who had a TTI less than the yellow light duration and decided to pass; and

*Aggressive Pass* — the driver who had a TTI equal to or greater than the yellow-light duration and decided to pass.

Another classification system was developed to classify the maneuvers of red-light violators; drivers who crossed the intersection prior to red were not considered in the research (Zimmerman & Bonneson, 2005). Red light violations were categorized as either intentional (avoidable) or unintentional (unavoidable), depending on the circumstances leading to the incident. Intentional drivers represent the group that knowingly and purposefully attempts to beat the signal change. Unintentional violations are a result of driver who is either inattentive or is unable to stop prior to entering the intersection (dilemma zone problem).

**Existing Algorithm Related Research**

Most human factors research is concerned with how a typical person responds under a given set of circumstances. Often, human factors engineers design a system for use by most people by considering some percentile of the population (Sanders & McCormick, 1993). In contrast, a collision avoidance system is specifically designed to address uncommon driver decisions. For an ICAS-V, these decisions consist of two similar groups: 1) Drivers who will violate the traffic control device; and 2) somewhat aggressive drivers who appear to be violators even when they are behaving normally (and complying with traffic regulations). To avoid false alarms, the ICAS-V algorithm must distinguish between aggressive drivers and violators, such that a countermeasure is directed to those drivers who need it.
Prior ICAS-V Algorithm Research

Support for the feasibility of a ICAS-V algorithm at live intersections is provided by a naturalistic observation study of human intersection approach behavior (White & Ferlis, 2004). A hand-held radar gun was used to collect the intersection approach behavior of drivers at four intersections. The researchers collected data for two groups of drivers: those who were stopping for a red light and those who were going through a green light. It was presumed that drivers who went through a green signal would act identically to an inattentive violator. Drivers who received the phase change were not included in the sample, so the scenario is similar to a stop sign approach (approaching a red light should be similar to approaching a stop sign).

The data set consisted of 270 samples taken at four separate intersection sites. Only approaches in which the subject vehicle was alone were included. The speed and acceleration profiles of vehicles were then used to graphically distinguish the groups prior to reaching the intersection. The initial speeds of both groups would overlap considerably. As drivers approached the intersection, those who intended to go would exhibit a relatively constant speed profile. The drivers who intended to stop would exhibit decreasing speed. At some point, the two curves would completely diverge, which was thought to indicate a location at which the threat assessment can be made.

For one example intersection, the authors concluded that the separation point was too close to the intersection, and thus the system would not work. However, the authors were only considering the effectiveness of an ICAS-V that samples speed at a single location—where the upper threshold of the stopping driver and the lower threshold of the violating driver separated. As will be demonstrated during this research, the problem is solvable if we instead assume a system with continuous detection that can identify a trend in the data, rather than wait for a clear separation point.

The authors also used acceleration measures to look for differences between the groups. In general, drivers who will go through the intersection demonstrate accelerations at or above zero; those who stop tend to demonstrate negative accelerations. The acceleration trend is apparent from a considerable distance and may provide earlier detection for drivers who are going to go.

White’s study provides proof-of-concept for an ICAS-V system in a simplified scenario. However, the assumption that drivers going through a green light are identical to inattentive violators needs to be validated. An inattentive violator may attend to the TCD at some point prior to entering the intersection. This could result in many different driver actions, such as acceleration, heavy braking, and perhaps even steering, which may influence the threat assessment. Furthermore, the White’s results will need to be confirmed for the stop-controlled case studied during the present work.

The ICAS-V work performed by VTTI under the IDS contract performed a preliminary algorithm development (Neale et al., 2005). Three general types of algorithms were constructed, based on three types of potential sensing equipment used in the ICAS: Single point (vehicle data were measured at a single point on the approach), multi-point (vehicle data were measured at several discrete points on the approach), and continuous...
(vehicle data measured at all points on approach). A comparison of the schemes clearly showed that an algorithm based on continuous detection performed more accurately than the other two options. In addition, the ongoing CICAS-V project indicates that continuous detection scheme is the most likely deployment architecture. Therefore, only the algorithms based on continuous detection will be discussed further.

Seven continuous detection algorithms in all were tested during the IDS project. The relevant algorithms will be discussed further in the algorithm development section of the results chapter. The curious reader should refer to (Neale et al., 2005) for more information regarding original algorithms. As discussed in Chapter 2, the data used to test these algorithms had limitations. In particular, the data were based on a small sample of drivers who approached a signalized intersection on a test track. The small sample of drivers will not capture the range of possible intersection approaches. Furthermore, the study did not account for the variety of factors that can affect the intersection approach trajectory (i.e. distractions, motivations, and weather).

However, despite these limitations, the preliminary IDS algorithm work guided the initial methods that were expanded and refined during this dissertation. The results of the IDS analysis lead to conclusions regarding the usefulness and applicability of the various algorithm options. The tests eliminated some basic algorithms, based on high rates of false alarms when compared with other options. Five algorithms were recommended in the IDS report (Neale et al., 2005) for future consideration. These algorithms were reviewed during the algorithm development and three were included in the algorithm evaluation analyses.
CHAPTER 4 - RESEARCH QUESTIONS AND TASKS

After reviewing the literature, it became clear that further data collection need be undertaken to develop the threat assessment algorithm. To this end, the present dissertation was formulated and carried out. Looking at the gaps in the present state of ICAS-V knowledge, the following research questions were developed. To address each of the questions, a set of tasks was devised. These tasks are presented after the research questions as an overview of the work described in the reminder of this dissertation.

Research Questions

Prior to starting data collection, a set of research questions were developed. These research questions are designed to expand on the past research by filling in knowledge gaps with an emphasis on ICAS threat assessment. Three main research questions with eight sub-questions were addressed. Answers to these research questions will provide ICAS-V engineers and researchers with background on driver intersection approaches, the occurrence of violations, possible methods for predicting driver intent, and finally threat assessment algorithms and design implications.

Question #1: When do violations occur and how can we predict them?

The first research question examines the sample of violations obtained during the course of study. The purpose of this question is to learn more about violations in an effort to provide information on their prediction. Two sub-questions will be investigated:

Question #1.1: How often do violations occur?

As discussed in chapter three, the prevalence of signal violations has been measured as high as 15 per hour. However, at stop-controlled intersections there are no comparable estimates for violation rates. This question will look at the prevalence of stop-sign violations.

Question #1.2: What environmental characteristics best predict a pending violation

Several factors shown to influence the rate of violations were identified in Chapter 3. The previous work primarily focused on signalized intersections and was limited to measures available through epidemiological sources. With the data obtained through video reduction, reduction some environmental variables were measured. This question makes use of this data by investigating the factors which make violations more likely.

Question #2: What are the kinematic signatures of intersection approaches?

The second research question aims to describe the way in which drivers approach intersections. This research question provides a foundation for the algorithm development in question three and guides the analysis process. Differences in approach styles between the approach classifications (e.g., conservative stop vs. violation) are of particular interest and were studied during each of the following sub-questions.
**Question #2.1:** What is the best way to operationally classify the approach type?

The purpose of this research question was to objectively group drivers based on their stopping maneuver at the intersection. Previous classification systems have been based largely on subjective groups constructed by the experimenters. This research question investigates natural differences in the stopping maneuvers to suggest an objective classification scheme. Subsequent research questions used the developed scheme to examine differences for a variety of approach variables as a function of the driver’s stopping maneuver.

**Question #2.2:** How prevalent are rolling stops and at what speed do they occur?

Rolling stops present a significant challenge for ICAS-V at stop signs. Presumably, rolling stops are performed by a driver who is aware of the TCD but feels it is safe to proceed. A driver rolling through the stopbar may appear to be a violator. However, because this driver is aware and likely making a safe maneuver, it may be inappropriate to issue a warning. This question defined rolling stops in terms of their frequency and the speeds at which they occur as a function of the clusters determined in question 2.1.

**Question #2.3:** When do drivers begin stopping?

As discussed in Chapter 3, most intersection crashes are the result of unintentional violation of the TCD. It is reasonable to assume that an inattentive driver will not initiate braking at the same point as an attentive driver. Thus, it may simplify the threat assessment if all drivers who initiate a stop by a specified distance are assumed to be attentive and not warned. The initial braking point was determined for the clusters defined in question 2.1 with the aim of differentiating the drivers based on their brake onset location.

**Question #2.4:** What does the stopping profile look like?

This research question investigated the kinematic attributes of the vehicle as a surrogate for how drivers choose to control the vehicle during a stop. This includes the measures of acceleration and speed for each of the approach classifications developed in question 2.1. Viewing the stopping profiles provided valuable information on how to configure algorithms and in what regions of the approach trajectories assessment should be made.

**Question #3:** Can driver intent be predicted based on vehicle attributes?

From the framework introduced in Chapter 3, can the driver’s intersection crossing intent be measured through the vehicle’s kinematic attributes? Essentially, this question represents the formulation and testing of a threat assessment algorithm for ICAS-V. The literature suggests the dynamic attributes of the vehicle do vary with driver intent. However, it is currently unknown if the differences in these groups are large enough to reliably predict a violation at a sufficient distance for a driver to react to a warning and successfully stop the vehicle. This question was addressed through the following four sub-questions:

**Question #3.1:** What algorithms can be developed to predict intent?

This segment of the research question required a substantial portion of the analysis effort. Assimilation of the literature described in Chapter 3, as well as the information gleaned
while answering the previous questions, was used to develop prototype algorithms. These prototype algorithms were based on a combination of kinematic laws and empirical regression.

**Question #3.2: What is the performance of the devised algorithms?**
The algorithms developed in 3.1 were tested to address this sub-question. Each algorithm was thoroughly tested to identify its associated weakness. When possible, the results of the tests were fed back into 3.1 to modify the algorithm to address the weakness. This iterative process continued until no apparent weaknesses remained.

**Question #3.3: What is the most effective algorithm for ICAS-V?**
The primary focus of this research is identification of the best algorithms for use in ICAS-V systems. The observational data collected provides an excellent resource for evaluating when violating trajectories can be differentiated from compliant approaches. This research question combined this information with the results from the previous warning experiments to determine which algorithms are best suited for the ICAS-V application.

**Research Tasks**
Four main research tasks were performed to address the research questions. The research tasks are provided as a summary of the work completed as part of this dissertation. Each of the tasks summarized below is discussed in a corresponding chapter through the remainder of this dissertation.

**Sampling, Site Selection, and the Collection Apparatus**
The first stage of this task was to determine the appropriate measures and sampling procedure. Measures were selected based on the literature review, potential algorithm requirements, and engineering judgment.

The next stage was to establish the appropriate number and locations of data collection sites. The number of sites was determined based on a projection of instrumentation costs, the allocated project budget, and obtaining the desired balanced set intersection characteristics. Each of the proposed sites was selected based on local crash statistics, geometry, posted speed, and proximity to VTTI.

The collection equipment was designed to support the data collection needs of the research questions. During this task the data acquisition system (DAS) was developed and constructed in-house at VTTI. The system acquired and recorded variety of measures from a sensor network installed at the intersection. The components of the sensor network consisted of both commercially available off-the-shelf hardware and unique hardware developed by VTTI, as appropriate.

Finally, a data management protocol was developed. The data management protocol defined when and how the data were collected, retrieved, and stored. Methods were devised for visiting the collection sites to retrieve data, perform health checks, upload
data to secure locations, validate data, perform data backups, and develop methods for data access.

Post-Processing and Data Reduction
The data post-processing task was initiated in parallel with the data collection period. Post-processing began with the development and execution of data cleansing methods. First, a tracking algorithm was devised and implemented to convert the raw radar data into a format ready for analysis. Incomplete data from bad sensor tracks or hardware malfunctions were isolated and subsequently either fixed or removed from the data set. A series of post-processing functions were developed to derive additional measures from the raw data that were not collected natively by the DAS.

Along with the post-processing, the collected data also underwent a manual data reduction process. Manual data reduction allows additional measures to be obtained that could not be feasibly collected directly from sensors. Trained data reductionists viewed video collected at the sites for a subset of intersection approaches. The reductionists recorded variables such as weather, maneuver, and vehicle type for aggressive intersection approaches. This permitted analysis of aggressive and violation intersection approaches with an additional set of variables.

Investigation of Stop-Controlled Intersection Vehicle Trajectories
The heart of the analysis performed for this dissertation began with this task. The analysis focused on discriminating the different types of intersection approaches. The goal of these first analyses was to determine how drivers approach intersections and to identify measures with potential for predicting the differences in these approach types. As a first step, logistic regression based on the data reduction sample suggested some possible inputs to the algorithm. After considering the results, many of the dependent measures were graphically represented across the different stopping maneuvers. A graphical inspection enhanced the researcher’s knowledge of variable relationships and suggested algorithm components.

To objectively investigate the differences in the driver intersection approach types, a cluster analysis was performed. The purpose of the cluster analysis was to define natural differences in driver approach types. These natural differences were used to help identify the target population for the ICAS-V system at stop signs. The groups defined through this analysis were also used to further investigate the differences in the approach styles.

A graphical analysis was performed across the groups defined in the cluster analysis. Frame by frame trajectories of the different groups were viewed and interpreted to identify trends in the data. These trends were later used to develop the algorithms tested in the final task.

Design, Develop and Test Potential Threat Assessment Algorithms
The focus of the work completed in the previous tasks was primarily performed to aid in the threat assessment algorithm development. During this task, information from the previous tasks was integrated and interpreted in terms of threat assessment capability. Adaptations of existing algorithms as well as novel algorithms were devised. Each
algorithm underwent a simulation and subsequent evaluation procedure. Algorithms were evaluated based on the number of incorrect predictions issued. The output of this task and the primary goal of this research was a set of recommended threat assessment algorithms for future ICAS-V work.
To obtain the data required to address the research questions, six stop-controlled intersection approaches across five intersections in the New River Valley area of southwestern Virginia were selected for data collection. Inputs into the site selection consisted of the literature described previously, intersection characteristics, crash statistics, and Virginia Department of Transportation (VDOT) recommendations. Data were collected from the sites for approximately two months, resulting in a total of 16 months of intersection approach data.

The following sections describe the methods used to generate a database of stop-controlled intersection approaches. The sections describe the process of selecting the test sites, development of the Data Acquisition System (DAS), test site installation, data sampling strategy, data management methods, and approvals.

**Site Selection Method**

Potential test sites were identified based on locality, DAS compatibility, geometric attributes, design speed, traffic volume, and crash statistics. Detailed information about the intersections was gathered with the assistance of representatives from the Salem District VDOT, the Blacksburg Police Department, and the Christiansburg Police Department. The information provided anecdotal data, as well as crash and violation data, on intersections in the region. From these data, several intersections were chosen for site visits wherein further information regarding geometry, signage, locality, and intersection type was gathered.

Site visit information was added to a database and compared to a list of selection criteria. Sites meeting the selection criteria were kept for further consideration. These criteria are listed below, and were established based on literature previously reviewed, the requirements of the study, the types of collection apparatus, and the feasibility of implementation.

Selected intersections must

- Represent intersections of the configuration found across the U.S.
- Contain balanced set of posted approach speeds
- Be free from obstructions to radar sensor
- Contain a Stop-sign located on the approach of interest
- Contain a suitable location to mount DAS
- Be equipped with sufficient shoulders to allow for safe DAS access
- Have a location reasonably close to VTTI for data retrieval
- Have availability of the Southwest Region VDOT for installation assistance and approval
- Be in range of differential global positioning system (GPS) corrections for calibration/validation
- Have a minimum of 150m radar site distance
- Contain speeds limits of 25 mph, 35 mph, or 45 mph
The final selection was based on the probability of obtaining relevant data. This included crash and average daily traffic (ADT) statistics, and creating a balanced set of approach speeds. Six approaches at five intersections were selected that represented the most common speed limits: 25 mph, 35 mph, and 45 mph. Table 4 below provides a list of all the selected stop-controlled intersections and the corresponding speed limits. The following pages provide images depicting a map that details measurements of each of the selected stop-controlled intersections, an aerial view, and ground images of each site.

<table>
<thead>
<tr>
<th>Intersection</th>
<th>Posted Speed Limit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Clubhouse &amp; Luster’s Gate</td>
<td>25 mph</td>
</tr>
<tr>
<td>Plank &amp; Luster's Gate</td>
<td>25 mph</td>
</tr>
<tr>
<td>Nellie's Cave &amp; Woodland Hills</td>
<td>35 mph</td>
</tr>
<tr>
<td>Fairview Church &amp; HW8</td>
<td>35 mph</td>
</tr>
<tr>
<td>Meadow Creek &amp; Childress Eastbound</td>
<td>45 mph</td>
</tr>
<tr>
<td>Meadow Creek &amp; Childress Westbound</td>
<td>45 mph</td>
</tr>
</tbody>
</table>
The intersection of Clubhouse Road and Luster’s Gate Road is a three-way intersection with a single stop sign for vehicles traveling east on Clubhouse (Figure 7, Figure 8, Figure 9). A driveway opposite to the clubhouse approach may appear to some drivers as a fourth leg of the intersection. The posted speed limit on Clubhouse is 25 mph and the posted speed limit for traffic traveling on Luster’s Gate is 45 mph. The entering ADT for this intersection is 2,084 and typically has less than one accident per year.

Figure 7: Diagram of Clubhouse & Luster’s Gate intersection.
Figure 8: Aerial view of Luster’s Gate & Clubhouse intersection.

Figure 9: Ground images of Clubhouse & Luster’s Gate intersection.
The intersection of Plank Drive and Luster’s Gate Road is a three-way stop-controlled intersection with a single stop sign for vehicles traveling east on Plank (Figure 10, Figure 11, Figure 12). The speed limit approaching the stop sign is 25 mph and traffic traveling on Luster’s Gate has a posted speed limit of 45 mph. VDOT records show the entering ADT at 1,794 and a typical crash rate of less than one per year.

![Diagram of Plank & Luster’s Gate intersection](image)

**Figure 10:** Diagram of Plank & Luster’s Gate intersection.
Figure 11: Aerial view of Plank X Luster’s Gate intersection.

Figure 12: Ground images of Plank & Luster’s Gate intersection.
The intersection at Nellie’s Cave Road and Woodland Hills is a three-way intersection with a single stop sign for vehicles traveling north on Nellie’s Cave (Figure 13, Figure 14, and Figure 15). Vehicles traveling through the Nellie’s Cave and Woodland Hills intersection have a posted speed limit of 35 mph. The entering ADT for this intersection is 1,674 and there was an average of one accident per year reported at this intersection.

Figure 13: Diagram of Nellie’s Cave & Woodland Hills intersection.
Figure 14: Aerial view of Nellie’s Cave & Woodland Hills intersection.

Figure 15: Ground images of Nellie’s Cave & Woodland Hills intersection.
The intersection of Fairview Church Road and Highway 8 is a four-way intersection with stop signs presented to traffic traveling both directions on Fairview Church Road (Figure 16, Figure 17, and Figure 18). The posted speed limit for traffic traveling through this intersection is 35 mph. The entering ADT for this intersection is 8,110 and there is an average of four annual crashes at this intersection.

Figure 16: Diagram of Fairview Church & HW8 intersection.
Figure 17: Aerial view of the Fairview Church & HW8 intersection.

Figure 18: Ground images of the Fairview Church & HW8 intersection.
The intersection of Meadow Creek and Childress is a four-way intersection with four stop signs presented to traffic traveling in each direction on Meadow Creek (Figure 19, Figure 20, Figure 21). The posted speed limit for traffic on both Meadow Creek and Childress is 45 mph. The entering ADT for this intersection is 3,010 and there is an average of five annual crashes at this intersection. This intersection is listed in VDOT’s 2006 Critical Rate Report, which identifies dangerous intersections in the state.

Figure 19: Diagram of Meadow Creek & Childress intersection.
Figure 20: Aerial view of the Meadow Creek & Childress intersection.

Figure 21: Ground images from Meadow Creek & Childress intersection.
Data Collection Apparatus

A custom, non-obtrusive DAS installed at the selected intersection approaches acquired data at the stop-controlled intersections. The characteristics of the stop-controlled intersections created some unusual requirements for the DAS. In particular, the rural nature of some sites meant the DAS would not have access to power or communication lines. Therefore, the DAS was designed to be completely self-contained and self-powered. Furthermore, the relatively short data collection period suggested that tunneling under the roadway should be avoided. To instrument multiple approaches at the Meadow Creek intersection, four independent DAS units had to be installed. The data from these four DAS were synchronized post-hoc, based on the GPS time. The resulting DAS was designed from the ground up specifically for this collection effort.

The apparatus consisted of a sensing network, a custom digital signal processor (DSP) circuit board, a digital video recorder (DVR), and an enclosure with a power source. The sensing network measured raw inputs and provided the measures to the DSP at 20Hz. The DSP pre-processed the inputs and assembled the dataset while archiving digital data files on the DVR. This system was completely contained at the intersection site and virtually invisible to drivers. The DAS time stamped the vehicle data acquired from automotive radar with millisecond time provided by the GPS. This parametric data were accompanied by a MPEG 4 video stream obtained from a charge coupled device (CCD) camera focused in the same orientation as the radar. To avoid tunneling below the roadway, each approach of the intersection was monitored by an independent DAS. The DAS is illustrated in Figure 22, with pictures provided in Figure 23. The subsequent sections contain detailed descriptions of each DAS component.

Figure 22: Diagram of stop-controlled DAS.
Sensing Network
The sensing network consisted of two major components: vehicle sensing and uncompressed video. A thorough investigation of current sensing technology identified radar as the most promising technology for obtaining vehicle kinematic information from the roadside (Neale et al., 2005). Previous research indicated that a minimum range of 150m with an accuracy of plus/minus 3m and a range-rate accuracy of plus/minus 1 km/h is sufficient for ICAS operation (Neale et al., 2005). The radar must also be relatively inexpensive, weatherproof, and have Federal Communications Commission (FCC) approval. The AC20 Autocruise radar from TRW is adaptive cruise control radar that exceeded the requirements of this study. The AC20 has the following specifications:

- Dimensions: 95 mm x 95 mm x 63 mm
- Waveform: 76 GHz
- Interface: CAN
- Distance Measurement
  - Range: 1 m – 200 m
  - Accuracy: ± 5% or 1 m
- Speed Measurement
  - Range: ± 250 kph
  - Accuracy ± 0.1 kph
- Lateral Position Measurement
  - Range ± 6°
  - Accuracy ± 0.3°

The second raw data input provided by the sensing network is uncompressed video. This video was later used to derive measures via manual reduction techniques. The video was recorded using a robust all-weather NTSC video camera, mounted in an inconspicuous
location that provided a view of the desired approach. The camera selected was a SuperCircuits PC219ZWPH with the following specifications:

- Horizontal Resolution: 480 Lines
- Illumination: 2.5 Lux / F1.8
- Image Sensor: 1/3" CCD Sensor Interline
- Power Requirements: 320 mA at 12V DC
- Video Format: NTSC
- Pixels: 492 (V) x 771 (H)
- Video Connection: BNC Female S/N Ratio 48 dB
- Lens Type: 5-50 mm
- Zoom Lens Control: Auto Iris DC Driven
- Backlight: Built-in Backlight Compensation
- Weight: 27.87 oz (790 grams)
- Dimensions: 19.4 cm x 8.9 cm x 19.1 cm

The NTSC signal provided by the camera was attached to the DVR for compression as choreographed by the DSP. The compressed video along with the other raw data from the sensing network was transmitted to the data DSP for pre-processing.

**Digital Signal Processor Circuit**

The DSP, housed on a proprietary circuit board with hardware and firmware, was designed specifically for this study. The DSP detects inputs from the sensing network, and pre-processes, aligns in time, integrates, and transfers them to the DVR and solid state memory for storage.

In addition to the data collection tasks, the DSP board housed the power management system and sampling scheme. The power management system controlled the on/off state of the sensing network and DVR. Battery voltage was monitored, and if it dropped below a specified threshold, the entire DAS would systematically shut down to prevent data loss. Furthermore, to maximize battery life, the DSP would switch the sensing components and the DVR off when vehicles were not present at the approach.

Data from the sensing network was sent to two separate locations by the DSP. Parametric data were processed by the DSP, time stamped, and sent to a 2 GB solid state memory card. Video data were time stamped and sent to the 100 GB DVR for compression and storage.

**Digital Video Recorder**

An Archos AV 500 was selected for compressing and storing the video collected by the DAS. This highly portable DVR uses an extremely efficient MPEG4 compression algorithm for reducing video file size. The hardware-based compression system is configurable such that the balance between file size and quality can be manipulated. For the purpose of this study, a high compression was selected to minimize file size and reduce the possibility of attaining personal information (e.g., license plate number – discussed further in the approvals section of this chapter).

The compressed video was written to a 100 GB hard drive housed within the DVR. The storage space needed to be sufficient for collecting over a week of uninterrupted video.
This hard drive was retrieved as needed and transported to VTTI for storage. The AV 500 has the following specifications:

- Capacity: 100 GB Hard drive
- Display: 4" LCD 480x272 pixels, 262,000 colors
- Video recording: MPEG-4 SP up to 640x480 @ 30 f/s, in AVI format.
- Video playback: MPEG-4 SP up to 720x480 @ 30 f/s
- AV connections: Audio & Video line out. IR emitter
- Interfaces: USB 2.0 high-speed device
- Power source: Rechargeable Lithium-Ion Battery
- Battery life: Up to 15 hours
- Dimensions: 7.6 x 12.4 x 2.4 cm
- Weight: 315 g - 11.11 oz

Enclosure and Power Source

To minimize behavioral adaptation by the driver, it was essential for the DAS to be as unobtrusive as possible. The sensing network was mounted inside a standard telecommunications box frequently seen on roadsides. These boxes were buried approximately 1/2 m underground with roughly 1 m protruding above the surface. The above-ground portion included a lid that was field-removable and was secured with a tamper resistant bolt. The telecommunications box was constructed from thin uniform plastic which was easily penetrated by the radar without any cutting, making it completely invisible to drivers. A small hole was drilled for the camera which provided a clear image of the intersection. Finally, a small box was mounted inside the enclosure that contained the DSP board and the DVR. The telecommunications box located the sensing equipment at the recommended heights while protecting them from direct moisture and ultraviolet rays (See Figure 24).

In addition to the above-ground sensing enclosure, a second enclosure resided underground near the telecommunications box. The second enclosure was a Pelican® waterproof high-impact case with security lock. The enclosure provided storage for the power source. The enclosure was buried in order to be inconspicuous and to provide temperature stability for the power source. The enclosure had the following specifications:

- Temperature Rating: Minimum -23°C, maximum +99°C
- Inside dimensions: 55.2 cm x 42.7 cm x 20 cm
- Outside dimensions: 61.6 cm x 49.4 cm x 22 cm
- Water proof
- Weight: 6 kg

The DAS was designed to operate at low voltage for at least six days, at which time the batteries (two large capacity 12v gel-cell built by MK part number VRLA-Gel 8G31) would need to be exchanged for a freshly-charged cell. At the time of the battery exchange, the DVR was also swapped for an empty unit. Data from the test site was transported back to VTTI and uploaded to a secure fiber channel server for long-term storage. The battery has the following specifications:
Cranking amps: 550 amps @ -17°C, 780 amps @ 0°C
Discharge time:
100 hrs at 1.08 amp to 1.75VPC @ 27°C
48 hrs at 2.15 amp to 1.75VPC @ 27°C
Weight: 32.2 Kg
Dimensions: 32.9 cm X 17.1 cm X 23.8 cm

Figure 24: Stop-controlled DAS.

Test Site Installation
Test sites were sequentially outfitted with the DAS, with each site taking approximately one day to install, calibrate, and validate. VDOT assisted in the installation by providing the necessary signage and equipment support. The enclosures were mounted first, followed by the installation of the DAS hardware and cabling. The battery pack, used to provide power at each site, was buried in order to remain as unobtrusive to traffic as possible.

A calibration procedure was initiated once the hardware was installed and powered up. During calibration, the camera focal length and zoom were set to obtain the desired image. This image captured the entire vehicle approach into the intersection. The radar was aimed to capture the vehicle from at least 150 m continuously through the stopbar. Calibration values, such as the distance from the radar to the stopbar, were also set to correct sensor mounting configurations.

Data Retrieval and Management
As with most stop-controlled intersections, traffic volume at the test sites would decrease substantially during non-peak hours. Collecting data when vehicles were not present on the intersection approach would be inefficient. The power supply would drain faster and
the storage devices would reach capacity sooner. Thus, a triggering scheme was used to
determine when to collect data. In particular, data were only written to the storage
devices when a vehicle was present on the intersection approach. When no vehicles were
sensed, the DAS entered a low-power mode in which the camera and assorted other
components were powered off or put into a standby mode.

The frequency with which data were collected from the stop-controlled intersections was
dependent on the traffic volume at a given site. Sites with higher traffic volumes placed
higher demands on the DAS, consuming battery life at a higher rate. On average, data
retrieval occurred every five (Meadow Creek intersection) to seven (Nellie’s Cave
intersection) days.

Trained data retrievers maintained each of the sites in order to eliminate down time
during which data were not collected. The system was temporarily shut down for
approximately two minutes in order to replace the DVR, memory card, and batteries.
During this time a health check was performed on the system to ensure data quality was
being maintained.

Following data retrieval, the files were transported to VTTI and uploaded onto the VTTI
data storage servers. Each of the files was named based on the intersection, day, and time
at which they were retrieved. This process was completed automatically using a custom
software program written for this purpose. The data servers reside on a secure network in
which daily incremental and full weekly offset backups are performed.

**Approvals**

To collect data on human participants, approval from the Virginia Tech Institutional
Review Board (IRB) was first obtained (Appendix A). This research project collected
observational data, including video, of thousands of participants in a naturalistic
environment. It was neither feasible to control who entered the test sites nor was it
possible to obtain an informed consent from drivers passing through the test sites. For
this reason, the IRB approvals were obtained early in the process to ensure the proposed
work could be carried out. As part of this approval, the participant’s anonymity was
protected by reducing the quality of the video to make it impossible to read the license
plate numbers or identify the vehicle occupants. Other measures, such as secure data
storage, analyst authentication, and breakaway roadside equipment, also protected
participants in the study. For additional information regarding the protection of human
subjects, please consult the IRB review (Appendix A).

A second approval permits the installation of the DAS at the test locations. As a partial
sponsoring agency, VDOT granted permission to install DAS at the proposed test sites.
As discussed earlier in this chapter, these installations were nearly transparent to the
driver and did not impact the safety of participants at the test sites.
CHAPTER 6: METHODS II:
DATA OVERVIEW, POST-PROCESSING, AND DATA REDUCTION

To overcome limitations present in the raw dataset, an extensive post-processing effort was undertaken. Post-processing applied a series of data cleansing, extrapolation, and smoothing techniques to prepare the dataset for analysis. The following sections first describe the raw dataset that resulted from the data collection effort. Next, the validation procedure and subsequent analysis to validate the DAS and post-processing method are presented. Finally, the post-processed data is described and summary statistics for the final dataset are provided. This final dataset was used for the remaining analyses described in the subsequent sections.

Raw Dataset
Data were continuously collected at six stop-controlled intersections in Montgomery County, Virginia. The data were natively recorded by the DAS in two file formats. The first file type stored the parametric data in a compact binary format. In conjunction with the binary files, an MPEG4 video file was recorded. Each pair of files was written for every hour of clock time (e.g., 48 files per day). The total number and size of files collected for each intersection are provided in Table 5.

<table>
<thead>
<tr>
<th>INTERSECTION</th>
<th>NUMBER OF BINARY FILES</th>
<th>SIZE (binary)</th>
<th>NUMBER OF VIDEO FILES</th>
<th>SIZE (video)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Meadow Creek &amp; Childress (2 approaches)</td>
<td>3,270</td>
<td>2.59 GB</td>
<td>2,732</td>
<td>574GB</td>
</tr>
<tr>
<td>Clubhouse &amp; Luster's Gate (1 approach)</td>
<td>1,501</td>
<td>568 MB</td>
<td>1,205</td>
<td>169 GB</td>
</tr>
<tr>
<td>Fairview Church &amp; HW8 (1 approach)</td>
<td>1,331</td>
<td>622 MB</td>
<td>1,331</td>
<td>119 GB</td>
</tr>
<tr>
<td>Nellie’s Cave &amp; Woodland Hills (1 approach)</td>
<td>1,192</td>
<td>483 MB</td>
<td>1,027</td>
<td>142 GB</td>
</tr>
<tr>
<td>Plank &amp; Luster’s Gate (1 approach)</td>
<td>1,659</td>
<td>384 MB</td>
<td>1,147</td>
<td>94.8 GB</td>
</tr>
<tr>
<td>TOTAL</td>
<td>8,953</td>
<td>2.06 GB</td>
<td>6,416</td>
<td>1.10 TB</td>
</tr>
</tbody>
</table>

The raw dataset was converted from binary to a Structure Query Language (SQL) database format to allow rapid testing of algorithms. The raw SQL dataset is essentially a copy of the binary files stored in a single clustered index table with null values removed. This resulted in a table containing 135,063,981 rows and 38 columns.

The raw data were limited in utility. The best radar sensor available at the time of the stop-controlled data collection was the AC20. The AC20 was developed for adaptive
cruise control systems that place the radar on the front of a vehicle. While the AC20 likely works well in its intended application, performance was disappointing when it was placed at the intersection. Although the radar did return accurate measurements of range and velocity, it did not reliably return these measures for a given vehicle. It was common for the sensor to provide sparse data such that a measurement was returned at rates well under the data collection rate. Data dropouts were also common in which a vehicle was only returned for a portion of the overall approach.

In addition, the radar sensor did not provide a unique vehicle ID. The track ID variable used by the sensor would repeat as soon as the vehicle with a given ID was not visible. For example, three vehicles approaching the intersection may be assigned IDs one through three. If a fourth vehicle were to enter the field of view of the sensor just after vehicle two exited the view, the new vehicle would be designated as vehicle two as well. For the analysis, it was imperative that each vehicle be indexed individually so the algorithm could be executed independently on each vehicle trajectory. Data provided by each vehicle needed to be continuous in order for the algorithm to be functional on each data frame.

Post-Processing
Post-processing began once the raw binary files were uploaded to the server at VTTI. The first step was to populate an SQL database from the binary data files. This was accomplished by using a file conversion tool programmed specifically for this purpose. The resulting database stored the raw data and did not perform any computations.

The erroneous radar returns (e.g., image shadows, trees, deer, etc.) were then cleaned from the database. This process was performed primarily by passing data through a filter that depended on a combination of values for several metrics calculated by the sensor. These metrics were measures of signal quality and magnitude. Queries were then constructed to filter out the erroneous data. It should be noted that the best available sensor at the time this data collection was performed had limitations. Data drop-outs and incomplete tracks were commonly reported by the radar. Furthermore, the radar did not provide a unique ID to group data points from each vehicle. These data limitations required that a substantial effort be undertaken to improve the raw data.

Once the first-pass of filtering was complete, a more sophisticated set of Matlab programs was developed and executed. This set of programs performed three primary functions. First, a program was developed to assign a unique identity to each vehicle that approached the radar. Second, the radar reported the location of four vehicles at a time but could track up to 24 vehicles simultaneously (i.e., six frames would be needed to report all 24 vehicles). Lastly, the radar assigned an ID to each vehicle on a temporary basis. Each time a vehicle was out of view, the radar would recycle that ID. This method used by the radar made the derivation of a unique ID difficult. In addition, IDs were frequently assigned to the inappropriate vehicle (e.g., track switching).

To develop the unique ID and fix the track switching problem, a post-hoc tracking algorithm was developed to enhance the radar tracking. This was accomplished by developing software that crawled through the data, frame by frame. For each frame, the associated radar returns were compared to the returns in the previous points in time at which the subject vehicle was believed to exist in the data. Thus, even if a vehicle
dropped out for some time, the program would hold information about that vehicle’s prior dynamic state while waiting for it to reappear.

The time-based comparison was made by the program for up to 24 simultaneous vehicles. For a point to be assigned the current vehicle ID, the tracking algorithm required a series of criteria to be met. The criteria were based on a dynamic prediction of the vehicle’s location at the current frame, based on the dynamic state of the vehicle during its previous incarnation in the data. This prediction was made using the fundamental kinematic equations of motion. In addition, the time between returns, overall distance traveled for the vehicle, and overall number of points returned were also part of the comparison. For the vehicle ID, the assigned track could not last more than 15 s, had to contain at least two data points, have reported ranges greater than zero, and travel at least one meter. The resulting vehicle ID was a database-wide unique ID associated with each vehicle that approached the intersection. Thus, all of the data points returned from a single vehicle were assigned a single ID.

In conjunction with the vehicle ID, a “fit ID” was also created. The fit ID was essentially a more stringent version of vehicle ID. Where vehicle ID contained all the data points from one vehicle, the fit ID contained only the series of points that include sufficient information for repairing broken tracks and deriving the acceleration measure. For a set of points to be assigned a fit ID, they were required to contain at least 10 data points, cover at least 2 m, and drop out for no more than four seconds.

It is possible for a single vehicle ID to have multiple associated fit IDs. For instance, consider a vehicle track that was returned by the radar at a long range, then disappeared for some time, and then reappeared later. If that dropout was less than 4 s, a single fit ID would have been created; however, if that dropout lasted more than 4 s, a second fit ID would have been assigned to the second collection of points within that vehicle ID. The resulting fit ID grouped sets of points together such that it was feasible to perform additional post-processing to improve the data.

The dataset contained dropouts in which the radar would stop providing updates for a period of time. In addition, the radar sensor used in this project performed some real-time smoothing using a Kalman filter; however, based on the data, it was apparent that additional smoothing would reduce data dither. This dither is inherent in all radar systems as a result of the changing scattering center of the returned reflections over time. Thus, a non-parametric smoothing spline (Figure 25) was fit to each collection of data points within a single fit ID. The smoothing spline was a knotted piecewise polynomial that responds very quickly to changes in the underlying form of the data. No latency was introduced though the use of this fitting technique.

The polynomial produced by the smoothing spline was used to repair vehicle ID tracks with short dropouts. Thus, the fit ID provided the means to reproduce a complete vehicle approach despite missing data points. In addition, the derivative of the polynomial function created by the spline was used to calculate the vehicle acceleration. Thus, derived acceleration was available within each fit ID. In general, the fit ID will be used for all analysis, as it contains data of the fidelity required for assessment.
Figure 25: Raw data collected by the DAS with the smoothing spline fit to the range and velocity data. The acceleration was then derived based on the data fit. Residuals for the velocity fit are also provided to convey the typical quality of the fitting procedure.

In addition to acceleration, four other continuous measures were also calculated. These included the time to intersection (TTI), required deceleration parameter (RDP), traffic volume, and brake status. TTI is a calculated value based on the current distance to the intersection and speed of the vehicle. TTI is believed to be a good approximation of the measure used by the human visual system to judge whether or not to stop (Horst, 1990). It combines the effects of speed and distance into a single measure (Equation 2).

\[
TTI = \frac{D_i}{V}
\]
Where:

\[ V = \text{Vehicle speed at the point when driver initiated braking (m/s)} \]
\[ D_s = \text{Distance to the trailing edge of the stopbar or start of perpendicular roadway when a stopbar was not present (m)} \]

RDP represents the calculated constant acceleration required to stop at the stopbar based on the vehicle’s current speed and distance from the intersection. RDP is an easily interpreted variable representing the required braking effort to stop at any point during the intersection approach. This equation is provided below.

**Equation 3**

\[
RDP = \frac{V^2}{2 \cdot D_s \cdot g}
\]

Where:

- RDP = Required deceleration parameter (g)
- V = Vehicle speed at the point when driver initiated braking (m/s)
- Ds = Distance to stopbar when driver initiated braking (m)
- g = gravitational acceleration constant (9.81 m/s²)

The traffic volume through the intersection previous to the subject vehicle was calculated for each vehicle that crossed through the intersection. The traffic volume was computed as the number of vehicles that passed through the intersection in the previous hour before the subject vehicle arrival. Discussed during the literature review, traffic volume influences stopping behavior and will be used during the analysis.

Brake status is a binary indication of whether or not the driver is pressing the brake. The brake status is an indication of driver intent and is often monitored by in vehicle collision warning systems to determine if a warning should be provided. While this variable cannot be directly measured with the radar, it can be accurately approximated. To approximate brake status an algorithm was devised to monitor the acceleration rate throughout each vehicle’s intersection approach. The algorithm first used a ten point zero-phase-shift moving-average-filter to smooth the acceleration. The smoothed acceleration was monitored for a change point that dropped below a set deceleration level. Searching for this change point allowed vehicles to coast, slowing through engine braking, without actively pressing the brake. This threshold was selected through a controlled investigation of a naturalistic driver performance database housed at VTTI (Appendix B).

First, the data used for the validation procedure described previously were analyzed to determine the threshold at which the radar would reliably show braking when compared to the actual brake status information provided by the vehicle data. This study indicated that a -0.05 g rate was a reliable indicator of brake activation. Next, stop-controlled approaches in the 100-car database (Dingus et. al, 2004) were analyzed to determine the minimum acceleration rate present before drivers initiated braking (i.e., beyond slowing
provided by engine braking). This threshold was found to be approximately -0.06 g. To ensure that drivers were indeed actively braking, the threshold was set at -0.075 g for identifying the initial brake activation. Data from the analysis of 100-car data were then used to correct the brake point by the average reaction time such that the brake status flag was activated when the driver was predicted to have actually pressed the brake (Figure 26).

Figure 26: Example of an intersection approach showing the derived brake onset point for range, velocity, and acceleration kinematic measures

After initial brake activation, the brake flag remained on until the smoothed acceleration variable exceeded -0.05 g. After initial braking, -0.05 g was used as the threshold for determining ongoing brake status throughout the remainder of the approach. As described above, this value was selected because it could be reliably detected by the radar and represented a threshold that was in excess of most vehicles engine braking rate.

Additional details of the 100-car analysis to determine the brake activation status are provided in Appendix C. Each vehicle tracking variable and its associated operational definition are provided in Table 6.
Table 6: Variables and operational definitions

<table>
<thead>
<tr>
<th>Variable</th>
<th>Operational Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vehicle_ID</td>
<td>Groups a series of radar measurements into a single vehicle observation. This ID is unique across the entire database.</td>
</tr>
<tr>
<td>Frame</td>
<td>Incrementing counter for the current frame. Started at one for each file and incremented at 20 Hz.</td>
</tr>
<tr>
<td>File_ID</td>
<td>DAS-assigned unique file ID. One file per hour of clock time was written to the hard drive.</td>
</tr>
<tr>
<td>Fit_ID</td>
<td>Groups a series of radar measurements into a single observation. This group of data contained a series of high quality densely-populated vehicle measures. Only point series contained in a Fit_ID were used for deriving measures such as acceleration. This ID is unique across the entire database.</td>
</tr>
<tr>
<td>Range</td>
<td>Range as measured by the radar but cleaned and smoothed during post-processing. Also, the range was offset such that stopbar or adjacent traffic lane is used as the origin (i.e., Range=0 is the stopbar)</td>
</tr>
<tr>
<td>Velocity</td>
<td>Velocity as measured by the radar but cleaned and smoothed during post-processing</td>
</tr>
<tr>
<td>Accel</td>
<td>Acceleration as measured by the radar but cleaned and smoothed during post-processing</td>
</tr>
<tr>
<td>RDP</td>
<td>The kinematically-calculated average deceleration required to stop at the stopbar given the present vehicle speed and distance to the intersection</td>
</tr>
<tr>
<td>Brake_Status</td>
<td>An on/off flag that approximates when the driver is actively braking the vehicle</td>
</tr>
<tr>
<td>TTI</td>
<td>The time that will elapse until the vehicle reaches the stopbar based on speed and intersection distance, assuming there is no change in speed</td>
</tr>
<tr>
<td>Angle</td>
<td>Angle as measured by the radar but cleaned and smoothed during post-processing</td>
</tr>
<tr>
<td>GPS_Time</td>
<td>Common time base that permits synchronizing all four intersection approaches</td>
</tr>
</tbody>
</table>

System and Post-Process Validation

A system accuracy validation was performed to ensure accuracy of the stop-controlled DAS and post-processing methods. A small experiment was devised and executed on the Smart Road test track in Blacksburg, Virginia. The DAS described above was installed at the Smart Road intersection and set to collect data in the same manner as the live intersection sites. Next, a series of intersection passes were performed using an instrumented vehicle with an independent DAS.

To evaluate the DAS accuracy over a range of realistic scenarios, a total of 36 runs were performed. These runs included three replicates at 25 mph, 35 mph, and 45 mph stop approaches with soft (~0.2 g), medium (~0.4 g), and hard (~0.6 g) average braking rates. In addition, one violation at each speed was also performed.

The vehicle used for this experiment was a highly-capable VTTI test vehicle. The instrumentation included a high-accuracy differential GPS system that has been validated in past studies and that measures position to within a few centimeters and velocity (within one-fourth of a meter per second). The data collected by the roadside and the in-vehicle DAS were compared post-hoc. Data alignment was performed using the millisecond GPS time recorded in each of the two systems. The reported measures were compared using the vehicle DAS as the ‘true’ measure. Any deviation of the infrastructure DAS from the vehicle DAS was considered an error. These errors were evaluated to develop an overall estimate of system accuracy.
Measurements from both the infrastructure and vehicle DAS were recorded and subsequently compared post-hoc (Figure 27). The figure below depicts an exemplar vehicle approach trajectory as measured by the vehicle and infrastructure DAS. Each subplot contains a line series for the post-processed radar data, a scatter plot of the raw radar data, and a line series for the vehicle data, as appropriate. Note that an approach with sparse raw radar data were intentionally selected to demonstrate the effectiveness of the post-processing method (only 13 points were returned by the radar during this approach). The top subplot depicts the range as reported from the two data sources. On this particular approach, the vehicle was initially detected by the radar at 178 m and was tracked up to the stopbar. The second subplot shows the vehicle’s velocity during the approach initially traveling at 11.5 m/s. The third subplot depicts the acceleration as measured by an accelerometer inside the vehicle and the acceleration that was computed as the first derivative of the post-processed radar velocity. Finally, the bottom subplot depicts the difference between the radar-derived acceleration and directly measured acceleration. For this example, the maximum error in the computed acceleration occurred near the stopbar and resulted in a 0.03 g error.

Figure 27: Infrastructure and vehicle DAS measurements.
Based on the results (Table 7), the final dataset was deemed sufficient for the purposes of the intended analyses. The overall accuracy levels demonstrated through the validation met or exceed the accuracy guidelines presented in the ICAV Task 5 report (Lee et al., 2005). No speed- or approach-type bias was observed in the error data (Appendix D). Thus, the radar error should be consistent across a variety of intersection approach types. There are some occasional large errors produced by the radar; however, these events are rare and will be mitigated though the statistical techniques used in the subsequent analysis. Given the moderate quality of the initial data, the relatively high accuracy of the final dataset demonstrates a successful post-processing method. However, if feasible, future DAS should make use of alternative radar that provides a more reliable data source that will not require such involved post-processing.

| Table 7: Infrastructure DAS system error relative to the vehicle high-accuracy DAS. |
|----------------------------------|-----------------|-----------------|---------------|
| Range                           | Speed           | Acceleration    |
| Mean                            | 0.829 m         | 0.062 m/s       | -0.002 g      |
| Standard Deviation              | 2.401 m         | 0.151 m/s       | 0.026 g       |

Post-Processed Dataset

During post-processing, the data structure was re-organized for ease of analysis and efficiency. In this database, 311,753 unique vehicle IDs were generated at a range greater than 20 m. This range cutoff was used to avoid including secondary IDs generated by the radar when vehicles start and stop. The breakdown of traffic at each site is provided in Table 8 below.

In addition to the vehicle ID, a fit ID (as discussed in the methods section) is also provided in the table. Recall from the methods section that the fit ID contains the level of fidelity needed for assessing frame by frame vehicle trajectories.

| Table 8: Unique vehicle IDs generated for each site. |
|-----------------------------------------|-------------|-------------|
| Intersection Approach                  | Unique Vehicle IDs | Unique Fit IDs |
| Meadow Creek & Childress (westbound)   | 73,328      | 14,714      |
| Meadow Creek & Childress (eastbound)   | 79,510      | 7,759       |
| Plank & Luster’s Gate                  | 14,152      | 877         |
| Clubhouse & Luster’s Gate              | 25,348      | 1,592       |
| Nellie’s Cave & Woodland Hills         | 22,240      | 5,073       |
| Fairview Church & HW8                  | 10,141      | 610         |
| TOTAL                                  | 224,719     | 30,625      |
**Event Validation and Video Reduction Process**

The data collected for this study was obtained primarily from an infrastructure-mounted radar sensor. Radar has some additional limitations relative to in-vehicle sensors. While the measurements of speed and range are accurate, it is the association of those measures with a particular vehicle that is prone to error. This means that a vehicle reported by the radar is not necessarily a valid vehicle. The quintessential example of this behavior occurs with large vehicles and trailers. The radar used for this study would frequently treat a large vehicle as two separate targets, particularly if a trailer was in tow. As a result, the subject vehicle may have completed a stop; however, the secondary false-target located on the rear of the vehicle or trailer would appear to violate the TCD as it was pulled through the intersection at-speed.

The primary purpose of the video reduction was to validate the events of interest. It was important to ensure that false targets were not inadvertently being included in the sample of violating and aggressive driver approaches. In addition to false triggers, other invalid events also needed to be removed from the dataset. These included violations that were a result of atypical scenarios such as a funeral procession and the crossing of in-service emergency vehicles. All of the invalid events were marked and were removed from the analysis.

The dataset contains over 200,000 unique vehicle trajectories. The time for a typical validation is five minutes per event, suggesting that well over 1600 person-hours would be required to reduce all events. While reducing all of the events would provide an excellent dataset for investigation, it was simply not possible to perform within the time and budget constraints of this study.

Therefore, a strategy was devised to methodically select approaches of interest for an ICAS investigation. The selection process occurred through the development of a trigger that swept through the parametric data and flagged events requiring attention. The flagged events were automatically collected for easy retrieval and accessible to the data reductionists. A detailed discussion of the method used to identify validation events is available in Appendix B.

The validation process required a reductionist to view each event. Once the event was opened and viewed, it was logical to collect a few additional measures that were not available natively in the data collection system. These measures, discussed in the subsequent section, were used to identify potential relationships between environmental factors and the prevalence of violations.

The Data Analysis and Reduction Tool (DART) software package is the result of over five years of software development at VTTI. DART provides a user interface for the viewing and reducing of digital data (Figure 28). It contains user-configurable video and graphical interfaces to aid in manual reduction. Users can simultaneously view synchronized video and graphical data streams frame-by-frame. This analysis tool was used for several tasks, including data reduction.
First, the user interface was used for data validation purposes. Anytime a violation or near violation occurred, the data were validated by viewing the associated video files. Invalid events (i.e., cyclists) were removed or re-classified as needed.

Next, the DART interface was used to derive measures that require manual reduction. A trained reductionist viewed the video and graphical interfaces to identify the value for each required measure. The measures are listed below with operational definitions of each possible response in Appendix E.

- Vehicle Type
- Turn intent
- Stopping behavior
- Lead vehicle presence
- Lead vehicle stopping behavior
- Weather
- Ambient lighting

Finally, DART was used throughout the entire analysis to view individual vehicle approaches. DART was particularly useful for determining why an irregular behavior was identified during an analysis. For instance, when the radar data suggested a vehicle had stopped 30 meters from the stopbar, DART was used to identify the driver of the subject vehicle making an illegal U-turn upstream of the intersection.

**Reductionist Training and Protocol Development**

The events created were analyzed by a team of trained video analysts in VTTI’s data reduction lab. This section describes the reduction protocol, the training of the data...
recruiting and training data reductionists

in all, five data reductionists were recruited and/or assigned to work on this project. training included discussions on proper treatment of human subject video data (and signed confidentiality/non-disclosure agreements), a demonstration of how to access the data from the server, and hands-on training in how to operate the data reduction software. next, reductionists were provided with a data reduction manual for the stop sign reduction; this manual provided steps for operating the software, background about the study, and a detailed description of the steps to take in analyzing each event. examples were demonstrated by the data reduction manager and/or project manager, and then reductionists practiced on their own under the observation of the data reduction manager.

the orientation and training sessions took approximately four hours. once the reductionists felt comfortable with the process, they began working independently to interpret events and record responses into the database with “spot check” monitoring and supervision from the reduction manager. any questions asked were documented, and written responses were prepared for reductionists to refer to as they worked. with the full staff of reductionists, triggers were reviewed at the rate of approximately 50 per hour (10 per hour per reductionist).

data reduction reliability assessments

two measures of rater reliability were conducted on the stop sign trigger validations. first, reductionists performed 30 minutes of spot checking (of their own or other reductionists’ work) during each 4-hour shift. any disagreements were flagged for review by the data reduction manager. approximately 20% of all data points were spot checked. any errors noted were addressed with the data reductionists.

the second measure of rater reliability was an inter-rater reliability test administered to each reductionist. the test contained 30 triggers representing a variety of scenarios and a range of interpretation complexity. triggers were first evaluated by the project manager and a “gold standard” was developed against which rater tests were scored. test scores are reported in table 9 below, based on overall scores (average across all events), subject driver stopping behavior (% correct out of 30 events), and event classification (% correct out of 30 events). average overall scores were over 95%. overall, stopping behavior was assessed correctly 80.7% of the time. over half (65.6%) of the errors in assessing subject stopping behavior were due to the subjectivity of discriminating between a “rolling violation” and a “violation with caution”, 27.6% were due to “violation with caution” versus “violation without caution” disagreements, and 6.9% were due to “no violation” versus “rolling violation” disagreements. errors occurred in event classification only 3.3% of the time, including 2 disagreements in non-crash versus near crash and 2 disagreements in non-crash versus non-conflict.
Table 9: Inter-rater test scores for stop sign violation reduction.

<table>
<thead>
<tr>
<th>Rater</th>
<th>Test Score: Average all Events</th>
<th>Test Score: Driver Stopping Behavior</th>
<th>Test Score: Event Classification</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>95.8%</td>
<td>80.0%</td>
<td>96.7%</td>
</tr>
<tr>
<td>2</td>
<td>97.3%</td>
<td>90.0%</td>
<td>96.7%</td>
</tr>
<tr>
<td>3</td>
<td>95.8%</td>
<td>76.7%</td>
<td>96.7%</td>
</tr>
<tr>
<td>4</td>
<td>95.1%</td>
<td>83.3%</td>
<td>96.7%</td>
</tr>
<tr>
<td>5</td>
<td>96.1%</td>
<td>73.3%</td>
<td>100.0%</td>
</tr>
</tbody>
</table>
CHAPTER 7 – INVESTIGATION OF INTERSECTION APPROACHES

The purpose of this chapter is to describe explorative analyses of the intersection approaches performed by drivers at the test sites. The analyses included investigations of driver decisions with regard to stopping, minimum stopbar speed, brake onset, and overall vehicle trajectories. These analyses were performed with the goal of working toward the development of the ICAS-V algorithm presented in Chapter 8.

An ICAS algorithm must be capable of predicting the driver’s stopping decision at a distance that provides sufficient time for the driver to stop before entering conflicting traffic paths. The analysis reported in this section has three purposes. The first is to investigate attributes of the vehicle’s intersection approach that indicate a target driver population for ICAS-V. The second purpose is to investigate the different types of stopping maneuvers that are performed by drivers as they approach stop-controlled intersections. Finally, the third purpose is to identify trends in the approach trajectories that could be leveraged by an ICAS-V algorithm.

**Aggressive Approach Analysis**

Recall the primary purpose of the manual data reduction was to validate events captured by the automated violation detection triggers. While data reductionists had the files open for review, it was logical to collect some additional information regarding the event. The triggering scheme, described in detail in the methods section, was designed to acquire highly aggressive intersection approaches to look for violations. During these approaches, the drivers may or may not have actually violated the stop sign. This investigation is not the main focus of this research project, but may provide insight into factors that differentiate violators from near violators.

Logistic regression is a multivariate method that predicts the probability of a binary response based on the values of a set of independent measures (Johnson, 1998). For the present analysis, the binary response variable represents whether or not the driver violated the stop sign. During data reduction, the stopping maneuver was subjectively coded for each driver. The coding initially included four levels: 1) no violation; 2) rolling violation; 3) violation with caution; and 4) violation without caution.

In subsequent analyses, it will be shown that low-speed, rolling violations should not be the target violation for the ICAS-V system. For this reason, the four categories were collapsed into two categories: 1) “no violation” and “rolling violation” both represent the near violations category; and 2) “violation with caution” and “violation without caution” represent the violation category.

The logistic fit procedure was performed to fit the environmental data collected through reduction. Odds ratios were computed for each of the predictor variables to investigate the effects of the surrounding environment on violation likelihood. The following table provides the odds ratios computed through the logistic regression for all the predictors analyzed. If the confidence limits include a one, the effect is not significant.
Table 10: Odds ratios for environmental variables

<table>
<thead>
<tr>
<th>Risk factor</th>
<th>Risk factor</th>
<th>Odds ratio</th>
<th>95% CI Low</th>
<th>95% CI High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Turn Intent</td>
<td>Straight vs. Right</td>
<td>2.8197</td>
<td>2.4298</td>
<td>3.2721</td>
</tr>
<tr>
<td></td>
<td>Straight vs. Left</td>
<td>3.7384</td>
<td>2.962</td>
<td>4.7183</td>
</tr>
<tr>
<td></td>
<td>Right vs. Left</td>
<td>1.3258</td>
<td>1.0669</td>
<td>1.6476</td>
</tr>
<tr>
<td>Conflict Vehicles</td>
<td>No-conflict vs. Conflict</td>
<td>2.4118</td>
<td>1.8558</td>
<td>3.1344</td>
</tr>
<tr>
<td>Vehicle Type</td>
<td>Car vs. Minivan &amp; Pickup</td>
<td>0.9544*</td>
<td>0.8231</td>
<td>1.1067</td>
</tr>
<tr>
<td>Weather</td>
<td>Cloudy vs. Clear</td>
<td>1.3848</td>
<td>1.1282</td>
<td>1.6997</td>
</tr>
<tr>
<td></td>
<td>Inferior vs. Clear</td>
<td>1.152*</td>
<td>0.8934</td>
<td>1.4854</td>
</tr>
<tr>
<td></td>
<td>Cloudy vs. Inferior</td>
<td>1.2021*</td>
<td>0.8835</td>
<td>1.6356</td>
</tr>
<tr>
<td>Time of Day</td>
<td>Daytime vs. Dawn/Dusk</td>
<td>1.0494*</td>
<td>0.8509</td>
<td>1.2942</td>
</tr>
<tr>
<td></td>
<td>Nighttime vs. Dawn/Dusk</td>
<td>2.6775</td>
<td>1.9381</td>
<td>3.699</td>
</tr>
<tr>
<td></td>
<td>Nighttime vs. Daytime</td>
<td>2.5515</td>
<td>1.947</td>
<td>3.3437</td>
</tr>
<tr>
<td>Leading Vehicle</td>
<td>L.V. Violate vs. no-Violate</td>
<td>6.1388</td>
<td>3.6489</td>
<td>10.3276</td>
</tr>
</tbody>
</table>

*Odds ratio is NOT significant

The likelihood of a violation vs. a near violation depends on the turn intent of the driver. A driver is nearly three times more likely to violate if their intended maneuver is straight vs. right and nearly four times more likely if the intended maneuver is straight vs. left. Of the possible maneuvers, drivers were least likely to violate if they made a left turn.

Drivers are more than twice as likely to violate if there is no conflicting traffic present on the adjacent traffic lanes at the intersection. This effect is probably due to the subject vehicle yielding right of way to the conflicting vehicle.

Inferior weather was categorized as any form of precipitation, including fog. Interestingly, inferior weather did not influence the likelihood of a violation. There was a small effect noted for clear vs. cloudy weather conditions. It is unclear why violations are slightly more likely when clouds are present. One possible explanation may be the protection from glare which is afforded by the cloud cover. When the skies are clear, visibility may be somewhat reduced due to sun glare such that drivers are more cautious at the junction.

The time of day effect may also be attributed to visibility. There was not a significant difference between daytime and dawn/dusk; however, violations were more likely to occur at nighttime. The stop sign intersections investigated were not located in regions with street lighting. Lower visibility may have lead to lower detection of the stop sign resulting in more violations. The other possibility is that headlights from other vehicles are highly visible at night, making drivers more willing to violate in the absence of adjacent headlamps.

Finally, the largest factor impacting the likelihood of violations is the presence of a lead vehicle that violates. When a lead vehicle violates, the subject vehicle is more than six times as likely to violate. It would be interesting to investigate whether these drivers are intentionally following the lead vehicle, or whether they are blindly trusting the lead to
perform the correct traffic maneuvers. Unfortunately, such an investigation requires information from inside the vehicle and cannot be performed with the present dataset.

**Driver Approach Type Classification**

In theory, drivers are expected to perform a complete stop each time they approach a stop-controlled intersection, regardless of the environmental state (e.g., traffic, site distance, etc.). In practice, however, drivers frequently cross stop-controlled intersections without placing their vehicle in a stationary condition. For this report, these slow-moving violations are referred to as ‘rolling violations’.

Consider a driver approaching a stop-controlled intersection at the suggested speed limit. This driver may slow his/her vehicle at a sufficient rate to stop at the stopbar, if required. However, if visibility of the adjacent traffic lanes is good near the intersection box, the driver may cease braking and perform a rolling violation. While a rolling violation is technically illegal, if the driver is cognizant and prepared to stop, it is unlikely that this behavior contributes to the target population (i.e., behaviors leading to crashes).

From the stop-controlled data collected, it is clear that rolling violation behavior is very common. If a warning is provided to all drivers performing a rolling violation, a nuisance alarm problem is likely to result. Thus, a binary discrimination based on traffic laws is insufficient for determining the algorithm effectiveness. Rather, a classification scheme is required to discriminate the infrequent unsafe behaviors from the numerous safe behaviors. The purpose of this section is to objectively investigate natural groupings of driver-selected vehicle intersection approach characteristics. This classification system will later be used to develop the definition of an ICAS target violation with which the performance of algorithms will be evaluated.

Although stopping behavior was classified subjectively as part of the data reduction, there are reasons to develop a corresponding objective partitioning scheme. In particular, manual reduction was only performed on a subset of the data; therefore, a majority of the intersection approaches were not classified in the reduction. During algorithm development, it is desirable to use a large dataset. An objective measure of stopping behavior will provide a performance metric that is applicable to intersection approaches that were not considered during the reduction. In addition, objective measures are generally preferred over subjective measures, due to higher repeatability and accuracy.

A cluster analysis was performed to objectively explore and categorize the types of stops performed by drivers approaching a stop sign. Cluster analysis is a statistical method designed to partition data into subsets so that data within each subset shares some common trait. In the present context, the clusters represent different driver approach groups.

There are several potential measures by which the driver’s approach type may be classified. For instance, the speed at the stopbar may be indicative of the driver’s approach type (i.e., a violator would have a higher speed than a compliant driver). Other possible measures include minimum TTI and average deceleration.
The variable selected for classifying driver approach type was the maximum RDP. This measure was selected because the value has a direct relationship to the ability of the vehicle to stop and is therefore easily interpreted. For instance, if the maximum RDP is 0.3g, the driver could have easily stopped by the stopbar. On the other hand, a driver with a maximum RDP of 4g was committed to the violation and would not have been able to stop by the stopbar. The maximum RDP was only calculated for ranges greater than 2 m from the stopbar.

A 2 m cutoff was selected because of the behavior of RDP near the stopbar. As a vehicle draws near to the stopbar, RDP will tend toward infinity regardless of travel speed. By only considering RDP values that occur at a range larger than 2 m, this portion of the RDP trajectory is not considered, making the measure sensitive to differences in approach type.

The non-parametric kmeans (MacQueen, 1967) method of clustering was selected for this analysis. Kmeans is a partitional unsupervised learning algorithm that minimizes a measure of distance between each data point and the center of the corresponding cluster. The optimization occurs in an iterative process that moves the cluster center and recalculates the distances until a minimum is obtained. Kmeans was selected because it is a common and well-understood clustering method (Davidson, 2002) that is computationally efficient (Matlab, 2007) and sensitive to rare observations (Hauskrecht, 2003), making it a logical choice for this large dataset.

The cluster analysis was performed on a subset of the data that contained a sample of complete vehicle approaches. As discussed in the post-processing section, it was not unusual for a new vehicle track to be generated when vehicles deployed from a standing queue. Thus, only vehicle approaches in which the vehicle was present from 100 m to 2 m were included in the analysis. The 100 m cutoff also ensures that the vehicle was present for the entire warning region which will be important when the clusters generated during this analysis are used for algorithm development. This resulted in a sample size of 30,623 observations.

The Kmeans procedure requires prior selection of the distance measure used for optimization, initial locations for the clusters’ centers (seeds), and the number of clusters to partition the data. The squared Euclidian distance was used as the distance metric over which the optimization was performed. Euclidian distance was preferred because of the low dimensionality of the clustering measure and ease of interpretation.

To mitigate the chance of a local optimization, the seed locations were determined using three methods. First, the seeds were allowed to be selected at random. Next, the seeds were selected based on the expected cluster groupings. These seed values were selected based on expert knowledge of vehicle deceleration kinematics. The last method selected seeds by evenly distributing them across the range of the cluster variable. For each of the three seed selection methods the kmeans optimization was allowed 100 iterations for convergence and was replicated 10 times. For all seeds and replicates, convergence was obtained and resulted at the same total sum of distances. Therefore, local minimums did not appear to exist in the clustering variable; thus, seed selection strategy did not influence the resulting clusters.
Selection of the number of clusters was based on the stopping behavior groups described in the literature review. In general, the previous research and experimenter experience suggested a range of potential groupings from a simple two level to a more comprehensive five level grouping scheme. The potential groups are provided below (Table 11). From these groupings a rolling violation is defined as a driver who nearly stops at the intersection. The attentive violation is a driver who violates but demonstrates some slowing before reaching the stopbar. The inattentive violation group represents drivers who demonstrate little or no slowing during the approach.

Table 11: Potential cluster groupings

<table>
<thead>
<tr>
<th>2 Level Clustering</th>
<th>3 Level Clustering</th>
<th>4 Level Clustering</th>
<th>5 Level Clustering</th>
</tr>
</thead>
<tbody>
<tr>
<td>No violation</td>
<td>Stop</td>
<td>Stop</td>
<td>Conservative stop</td>
</tr>
<tr>
<td>Violation</td>
<td>Rolling violation</td>
<td>Rolling violation</td>
<td>Normal stop</td>
</tr>
<tr>
<td></td>
<td>Inattentive violation</td>
<td>Attentive violation</td>
<td>Rolling violation</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Inattentive violation</td>
<td>Inattentive violation</td>
</tr>
</tbody>
</table>

To evaluate the appropriate number of clusters, the Kmeans analysis was repeated for two, three, four, and five groups. The quality of the clusters was evaluated through 1) the overall and within cluster silhouette widths (Rousseeuw, 1987) and 2) the functional implications of the cluster thresholds. The silhouette width is based on the proximity of an observation to other observations in its cluster versus the proximity to observations assigned to its brother cluster; the width ranges from -1 to 1. A positive silhouette width indicates an observation that belongs in the assigned cluster; the higher the value, the stronger the association. Negative values represent likely misclassifications.

Considering the analysis results (Appendix F), the ‘four group’ classification scheme was selected. Although the two group scheme resulted in the highest overall silhouette width (0.9924), the groupings were too coarse to segregate the desired behaviors. For instance, the first group contained drivers who demonstrated a maximum RDP of up to 2.23 g. It is desirable to break this group down further, as a driver with a very low RDP should not be grouped together with a driver with a 2g+ RDP. On the other hand, the five cluster model contained too much resolution with partitions in the data that were not necessary for the algorithm to discriminate. In addition, the five level models failed to converge in 100 iterations for a few of the replicates. This may indicate over-partitioning of the data, which could lead to lower repeatability in future investigations.

The three and four cluster models performed nearly identically when the overall silhouette widths were compared. However, the within-cluster silhouette widths tended to be better for the four cluster model. In addition, the clusters created (Figure 29) generate logical partitions of RDP. Cluster 1 consists of the normal driver approach containing nearly 25,000 approaches with an average RDP of 0.25 g. Cluster 2 contained 5573 drivers with an average RDP of 0.75 g and likely contains most safe rolling violations. Cluster 3 contained 51 drivers with an average RDP of 3.15 g representing violations. Cluster 4 contained the most severe violations with only four drivers and an
average RDP of 9.8 g. The error bars displayed on the figures represent the 5% and 95% of the population determined by a distribution fit, discussed below.

The cluster analysis provided a partitioning scheme to describe stopping behavior within the sample provided. However, clustering in itself does not describe how the population is distributed into the partitions. To obtain this information, a distribution fit was performed to the overall max RDP measure and within cluster groups. A variety of distributions were considered: normal, exponential, inverse Gaussian, Generalized Pareto, Rayleigh, Birnbaum-Sanders, and Gamma. However, the best performing and most applicable distribution for the measure was the Generalized Extreme Value (GEV) distribution.

The GEV distribution is a family of continuous probability distributions that are well suited for modeling the tails of other distributions (Kotz and Nadarajah, 2001). As such, it is particularly well suited for the max RDP measure that was used as the clustering measure. In addition, the GEV is good for capturing skewed data. This data includes unusual events which are of particular interest in this application (e.g., serious violations which are uncommon). Finally, when graphically comparing the GEV to the other potential distributions listed above, the GEV was superior at capturing the empirical distribution of the data.

Figure 29: Average RDP and the 5% and 95% population estimates show as error bars for each of the four assigned clusters describing different types of stop-controlled approach behavior.
To ensure that the GEV was appropriate, a one sample Kolmogorov-Smirnov (KS) goodness-of-fit test was performed. The KS test is a statistical comparison between the empirical distribution function of the data and the theoretical underlying population distribution (Chakravart, Laha, and Roy, 1967). The KS test can be sensitive to large data samples, so the datasets were ordered and down-sampled to 50 equally-distributed observations. These 50 observations were used to construct the cumulative distribution function, which was then compared to the GEV using the KS test. The KS test was significant at a 0.05 alpha for the overall max RDP (p=0.195) as well as for each of the within-cluster groups (Appendix G). Thus, the GEV distribution may be used to model driver stopping behavior at stop-controlled intersections. The resulting cumulative distributions are provided below (Figure 30) with the parameter estimates provided in Appendix G.

Figure 30: Cumulative distribution for the overall max RDP exhibited by drivers as they approached the stopbar.

For the overall distribution, the average driver RDP was 0.35 g which is consistent with typical driver braking levels. 95 % of the population will approach the stopbar with an RDP of 0.8 g or less. This suggests that most drivers approach the stopbar with an RDP that allows them to come to a complete stop if required. However, as will be demonstrated in the subsequent section, most of these drivers will roll through the intersection without bringing their vehicle to a complete resting state. These rolling
violations result in the seemingly high RDP values, which represent deceleration rates at which most drivers would not intentionally brake. The GEV fit also works well for describing the distribution of drivers within each of the cluster groups created (Figure 31). These GEV fits were used to calculate the error bars displayed in Figure 29. While the first cluster contains considerably more data than any of the other three clusters, it is also substantially more compact. As the clusters’ average RDP increases, the number of observations decreases and the variance increases. The fourth-cluster fit is based on only a few data points and is explorative in nature. Considering the four cluster scheme and the data reduction results described in a previous section, it appears that the target groups are primarily contained in the third and fourth clusters. These two clusters represent drivers that violate at speeds that do not permit them to come to a complete stop prior to entering adjacent traffic.

![Figure 31: Cumulative distribution for RDP within each of the clusters signifying differing group stopping behaviors.](image)

**Stopbar Speed Analysis**

The average RDPs found for the cluster analysis suggested that a large portion of drivers do not completely stop at the stopbar. These drivers are performing a “rolling stop” (i.e., a low speed violation performed by an attentive driver). This type of stopping behavior is performed intentionally by a driver who does not want to come to a complete resting state. Therefore, if a warning is issued to this driver, it will likely be considered a
nuisance. Such nuisance alarms will have a negative impact on driver acceptance, which may reduce the effectiveness of a necessary alert.

To investigate the stopbar speed of drivers at stop-controlled intersections, the distribution of minimum speed from 2 m prior to the stopbar up to 1 m over the stopbar was evaluated (Figure 32). This region was selected because it allows for variations in the drivers’ stopping location. Only vehicle approaches in which the vehicle was reported traveling through the stopbar region were included in the analysis, for a total sample of 28,880 observations. As expected, a significant number of drivers did not fully stop their vehicles. Half of the drivers maintained a speed of 2 m/s (4 mph) or more as they crossed the intersection. However, 90% of the drivers exhibited a minimum stopbar speed of less than 4 m/s (9 mph).

![Figure 32: Empirical cumulative probability of stopbar speed at stop-controlled intersections.](image)

This overall distribution may be partitioned into the driver stopping groups defined by the cluster analysis. The behavior grouping provides insight into the relationship between the RDP measure of stopping behavior and the driver’s corresponding stopbar speed. Figure 33 depicts the distribution for stopbar velocity for each of the clusters. A generalized extreme value distribution was fit to cluster 1, while normal distributions were fit to clusters 2, 3 and 4 (parameters are provided in Appendix H). However, the distribution fits for clusters 1 and 4 are for explorative purposes only. Cluster 4 only
contains four observations, which are not sufficient for modeling the population. Cluster 1 exhibited a mixed distribution with a substantial number of drivers completing a full stop; only the drivers who did not stop are modeled by the depicted fit.

As expected, stopbar speed tends to increase with the stopping behavior group. The cluster analysis suggested that the goal should be to warn all drivers in clusters 3 and 4. It also suggested that warning drivers in the tail of the cluster 2 distributions would not be considered a false alarm. This logic suggests that a minimum speed threshold of 4.4 m/s (10 mph) may be appropriate as a warning criterion. Any driver who is traveling at less than this speed threshold would not be warned. As illustrated in Figure 33, a speed threshold of 5 m/s (11 mph) is predicted to warn over 99.9% of the drivers in the third and fourth cluster while only providing alerts to 20% of the cluster 2 drivers.

![Figure 33: Distribution of stopbar speed partitioned by cluster. Curve fits for clusters 1 and 4 are for explorative purposes only.](image)

**Brake Onset Analysis**

The literature reviewed in the introduction suggested that nuisance alarms should be minimized to ensure warning acceptance and effectiveness. One potential method to avoid alerting an attentive driver is to monitor the brake status. If the driver is braking, it may be reasonable to assume that he/she is aware of the intersection and does not require an alert. Thus, when the driver is actively braking, an ICAS algorithm would suppress
the warning regardless of the vehicle’s other kinematic measures. To investigate the use of brake status as a component of the algorithm, a box plot of brake onset for clusters 1 through 3 was drawn (Figure 34). A box plot for the fourth cluster is not included, as only one driver in this group applied the brakes during the approach. Cluster 3 only includes ten observations, as the rest of this group also did not press the brake during their approach. Thus, the box plot is explorative.

A box plot is a statistical method that visually shows the empirical distributions of different populations without any assumptions of the underlying distribution. Most of the data within a group is contained inside the box which is bounded by the first and third quartile. The line within the box represents the median. The whiskers depict the regions that lie within 1.5 times the corresponding quartile. Values outside the whisker are unusual observations and may be treated as outliers.

The overlapping boxes indicate that a statistical difference for the onset of braking is unlikely. It is interesting to note that the conservative drivers of cluster 1 appear to brake closer to the intersection. This result was initially unexpected but may be explained by the approach style of the conservative drivers. Discussed further in the subsequent section, drivers in cluster 1 tended to initiate slowing earlier by coasting; thus, taking advantage of engine braking without actually applying the brake. At some point closer to the intersection, an increase in slowing is required so the brake is eventually applied.
The primary lesson that should be extracted from this plot is that conservative drivers do not necessarily brake further from the intersection than do aggressive drivers. Thus, algorithm designers should not assume that a braking criterion in the algorithm will preclude compliant drivers from receiving a warning. It may, however, help to suppress the warning for aggressive drivers that will perform a compliant stop.

Given that group differences for drivers that apply the brake do not appear to exist, the groups were collapsed while the distribution of brake onset was evaluated. Brake onset followed a normal distribution (Figure 35 & Figure 36, parameters available in Appendix I). The distribution of braking was calculated using both distance and TTI as the dependent measures. There are indications that TTI is a better measure for representing variables, such as brake onset, because it is a construct thought to be used by the human visual system to judge when slowing should occur (Horst, 1990).

![Figure 35: Cumulative distribution of brake onset as a function of distance to the intersection.](image-url)
In general, 99% of the drivers appear to have applied the brake by 51 m or a TTI of 4.3 s or greater. This brake onset does provide support for the use of a brake onset component in an ICAS algorithm. Smart Road experiments testing an ICAS warning interface have suggested a timing of 2.44 s TTI for issuing a warning and obtaining a high compliance rate. Based on the data above, most drivers who will brake would have applied the brake prior to this warning range.

**Investigation of Vehicle Trajectories**

Moving beyond the investigation of driver behaviors at a specified point, it is important for an ICAS algorithm to consider measures across the entire intersection approach. The algorithm will need to operate on a continuous basis in order to provide a timely warning to the violating driver (Neale et al., 2005). An exploratory graphical analysis was performed to identify trends that may be exploited during the algorithm development and evaluation presented in the subsequent chapter.

Plots of the vehicle kinematic measures provide insight into the differences between driver groups that may be used for threat assessment. A figure for each kinematic variable used in this study is provided below along with a discussion of the characteristics of the plot. Each plot was created by calculating the average of the depicted kinematic measure every 2 m to 100 m from the stopbar. The observations used to produce the figures are the same sample that was described in the driver stopping classification section above. For the sake of clarity, the figures in this section only depict the mean of each measure. When applicable, the confidence intervals for the data will be described.

The velocity trajectory plot (Figure 37) demonstrates the large separation between the cluster 4 stopping behaviors. Drivers in this group tend to exhibit higher velocities that demonstrate a minimal decrease over the entire intersection approach. Cluster 1 also tends to exhibit a different approach than the other clusters. As described above in the
brake onset results, drivers in cluster 1 slow their vehicles earlier resulting in a lower velocity at the maximum range reliably measured by the radar (100 m).

![Velocity Trajectory Graph](https://via.placeholder.com/150)

**Figure 37: Mean velocity trajectory of vehicles partitioned by the stopping behavior cluster.**

The second cluster parallels the velocity trajectory exhibited by the first cluster. It appears that drivers in cluster 1 and 2 are similar except in their desired stopbar speed. Functionally, their velocity patterns are identical, except cluster 2 drivers appear to brake later and thus carry more velocity into the intersection creating the rolling-stop behavior.

Clusters 3 and 2 are extremely similar at longer distances from the stopbar. As the intersection is approached, the two curves deviate with cluster 3 drivers carrying much higher speeds into the intersection than cluster 2. Partitioning drivers from clusters 2 and 3 will be the challenge for an ICAS algorithm. For the mean velocity depicted, the curves for these two groups diverge around 33 m. This distance from the intersection is likely sufficient for providing a warning to drivers. However, when the confidence intervals are considered, the point of separation (between the 15% and 85% confidence limits) is reduced to just 10 m. This distance may not provide sufficient warning time for higher speed approaches.

Like the velocity trajectory plots, the acceleration plots also provide substantial insight into the differences among the driver stopping behavior clusters (Figure 38). Drivers in the fourth cluster exhibited a minimal amount of braking early in the approach, which tends to drop off to nearly no braking after that point. It is doubtful that this mild acceleration is indicative of an intentional violation, as none of the intersections have site distances that would permit drivers to see the adjacent traffic at the speeds exhibited by
this group. It is possible that this early acceleration was the result of some other intersection characteristics (e.g., the incline present at the Nellie’s Cave intersection).

Clusters 1, 2, and 3 all exhibited similar decelerations for the first 50 m of the approach. Cluster 1 drivers demonstrated the lowest acceleration initially, likely because they pressed the brake furthest from the intersection, providing more time over which their speed was able to decrease. Interestingly, the cluster 2 drivers appear to brake harder toward the end of the intersection approach. This may indicate that this group of drivers is more aggressive with their approach behavior. These drivers are aware of the intersection and initiate braking fairly early, but carry more speed further into the intersection and brake harder and later than cluster 1 drivers. Drivers in cluster 3 may initiate braking such that they can stop if cross traffic is present. However, it appears that at around 40 m, these drivers may feel confident enough that cross traffic is not present such that they cease braking behavior.

The velocity plots indicated that clusters 2 and 3 would be difficult to discriminate. This discrimination may actually be somewhat more sensitive for acceleration. In particular, the cluster 3 group appears to stop braking earlier in the approach than cluster 2. This behavior may indicate an intentional violation of the stop-controlled intersection. However, clusters 1 and 2 are actually more similar with regard to their acceleration patterns. This may indicate an algorithm will be most effective if it considers a
combination of speed and acceleration to take advantage of the strengths of each measure.

In terms of algorithm assessment, RDP appears to have some significant advantages over the other kinematic measures (Figure 39). In particular, the confidence intervals for clusters 1 and 4 never overlap at any point during the entire intersection approach. This indicates that discrimination between these groups will be more effective than for any other kinematic measure. The cluster 1 and 4 groups, in general, are substantially more divergent from every other group demonstrated by the additional kinematic measures. The difficulty in discrimination is once again apparent when clusters 2 and 3 are compared. The confidence limits of these two groups do not completely diverge until the intersection stopbar is within 10 m. It is likely that some drivers in cluster 2 will be warned in order to catch most of the drivers in cluster 3. However, the drivers on the tail of cluster 2 will have relatively aggressive approaches and will contribute to roughly less than 5% of the overall population, based on the models presented in the cluster analysis.

![Figure 39: Mean RDP trajectory of vehicles partitioned by the stopping behavior cluster.](image)

The TTI trajectories contain the largest variability of any kinematic measure (Figure 40). The spikes present in the data represent locations in which vehicles began to enter queues at the intersection. When a vehicle slows, the velocity approaches zero which in turn causes TTI to approach infinity. Thus, the TTI for any given vehicle may tend toward
infinity at a variety of locations depending on the queue length at a specific stop-controlled intersection. However, this behavior is one-sided; TTI could make an effective algorithm component if the algorithm looks for values below a set value. This value, however, must be dependent on the distance to the intersection as TTI will always approach zero as the intersection stopbar draws nearer.

![Figure 40: Mean TTI trajectory of vehicles partitioned by the stopping behavior cluster.](image)

From the figure above, it appears that only clusters 1 and 2 regularly approached the intersection with a queue. Drivers in cluster 1 tended to encounter queues more frequently and at greater distances than cluster 2. If the cluster 2 TTI trajectory is projected for cases in which the queue was not present, it does not appear substantially different than cluster 3. This may indicate that TTI is not the optimal measure for determining when the warning should be initiated.

Overall the analyses described in this chapter provided the foundation on which the algorithm development process we build upon. The cluster analysis provided insight into how drivers should be classified based on their behavior at the stopbar. The subsequent stopbar speed, braking onset, and trajectory analyses provided data leading to the derivation of the threat assessment algorithms developed and tested in the next chapter.
CHAPTER 8 – DEVELOPMENT AND EVALUATION OF ICAS-V THREAT ASSESSMENT ALGORITHMS

The work described thus far has provided the foundation for the threat assessment algorithm development and analysis procedures. Synthesis of the literature described in Chapter 3, engineering theory, and the intersection approach analysis described in Chapter 7 generated data inputs for algorithm analyses. Algorithms were assembled from interpretations of the synthesized data and based on principles of human factors and physics. The devised algorithms were tested in a pseudo-real-time simulation using the actual vehicle trajectory data collected for this study. The primary output of this analysis is a set of tools to assist vehicle designers select a threat assessment algorithm(s) ICAS-V systems.

Each algorithm was evaluated using the theory of signal detection to compare the sensitivity and specificity of the predicted outcome. Results were analyzed to determine possible regions for improvement, based on the types of misclassified vehicle trajectories. Such improvements were made and the simulation cycle was iterated until additional improvements were no longer envisioned. For clarity, most of the iteration cycles were not reported directly. Rather, as possible improvements were devised, these improvements were applied to all of the algorithms in a balanced fashion. This was done so that all algorithms could benefit from the enhancements, even if they were intended to address the shortcoming of a particular algorithm.

Algorithm Testing and Evaluation Procedure

Signal Detection Theory (SDT) provides a general framework to describe and study decisions that are made in uncertain or ambiguous situations. Developed by Tanner and Swets (1953), SDT is an established statistical method. It has been applied in a variety of contexts across a variety of disciplines; from air traffic control to medical diagnostics (Parasurman and Hancock, 1997; Swets, 1996; Wickens, 2002). The method defines a signal which represents the true state of the world. There is a desire to evaluate this signal; however, the signal is masked by the presence of noise in the environment. This makes discrimination of the true state of the signal a probabilistic process based primarily on the ratio of the signal-to-noise.

Procedure, application, and extension of SDT method to the ICAS context

In the context of ICAS-V, the threat assessment algorithm must predict a violation (signal) upstream of the stopbar in the context of compliant intersection approaches (noise). This decision is difficult because it must be made without direct knowledge of the driver’s intent; rather, it is inferred through the vehicle trajectory information.

Drivers exhibit differing driving styles, which introduces rather dynamic noise into the decision process. In particular, the approach characteristics that would indicate a violation for one driver may be another driver’s typical driving style. In SDT, it is
assumed that the true state of the signal is unknown to the detector. In the present context, the threat assessment algorithm does not know whether or not the driver will violate. This results in four possible outcomes of the threat assessment (Table 12).

**Table 12: Possible outcomes of the threat assessment**

<table>
<thead>
<tr>
<th>Algorithm Response</th>
<th>True State</th>
<th>Violation</th>
<th>Compliant</th>
</tr>
</thead>
<tbody>
<tr>
<td>Violation</td>
<td>True Positive</td>
<td>False Positive</td>
<td></td>
</tr>
<tr>
<td>Compliant</td>
<td>False Negative</td>
<td>True Negative</td>
<td></td>
</tr>
</tbody>
</table>

The number of decisions that fall into each of the four categories depends on the algorithm used to make the decision. Different algorithms may result in higher sensitivity than others. Furthermore, within a single algorithm, criteria may be set to bias the response toward a violation or compliant decision.

This phenomenon is demonstrated in the theoretical distributions below (Figure 41). The figure depicts two normal probability distributions: one for the signal (violating drivers) and the other for the noise (compliant drivers). The horizontal axis represents a hypothetical dimension which the algorithm “experiences” for a given trial. The compliant curve represents a distribution of values that can be produced when a violator is not present. Conversely, the violator distribution represents values that can be produced when the compliant driver is not present.

![Figure 41: Theoretical representation of the SDT signal (violation) and noise (compliant) distributions. The distance between the peaks of the two distributions represents the sensitivity of a given algorithm. The overlapping regions of the two curves that lay on the incorrect side of the decision criteria line represent miss-classifications performed by the algorithm.](image)

The location and shape of the two distributions will depend on the measure evaluated by the threat assessment algorithm. If a particular measure is more sensitive, the two curves will exhibit less overlap. In SDT, sensitivity (also called d’) measures the ability of the
detector to successfully distinguish between the signal and noise. Considering Figure 41, 
d’ may be described as the distance between the means of the two distributions, relative 
to their variances.

The vertical line in Figure 41 represents the decision rule as defined by SDT, and is 
typically referred to as Beta. Beta is used by the threat assessment algorithm to place the 
current driver in the compliant or violation category. If the “experience” of the current 
vehicle trajectory falls to the left of Beta, it will be categorized as a compliant approach.

Depending on the driver’s true stopping behavior, this decision could result in either a 
true negative or a false negative. False negatives and false positives are the result of the 
present “experience” falling on the incorrect side of the decision criteria. The true 
positive rate represents the percent of violation approaches that were correctly identified 
as violators. Similarly, true negative rate represents the percent of compliant approaches 
that were correctly identified. The true positives and false positives alarms fully 
constrain the results as the false negatives and true negatives may be calculated as 1-
true_positive_rate and 1-false_positive_rate, respectively. The true positive and false 
positive rates will be used throughout the results section to describe algorithm 
performance.

Although d’ can only be changed by altering the underlying equations used by the threat 
assessment algorithm, Beta can be selected depending on the system objectives. In an 
optimal situation, a particular Beta would result in perfect discrimination. However, in 
real-world systems such as ICAS, the selection of Beta must be made considering the 
“give-and-take” of the four possible outcomes.

In considering the cost and benefits for ICAS, it is clear that the true positive rate should 
be maximized. A violator who is not identified by the warning could be involved in a 
crash that could have been avoided if a timely warning was provided. However, it is also 
important that false positives are minimized. As discussed in the literature review, an 
abundance of false alarms will result in annoyance and distrust, ultimately leading to a 
decrease in system performance.

The Receiver Operation Characteristic (ROC) curve is a tool for evaluating the 
discriminability of an algorithm through a range of Beta combinations. The ROC curve 
plots the combination of true positives and false alarm rates as Beta is varied within a 
given algorithm. In the present context, the area under the curve represents the sensitivity 
of a given threat assessment algorithm. The larger the area, the better the algorithm will 
discriminate between violators and compliant intersection approaches. For the present 
analysis, the ROC curve will play a vital role in indentifying the preferred threat 
assessment algorithm.

An example ROC curve is provided below in Figure 42 for one of the algorithms 
analyzed as part of this project. This ROC curve represents a simple RDP algorithm in 
which the vehicle’s instantaneous RDP is compared to a warning RDP over each frame of 
the intersection approach trajectory. The warning RDP value, which represents Beta, is 
set at a value while a simulation is performed. The resulting number of false positives
and true positives are recorded and then plotted as a single point on the ROC plot (see annotation). This process is repeated for various values of the warning RDP (Beta) until a curve is created across the plot space.

![Figure 42: Example ROC curve. The curve represents the hit and false alarm rate for a particular threat assessment algorithm across a variety of decision criteria (beta). The larger the area under the curve the better an algorithm is at discriminating violators from compliant drivers.](image)

There is an important distinction from many classical SDT problems that must be made when applying the technique to a time-critical system such as ICAS-V. Consider that a driver must receive the warning at a sufficient distance to allow time for perception, reaction, and vehicle braking before the intersection stopbar is crossed. Classic SDT would indicate that an algorithm performed perfectly, even if every warning was provided one meter before the vehicle crossed stopbar. Clearly, none of the drivers receiving the warning would have sufficient time to stop, thus negating the safety benefit of an ICAS.

Unfortunately, there is no single point on the intersection approach at which a warning becomes too late. Rather, as a warning is provided later in the approach a decreasing number of drivers will be able to stop. Discussed during the literature review, a substantial volume of test track research has been performed to determine the optimal ICAS-V warning. These test track experiments were primarily focused at comparing the effectiveness of a variety of warning modalities; however, warning timing was sometimes used as an independent variable. An auxiliary analysis of the warning timing results for the best warnings tested during these studies was performed (Appendix J).
The auxiliary analysis developed a model to describe the distribution of warning effectiveness as a function of the RDP at which a warning was provided. Two points on the distribution were extracted for use in the SDT analysis. First, the “too late” point was defined as the location after which a warning would have very low utility. The too late point is defined for drivers who would violate in the absence of an ICAS. If the violating drivers do not receive a warning prior to the too late point, at least 95% will not be able to stop in response to the warning. Based on the model, the too late point for the most effective warnings tested to date corresponds to a warning RDP of 0.49 g. Any warning presented such that an RDP higher than 0.49 g would be required to stop, is not considered a true positive during this analysis.

If an algorithm correctly identifies a violator after the too late point, the event is counted as a false negative. Thus, the true positive axis on the ROC plot only contains those warnings that were provided to the correct group of drivers and before the too late point was reached. The result is substantially lower true positive rates; however, these rates better reflect the actual effectiveness of the warning.

The second point extracted from the warning effectiveness distribution, is the “favorable” warning point. The favorable warning point represents the location at which nearly 100% of the drivers are predicted to stop when a warning is received. A preferred algorithm will provide all of the warnings at or before the favorable warning point (warning RDP <= 0.36). The favorable and too late warning points allow relative comparisons between the timing of different algorithms.

To compare the warning timing for the various algorithms, the optimal Beta value for each algorithm must first be selected. Considering different Beta values is akin to moving across the ROC curve depicted in Figure 42. Each permutation of Beta for a particular algorithm results in a corresponding true positive and false positive rate. Thus, there is an inherent trade-off between true positives and false positives that must be considered when selecting the optimal Beta. Selecting the highest possible true positive rate will result in an unacceptable number of false positives and vice versa. Typically, when SDT is used, Beta is selected by setting the allowable false positive rate and identifying the corresponding true positive rate.

There is an array of unanswered questions when selecting an allowable false positive rate. In particular, at the present state of knowledge, it is unknown how many false positives drivers will tolerate. No studies have been performed to evaluate the effect of false positives on warning efficacy. From other collision avoidance systems, we do know that every effort must be made to minimize the number of false positives (Neale & Dingus, 2006; Kiefer et al., 1999; Dingus, et al., 1998). Avoiding false positives is particularly important in the ICAS-V system because violations are so rare relative to the number of intersection crossings performed that even a low false positive rate will result in significantly more false positives than true positives.

Rather than select a single false positive rate, two possible values are investigated and subsequently modeled during this research. The two values will bound the problem space and will allow comparisons to be made across a reasonable selection of Beta. The false
positive rates are both low and include a very low false positive rate of 0.01 and a slightly higher false positive rate of 0.05.

After identifying the allowable false positive rate, the associated Beta was selected to maximize the true positive rate for each algorithm. This process resulting in the selection of an “optimal” Beta for each algorithm; which was then investigated further. First, the warning timing was investigated for the optimal Beta for each algorithm. This was accomplished by graphing the empirical cumulative probability across the warning RDP. The distributions included markers for the too late and favorable warning points identified earlier. The example selected to draw the ROC curve in Figure 42 is used to illustrate the warning distribution investigation below (Figure 43).

![Warning Distribution Graph](image)

**Figure 43:** Example warning timing distribution for true positives using the algorithms depicted in Figure 42 evaluated at the beta value corresponding to a false positive of 0.01

Only algorithms that contained an optimal Beta at a true positive rate of at least 0.5 were evaluated (using the above graphical method). Every algorithm that met the criteria was plotted on a warning timing figure. Comparisons were made in terms of the maximum true positive rate obtained at both the too late point and the favorable warning point. An algorithm that provides most of the warnings near the favorable warning point may be preferable to an algorithm that provides more true positives overall but provides them at warning timings near the too late point.

In addition to warning timing, the distribution of the false positives was also evaluated. This evaluation is based on the principal that not all false positives are created equal. The impact of a false positive will be different depending on the experience of the driver. A
driver who nearly violated may not consider the alert a nuisance and may even appreciate the warning. Thus, a false positive presented to a driver whose stopping maneuver is very near the violation definition is considered less annoying than a false positive provided to a driver who had a mild and compliant intersection approach. To evaluate this effect, the distribution of the stopbar speed for the false positive approaches was plotted relative to the violation criteria. Distributions that were skewed toward the violation threshold were preferred over those that occurred far from the criteria. The false positive distribution is demonstrated below using the same example algorithm depicted in Figure 42 and Figure 43. The vertical marker is the violation threshold (15 mph in this example). A distribution in which most false positives occur close to the threshold is preferred over a distribution in which most of the false positives occur further from the threshold.

Figure 44: Example stopbar velocity distribution for false positives using the algorithms depicted in Figure 42 evaluated at the beta value corresponding to a false positive of 0.01

The SDT method described in this section was deployed to over 160 algorithm permutations to arrive at a recommended set of threat assessment algorithms. The procedure used to employ the SDT method is described in the next section.

Algorithm Assessment Procedure
A structured approach was devised to develop and test a variety of potential stop-controlled intersection ICAS-V threat assessment algorithms. This approach was highly iterative and is outlined below. With the exception of steps two and three, which will be
discussed in detail in the following section, this section will describe each of the
following:

1. Define the target warning group
2. Generate prototype algorithms
3. Define Beta ranges for each algorithm
4. Run pseudo-real-time simulation for each algorithm/Beta combination to obtain true positives and false positive alerts.
5. Compare resulting ROC curves for each of the algorithm forms
6. Select the best performing algorithms, evaluate miss-classifications, and improve algorithm.
7. Re-define all algorithms with the enhancements identified in step six
8. Iterate steps 3 through 7 until no further enactments are realized
9. Select the algorithms with the highest final sensitivity
10. Compare the remaining algorithms in terms of:
   a. The warning timing distribution relative to the required warning timing for drivers receiving an ICAS warning
   b. The distribution of false alerts relative to the violation criteria to understand the severity of the false alarms
11. Provide recommendations for ICAS algorithm based on overall results

A basic underlying assumption of SDT is a binary signal. The first step in applying SDT to the ICAS-V threat assessment context is to define the signal (violators) and the noise (compliant drivers). According to Virginia law, any driver who does not come to a complete stop at the stopbar is a violator. However, in reality few drivers will receive a summons by slowly rolling through a stop sign. Furthermore, based on the data presented previously in Figure 32, most drivers passing through the intersection would be classified as a violator. If the warning criteria followed the “letter of the law”, most drivers would be violators which will result in a nuisance alarm problem.

It is not the purpose of this dissertation to determine one universally-agreed upon definition of the target violation population. Defining a violation is a political and safety related issue that should be a topic for debate for policy makers; however, the results presented earlier may be used to guide the decision process. In particular, the cluster analysis and subsequent graphical analysis demonstrated some natural groups in the data. These analyses suggested that clusters three and four represented the target population of violators, with some portion of cluster two representing less dangerous violations that would still benefit from a warning. Rather than assume a particular portion of the second cluster that should be warned, multiple thresholds may be selected. This allows interpretation of the results across a range of violation criteria.

Four violation criteria were tested as part of this investigation (Table 13). These criteria span a range of logical choices for determining when an approach should become a target violation for the ICAS-V system. Stopbar speed was selected to define the violation threshold because rolling stops are typically discussed in terms of the speed at which they occur. A regression was performed to relate stopbar speed to minimum RDP (Appendix K). Using this regression, a span of stopbar speeds were selected according to the
distribution of clusters addressed. The values selected in Table 13 ensure that clusters three and four are violators, while cluster two is made up of anywhere from just over one percent violators to consisting entirely of violators. A driver who never slowed their vehicle below the cutoff was classified as a violator for purposes of algorithm evaluation.

Table 13: The four selected violation threshold criteria and the resulting samples. Total number of samples in the dataset was 30,458.

<table>
<thead>
<tr>
<th>Stopbar Velocity</th>
<th>Minimum RDP (g)</th>
<th>Number of violators</th>
<th>Percent of Sample</th>
<th>Percent of Population</th>
<th>Percent of Cluster 1</th>
<th>Percent of Cluster 2</th>
<th>Percent of Cluster 3</th>
<th>Percent of Cluster 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.2 m/s (5mph)</td>
<td>0.34</td>
<td>10808</td>
<td>35.5%</td>
<td>36.5%</td>
<td>17.6%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>4.52 m/s (10mph)</td>
<td>0.80</td>
<td>1673</td>
<td>5.5%</td>
<td>5.0%</td>
<td>0%</td>
<td>27.7%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>6.72 m/s (15mph)</td>
<td>1.36</td>
<td>185</td>
<td>0.6%</td>
<td>1.1%</td>
<td>0%</td>
<td>4.2%</td>
<td>99.9%</td>
<td>100%</td>
</tr>
<tr>
<td>8.92 m/s (20mph)</td>
<td>2.00</td>
<td>49</td>
<td>0.2%</td>
<td>0.3%</td>
<td>0%</td>
<td>1.2%</td>
<td>93.8%</td>
<td>100%</td>
</tr>
</tbody>
</table>

The pseudo-real-time simulation refers to the process of coding the algorithm into a program that loads each individual intersection vehicle approach trajectory through the algorithm in a frame-by-frame fashion. Thus, the method simulates the process under which the algorithm would actually function if it was installed in every vehicle that approached the intersection during the data collection. For every vehicle approach, the algorithm classified the trajectory as either a violation or a compliant approach type. The algorithm classifications were then compared to the true actions of the driver to compute the true positive and false positive rates.

Once algorithm performance was obtained, an ROC curve was plotted for each algorithm across its potential settings of Beta. Every algorithm family (described in the subsequent section) was plotted on a single ROC plot space. The best in-family and across-family algorithms were selected for further analysis. The follow-up analysis continued using graphical methods to investigate the miss-classifications resulting from the algorithm simulation.

For example, trajectory plots such as the ones shown in Figure 45 were created for range, velocity, TTI, and RDP. These plots were viewed to determine trends in the trajectories that could be addressed by an algorithm enhancement. The approaches below resulted in false negatives for an algorithm that suppressed the warning if it detected that braking was active. For these approaches, violations resulted despite a mild level of braking. To address this, a new algorithm was developed that required the vehicle to be braking at a rate of at least 0.1 g before it would suppress the warning. Many similar algorithm enhancements were made in an iterative fashion.
Each time an enhancement was developed for a particular algorithm, it was applied to all of the algorithms and the simulation cycle was iterated. This ensured that a poorly-performing algorithm would not benefit greatly from an enhancement placed on an initially higher-performing algorithm. This cycle was repeated until no further algorithm enhancements were identified.

With each iteration cycle, the ROC curves were evaluated with all of the potential algorithms and Beta criteria represented. The most sensitive algorithms were selected for the warning timing and false positive evaluations described in the previous section. Algorithms were preferred if:

- They provided the highest true positive rate
- At the lowest false positive rate
- With true positives that obtained warnings sufficiently early to allow a violating driver to stop
- While resulting in false positives with the lower level of nuisance.

Over the course of the development and evaluation cycles, a few algorithms emerged as consistently high-performing predictors of stop sign violations. These algorithms were identified using a search heuristic and subsequently modeled using their associated base rates. This process will be further discussed in the Algorithm Evaluation Results section of this chapter.
**Generated Algorithms**

The following discussion opens with some general definitions for the variables used in the algorithms. Next, the basic two-level architecture of the algorithm is described. This is followed by a detailed description of each layer and the algorithms contained within them. The section closes with a description of the algorithm naming convention that will be used for describing the algorithms throughout the subsequent algorithm evaluation results.

**Variable Definitions**

The algorithms investigated frequently have overlapping variables. To avoid redefining the same variables as each equation is presented, all of the variables are defined below (Figure 46).

- SV = Subject vehicle (the vehicle that is being evaluated by the algorithm)
- T₀ = Initial time when vehicle enters intersection region
- R₀ = Instantaneous range from SV to stopbar
- V = Instantaneous velocity of SV
- V₀ = Initial velocity of SV
- Vᵢ = Final velocity of SV
- A = Instantaneous acceleration of SV
- TTI = Instantaneous time to intersection of SV
- TTIᵣₑᵢq = The time to intersection required for the driver to stop at the stopbar
- RDP = Kinematically calculated constant deceleration required to stop at the stopbar
- PRT = Perception reaction time: the time from the warning to the brake application
- a,b,c = Parameters used in regression equations

**Top-Level Architecture**

All of the algorithms tested in this research follow the same basic framework (Figure 47). An approaching vehicle first enters the region of the intersection that is being monitored...
at time $T_0$. Once the vehicle enters the region of interest, its’ kinematic state is measured at each time step. For the present research, the measurements were performed by the radar; however, in a deployed ICAS, these measures could be computed using onboard sensors as well. The kinematic measures available to the algorithms include the vehicle’s range to the intersection, velocity, and acceleration. From these measures, other composite measures such as TTI and RDP are frequently calculated (see Chapter 6 for derivations). Once the kinematic measures are evaluated, they are fed into the first layer of the algorithm.

The first layer contains a computational component that evaluates whether the warning should be provided based on the present kinematic state of the vehicle. This layer gathers a variety of measures together into a single metric, which is then compared to the decision criteria Beta. If the outcome of the comparison indicates compliance, the algorithm computations cease for the present time frame. The evaluation process then starts over the next time cycle. If the outcome of the comparison predicts a violation, the present vehicle kinematics is passed to the second layer of the algorithm.

The second layer of the algorithm was added to reduce the number of false alarms that were being produced by the first layer. The second layer evaluates the present state of the vehicle to infer whether the driver is attentive to the intersection. If the driver appears to be attentive (i.e., has started braking), the warning is suppressed. If the driver is not attentive the warning is set to active and the algorithm is shutoff for the reminder of the intersection approach trajectory. If the warning is suppressed, the entire process begins again the next time window and is repeated through the entire intersection approach trajectory unless a warning is presented.

![Figure 47: top-level algorithm architecture](image-url)
The remaining portion of this section will be devoted to describing the two major layers of the algorithm. These layers and their components were developed iteratively to address a variety of characteristics noted in the trajectory plots presented in the graphical analysis section of this dissertation. The iterative development is not reflected in this discussion; rather only the fully developed algorithms are discussed.

**Layer 1 Algorithm Component**

The first layer of the algorithm compares the vehicle’s current dynamic state to decision criteria that will determine when a warning should be activated. Each of the layer one algorithms described in this section actually represent a family of algorithms when they are combined with the second layer. Combinations of the two layers represent the decision criteria (Beta) in the SDT process.

There are two broad categories of layer one algorithms: kinematic and empirical. Kinematic algorithms are constructed based on the laws of physics. The empirical algorithms were created through regression of sampled behaviors. Each class of algorithm has advantages that were explored. For instance, the kinematic algorithms have a physics foundation which provides a generally accepted and easily modeled format. The empirical methods provided better performing algorithms, but potentially at the cost of a decreased ability to generalize to other intersections and a lack of acceptance in the engineering community. Other algorithms were investigated but are not presented in detail. A brief discussion of these other algorithms is provided at the end of this section. The following first layer algorithms (Table 14) are described next.

**Algorithm 1: Static TTI**

The first algorithm uses a static warning TTI that is compared to the driver’s instantaneous TTI. A similar warning strategy has been employed in the past for forward collision avoidance systems (Kiefer, 1999) and ICAS (Neale et al., 2005). Time based measures such as TTI are thought to be a good representation of the metric used human visual system to judge whether or not to stop (Horst, 1990). With this algorithm, a warning is provided to a driver when their vehicles required \( TTI_{req} \) is more than their instantaneous TTI.
The $T_{TIreq}$ represents the minimum $T_{TI}$ at which a driver must receive the warning in order to come to a complete stop before entering the intersection. The $T_{TIreq}$ is a composite of both the driver’s reaction time and the time necessary for the driver to stop the vehicle. For this algorithm $T_{TIreq}$ is the warning criteria $\beta$, over which the algorithm was simulated. Repetitions were made with a $T_{TIreq}$ ranging from 1 second through a $T_{TIreq}$ of 5 seconds with a step size of 0.25 seconds.

Algorithm 2: Static RDP

The second algorithm is similar to the first algorithm, except it uses a static level of required deceleration as the warning unit. This algorithm assumes that all drivers need a warning when the deceleration required to stop at the stopbar exceeds a pre-defined threshold. Research performed by Neale et al. (2005) indicated that the RDP needed by drivers to stop was constant across speed. This relationship suggests that RDP is a good metric for representing when drivers should begin responding to the stop sign. The RDP equation is developed based on kinematic relationships defined by particle motion physics. For simplicity of explanation, the derivation is performed below, starting with the classical engineering kinematic equation rather than with a derivation starting from the physical laws.
The goal is to get the driver to stop the vehicle at the stopbar, so the final velocity is set to zero. In addition, knowing that we want the driver to stop by the stopbar, “a” is the constant acceleration required to stop, defined previously as RDP. The equation may then be re-organized as follow.

\[ V_f^2 = V_o^2 + 2aR \]

\[ R_{warn} = \frac{V_o^2}{2PRR} \]

Warn if: \[ R < R_{warn} \]

An alert is issued if a driver approaches the intersection in such a way that their instantaneous range is less than the warning range. The RDP in the equation represents the maximum RDP at which a driver must receive the warning in order to come to a complete stop before entering the intersection. As with the static TTI algorithm, RDP for the static RDP algorithm is also a composite of both the driver’s reaction time and the time necessary for the driver to stop the vehicle. For this algorithm, RDP is the adjustable warning criteria Beta. The simulation was performed for an RDP of 0.025g through an RDP of 0.5g with a 0.25g step size.

Algorithm 3 & 4: Static RDP with an assumed PRT

As with the previous algorithm, the third and fourth algorithms assume a constant RDP at which a driver must respond to successfully stop at the intersection. The third and fourth algorithms also explicitly consider the driver’s reaction time. The advantage of this algorithm is the ease of interpretation of the parameters. The RDP value is the actual constant deceleration that the driver will need to perform rather than a composite of the constant deceleration and the PRT as is the case for the second algorithm described previously. The equation for the second algorithm is extended to consider the distance traveled while the driver is reacting to the warning:

\[ R_{warn} = \frac{V_o^2}{2RDP} + V_o * PRT \]
In this algorithm PRT is defined as the time from presentation of the warning to the application of the brake. It includes the time required for the driver to perceive the warning, release the throttle, and transition to pressing the brake. The PRT value is selected based on the research discussed in the literature review section of this dissertation. In particular, the studies performed under the ICAV contract looked at driver response to a variety of in-vehicle warning types. These ranged from a simple auditory warning to a haptic brake pulse. The overall average PRT from these studies was 0.78 seconds (SD=0.10). This value is consistent with other PRT measures from similar surprise studies that were discussed in the literature review (average PRT was 0.79 seconds; SD=0.10). Algorithm 3 uses the 0.78 second average as the PRT value. The fourth algorithm considers that it is desirable for nearly all drivers to have sufficient time to stop. Thus, it assumes the 99th percentile PRT of 1.01.

Algorithm 5: Warning range as a function of TTI

The next series of algorithms are based on models of vehicle trajectories developed as part of this investigation. For these algorithms, the data were placed into bins and subsequently modeled as a piecewise empirical distribution. A linear regression was next performed on the modeled data to define the threat assessment algorithm. This algorithm development process will be explained in more detail while describing the fifth algorithm.

The fifth algorithm compares the vehicle’s instantaneous TTI to a warning TTI. The warning TTI is calculated using an equation that was developed through a regression of velocity. The first step in this process was to place the TTI data into a series of velocity bins. For instance, the TTI for 30,458 approaches that occurred between 0.5 m/s and 1.5 m/s were placed into the 1 m/s bin. This process was repeated for each 1 m/s (2 mph) increment from 0 to 22 m/s (49 mph – just beyond the speed limit at the highest speed intersection). The data residing in each bin was modeled with an empirical cumulative distribution. Within the velocity bins, the distribution tails were selected to form a series across the velocity bins. For example, the top 3 points at each velocity bins on Figure 48 represent the 15th, 12th, and 10th percentile values from top to bottom.
Figure 48: Piecewise empirical percentiles over which the linear regression was performed

Each series of points represented by the percentiles was gathered and fit through a linear regression. Although several models would have been effective for fitting the data, a power function was selected (Figure 49– fit information provided in Appendix L). The power function has some advantages over other equations such as polynomials, Gaussians, and exponentials for this dataset. The power equation fits the data extremely well (typical $R^2 \sim 0.98$) and has a stable nature when extrapolated beyond the data collected.
Extreme behaviors that would result in a low TTI at long ranges are too rare for distribution fitting. To avoid late or early warnings for some drivers, it is desirable for the algorithm to function across all foreseeable inputs. This means the algorithm must behave predictably beyond the data collected. Most fit types tended to behave erratically outside the range of data used during the regression. Second order polynomials, for instance, dive rapidly toward zero after fitting the data points. Using such a distribution could result in late warnings for drivers approaching the intersections at high speeds.

The power equation continues in a nearly linear form beyond the regression data. This trend matches the trend exhibited by the data points for nearly half of the distribution. Therefore, it likely provides a valid warning threshold outside the regression range. Using the regression function, the following warning equation was devised (parameters in Appendix L).

Equation 10

\[ TTI_{\text{warn}} = a V^b + c \]
Algorithm 6: Warning range as a function of velocity

The sixth algorithm uses the same basic framework as the fifth algorithm. The main difference between the two is the measure used to discriminate a violation vs. a compliant driver maneuver. The sixth algorithm takes advantage of the large separation between highly aggressive and compliant approaches when they are viewed in the velocity domain (see Figure 37 in the graphical cluster analysis).

This algorithm predicts the minimum distance at which a warning must be provided in order for the driver to successfully stop. A warning is issued if the driver’s current range to the intersection is less than the warning range (Equation 12). The calculated warning distance is based on a piecewise regression and subsequent power equation fit of distance (as a function the vehicle velocity trajectory). The basic method for developing the equation follows the method described in the fifth algorithm section above. The logic employed by the sixth algorithm is provided in Equation 12 and Equation 13. The functions tested are depicted below (Figure 50) with details of the fits provided in Appendix L.

Equation 12

\[ R_{\text{warn}} = a \cdot V^b + c \]

Equation 13

Warn if: \( R < R_{\text{warn}} \)
Algorithm 7: Warning range as a function of velocity based on truncated data

The seventh algorithm uses the same measures employed by the sixth algorithm. The difference between the two is with regard to the data sample manipulated during the regression. While performing the regression, a plateau was noted at the higher velocities. Considering the implications of this trend, one possible concern was identified. The plateau occurred as the maximum speed limit across the intersection sample was approached. This plateau may be due to maximum speed limit at the test sites rather than to a warning distance as a function of speed trend. To investigate this possibility, the data sample was truncated by removing velocities greater than 18 m/s (40 mph) before the regression was performed. This resulted in better regression fits that exhibited a somewhat steeper trend at higher velocities than found for algorithm six. The array of fits used as the threat assessment algorithm is shown below (Figure 51 - fit details in Appendix L).

Figure 50: The series of curves used to calculate the warning distance as a function of velocity for the piecewise distributions fit with a power function
Figure 51: The series of curves used to calculate the warning distance as a function of velocity for the piecewise distributions fit with a power function based on truncated data

Algorithm 8: RDP as a function of range

The eighth algorithm follows the same basic strategy used for algorithm five as well; however, the regression equation now uses range to predict the warning RDP. Using RDP as the predictor could take advantage of the earlier separation of stopping maneuvers found for RDP vs. TTI during the graphical cluster analyses. The basic logic is shown below (Equation 14), followed by the array of fits (Figure 52) used as the threat assessment algorithm (fit details in Appendix L).

Equation 14

\[ RDP_{\text{warn}} = a \cdot R^b + c \]

Equation 15

Warn if: \( RDP > RDP_{\text{warn}} \)
Figure 52: The series of curves used to calculate the warning RDP as a function of range for the piecewise distributions fit with a power function

Other algorithms developed and tested but not presented

In addition to the layer one algorithms presented above, several other algorithms were developed and tested but are not represented in the results presented. These algorithms either performed very poorly or could not be fully developed without extending the scope of this work. These algorithms are briefly discussed below.

There are several existing algorithms discussed in the literature review that were developed for applications such as forward collision warning. On first glance these algorithms may appear to be applicable to the ICAS scenario; however, after further consideration they were not investigated. The algorithms were developed using empirical methods from data collected in a forward collision scenario. The ICAV project compared the results of a study performed for both ICAS and forward collision scenarios. They concluded that drivers do not respond similarly in the two conditions. Since the equations were constructed from regression techniques they did not transfer effectively to the ICAS. Some equations, such as the static RDP algorithm, did transfer effectively and was used as part of this investigation.

Other algorithms were developed a little further but eventually abandoned as well. A series of regression based algorithms were developed using a piecewise method similar to the one described in algorithm five above. The main difference was that rather than
assume empirical distributions, the abandoned algorithms used a normal distribution for the piecewise fit. These algorithms included RDP as a function of range, RDP as a function of velocity, TTI as a function of range, TTI as a function of velocity, and warning range as a function of velocity. While some of these algorithms performed decently, none of them could complete with their empirical distribution counterparts. There is an explanation for this effect.

Consider the results presented in the cluster analysis and graphical analysis sections of Chapter 7. Many of the kinematic measures are normally distributed at long ranges from the intersection. But, as the measures are evaluated closer to the stopbar, the distributions took on a highly skewed shape. Therefore, representing the data as a series of piecewise normal distributions is not an accurate representation of the underlying data.

Finally, two algorithms were not fully investigated because there were insufficient resources to fully explore their form. These two algorithms included the empirical regression of RDP as a function of velocity and TTI as a function of velocity. In both of these regressions the underlying data exhibited a discontinuity. This discontinuity could not be fit effectively with a single equation and represents a challenging mixed distribution problem. The discontinuity could represent an undefined trend in the data that would naturally help discriminate violators. Unfortunately, investigating this possibility was outside the scope of this dissertation.

In all, over 20 layer one algorithms were evaluated and/or considered. The eight best performing layer one algorithms are presented in this dissertation. When combined with the layer two algorithms, 160 algorithms are represented in the subsequent results.

**Layer 2 Algorithm Component**

The first layer of the algorithm determines when a driver should receive the warning. The second layer of the algorithm infers the drivers’ level of attentiveness towards the intersection. If it determines that a driver is responding to the intersection, the warning will be suppressed. The primary purpose is to reduce false positives by determining whether the driver needs a warning. If the driver is attentive, it is assumed that the vehicle’s dynamic state is the result of the driver’s intended behaviors. Providing a warning to a driver who is attentive could result in a false positive with a high level of nuisance. Therefore, if the second layer declares the driver as attentive, a warning is not provided, regardless of the sensor data.

The first evaluation of the driver’s attentiveness focuses on the level of braking present during the given time frame. If a driver is actively braking, they are attentive to the intersection and do not need a warning. This may be taken a step further by considering the level of braking that is present in addition to the brake status. The data presented during the brake onset analysis and the graphical trajectory analysis was synthesized to develop five possible methods for investigation. The following different possible combinations of the driver braking component were tested for all of the algorithms:
• No braking assumption
• Driver considered attentive if the brake status was active. Brake status was described in detail in the methods section of this dissertation.
• Driver considered attentive if braking at a rate of -0.1g or less.
• Driver considered attentive if braking at a rate of -0.2g or less.
• Driver considered attentive if their current level of braking was equal to or lower than the current RDP.

In addition to evaluations of braking to infer driver attentiveness, a speed-based evaluation was also added into the second layer of the algorithm. The purpose of the speed-based check was to reduce false positives that were occurring as a result of drivers who did not completely stop at the stopbar. As stated in Chapter 7, rolling stops are extremely common. Furthermore, the algorithm does not contain any hysteresis. This means the minimum speed threshold ensures that a driver who completely stops a short distance from the stopbar will not receive warning once they proceed.

During an early iteration, the speed cutoff was allowed to vary freely for each of the algorithms. The results indicated that, in general, the number of false positives decreases with an increasing cutoff speed. The number of true positives is relatively stable until about 9 m/s at which time it tended to drop-off rapidly.

Although it may seem that a speed cutoff should simply be set around 9 m/s (20 mph), there are some implications of this threshold that must be considered. A high threshold inevitably resulted in missing some violations at low speed intersections at which the speed limit may only be a few meters per second higher than the cutoff. In addition, setting the speed cutoff at a single value will not provide information regarding the correlation between algorithm cutoff speed and the violation criteria defined previously. Therefore, it was decided to test speed cutoffs over the same range of speeds that were used to define the violation. Thus, four speed cutoffs were tested: 2.2 m/s (5mph), 4.52 m/s (10mph), 6.72 m/s (15mph), and 8.92 m/s (20mph).

Algorithm Naming Convention
A naming convention was devised to allow interpretation of the large number of algorithms represented in the subsequent sections. This naming convention uses a three digit code to quickly identify the algorithm components. The first digit represents the layer one algorithm (often referred to as an algorithm “family”). Families of algorithms are typically plotted together on the ROC curve so that the best in-family curves can be identified. The second and third digits of the naming convention represent the second layer of the algorithm; specifically, the low speed cutoff and the braking thresholds respectively.
Figure 53: Diagram depicting the three digit code used to name each of the algorithms described in this dissertation.

The algorithm component identified by the value of each digit is provided in the list below. For instance, if the algorithm code is 324, the list below would identify that as a static RDP algorithm family using a 10 mph speed cutoff and a 0.2 g braking effort requirement.

1. Basic Algorithms Tested (First digit)
   1. Static TTS
   2. Static RDP
   3. Static RDP with PRT
   4. Variable RDP based on regression of Velocity
   5. Variable TTI based on regression of range
   6. Variable warning distanced based on regression of velocity
   7. Variable RDP based on regression of Range
   8. Variable Velocity based on regression of Range

2. Speed Threshold (second digit)
   1. Suppress warning if current speed < 2.2 m/s (5 mph)
   2. Suppress warning if current speed < 4.52 m/s (10 mph)
   3. Suppress warning if current speed < 6.72 m/s (15 mph)
   4. Suppress warning if current speed < 8.92 m/s (20 mph)

3. Braking Thresholds (third digit)
   1. Never suppress warning based on braking
   2. Suppress warning if Brake Status = on
   3. Suppress warning if present deceleration < -0.1g
   4. Suppress warning if present deceleration < -0.2g
   5. Suppress warning if present deceleration < -RDP
Algorithm Evaluation Results

The algorithm analysis process generated a series of graphical outputs. These outputs were methodically examined for trends across the violation thresholds and algorithm settings. This section will present the results from this graphical inspection process, as well as the output of a heuristic scheme devised to identify the best performing algorithms.

ROC Curve Graphical Analysis Results

This discussion opens with an exemplar inspection of the ROC curves. For clarity, an individual ROC plot was created for each algorithm family under each defined violation threshold. Within an ROC plot, a color and marker scheme was used to identify the different layer-one components of the layer-two family. For example, the cyan color always represented the 5 mph violation threshold while the diamond marker always represented the 0.2 g minimum braking threshold. This allowed quick assessments of the data trends within, as well as across, the ROC figures.

A comprehensive set of ROC curves is available in Appendix M. This discussion will use the 600 series to describe the general trends noted in the ROC curves. The 600 series algorithm proved to be one of the best-performing algorithms. It also exhibits many of the general trends noted across the other ROC curves; thus providing an excellent subject for demonstrating the analysis.

Recall from the literature review that warning systems such as ICAS need to result in a very low false positive rate. This fact will be demonstrated in detail later in this section. For now, assume that a good algorithm should provide a true positive rate of at least 0.5 at a false positive rate at or below 0.05. These minimum criteria result in correctly warning 50% of the violating drivers while inadvertently warning 5% of the compliant drivers. A good algorithm will exceed these minimum requirements.

Figure 54 below depicts the ROC plot for the 600 series family of algorithms when the violation threshold is set at 5 mph. Considering the minimum performance specification set above, the performance of all of the algorithms tested at 5 mph is disappointing. The 600 series algorithm is the best performing algorithm at this speed, yet at a false positive rate of 0.05, the best true positive rate we can hope for is just over 0.3.
It is reasonable to assume that a low speed cutoff that is equivalent to the violation threshold would provide the best performance. Nonetheless, the figure above indicates particularly poor discriminability for the 5 mph low speed cutoff when the violation threshold is set at a 5mph minimum stopbar speed. In fact, looking through the ROC figures this is a recurring phenomenon. The consistently high false positive rate produced by a 5 mph speed cutoff likely indicates the frequency at which compliant drivers exceed this speed threshold in the warning region. The clear suboptimal trend across all of the ROC curves indicates that a 5 mph low speed threshold should not be used in an ICAS-V threat assessment.

The next figure (Figure 55) displays the ROC curves for the same 600 series algorithm family but over the 10 mph violation threshold. The ability to discriminate among all the algorithms is improved, compared to a 5 mph violation threshold. Notice the 5 mph low speed cutoff continues to perform poorly. In addition, the 10 mph cutoff does not perform as well as the 15 mph and 20 mph cutoffs. This trend is also noted across all of the ROC curves.
Further inspection of the low speed cutoff results in more notable trends. Although this trend is not consistent across all ROC curves, the general shape of each algorithm is retained across the low speed cutoff. For instance, other than the shift in horizontal location, the curves generated from the 10 mph low speed cutoff in Figure 55 are nearly identical in shape to the ones produced by the 5 mph cutoff. This trend would likely be noted for the 15 mph and 20 mph cutoffs if a larger range of parameters were used in the algorithms.

Without a large range of Beta parameters, the ROC curves do not always appear complete. Care was exercised to ensure the curves were inclusive in the region where assessments were performed (e.g. false positives rate less than 0.05). In addition, the parameters were selected considering driver capability in response to the warning. Parameters extending beyond the values tested would be well outside the capabilities of all driver vehicle systems.

Figure 55: ROC curve for the 600 series algorithm family using a violation threshold of 10 mph
Figure 56: ROC curve for the 600 series algorithm family using a violation threshold of 15 mph

As the violation threshold is increased, all of the algorithms demonstrate an improved ability to discriminate (Figure 56). At this violation threshold, some of the algorithms start performing at levels that may be sufficient for the ICAS-V system. As with the 10 mph violation threshold in Figure 55, the 15 mph low speed cutoff also performs best when the violation threshold is 15 mph (Figure 56). In fact, across nearly all of the ROC curves, the 15 mph low speed cutoff is typically the best performing speed criteria. This trend continues even at a 20 mph violation threshold. This may indicate that compliant drivers typically exhibit speeds less than 15 mph in the warning region.

Consider the general trends exhibited by the minimum braking effort requirement. The typical trend across many of the ROC figures indicates best performance for 0.1 g and 0.2g minimum braking effort requirements. The “no-brake” requirement and the “braking at or above RDP” requirement tend to perform very similarly. Both of these requirements are occasionally represented in the top discriminating algorithms. Finally, the on/off binary brake status requirement is rarely represented in the best algorithms. In general, brake status appears to reduce the number of true positives. The brake status requirement is suppressing the warning for drivers that will exceed the violation threshold.
Figure 57: ROC curve for the 600 series algorithm family using a violation threshold of 20mph

The final ROC for the 600 series algorithm represents the increased ability to discriminate when a 20mph violation threshold is used. As represented across all the ROC curves, the ability to discriminate improves as the violation threshold increases. This is likely due to the more extreme behaviors that are being classified as violators. As discussed in detail during the cluster analysis, these extreme behaviors are substantially different from compliant drivers and thus easier to classify.

There is an inherent trade-off in assuming a higher violation threshold. As the threshold is increased there is an opportunity to miss some fairly severe violations. This is particularly true at low speed intersections where the speed limit may only be five miles-per-hour higher than the 20 mph violation threshold. It is foreseeable for some distracted drivers to inadvertently travel at 5 mph below the threshold and not receive a warning despite showing no response to the intersection.

There is another, less apparent trade-off being made as the violation criterion is increased. To understand this trade-off, we must consider the base rates at which the violations occur. To include base rates in our comparison, the frequency of true positives and false positives are calculated and subsequently represented as a ratio.
For example, with a 15 mph violation threshold algorithm 634 produced a true positive rate of 0.86 and a false positive rate of 0.05. From Table 13, we know that 185 violations occurred at the 15 mph violation threshold and that 30,458 total approaches were evaluated. Thus, 159 true positives will result (0.86*185) along with 1,523 false positives (0.05*30,458). The resulting ratio is 10 false positives for every 1 true positive. Now consider this same 635 algorithm at a 20 mph violation threshold. The rates appear much better, with a true positive rate of 0.97 at a false positive rate of 0.05. These rates will result in 48 true positives (49*0.97) and the same 1,523 false positives. The resulting ratio is much worse at 32 false positives for every 1 true positive. Therefore, the base rates must be considered when comparing algorithm performance across the violation thresholds.

**Threat Assessment Algorithm Recommendations for ICAS-V**

The series of ROC, warning, and nuisance distributions provided in Appendix M, N, and O are very useful for identifying trends. Simply viewing the numerous figures, however, does not provide an easy way to identify the optimal algorithms. A heuristic search procedure was developed to identify and evaluate the best instantiations across all 160 algorithms and all four violation thresholds.

The search heuristic began by limiting the pool of algorithms by setting a minimum performance specification. To be considered for review, the algorithm must result in a true positive rate of at least 0.5 while producing a false positive rate no higher than 0.05. These minimum criteria eliminated over half the potential algorithms and abolished the 5 mph violation threshold.

Indicated in the ROC curves presented in the previous section, the 5 mph threshold tended to make the discrimination of violation and compliant behavior difficult. As a result, none of the tested algorithms were capable of meeting the minimum requirements when a 5 mph violation threshold was selected. Therefore, the 5 mph violation threshold will not be considered in the remainder of this discussion.

The minimum false positive criteria of 0.05 may not be sufficiently stringent for a deployable ICAS-V. To explore tighter requirements, the highest performing algorithms were also identified for a minimum false positive criterion of 0.01. With this second set of minimum criteria, the 10 mph violation threshold also failed. None of the algorithms tested could satisfy the minimum criteria at a violation threshold of 10 mph.

The remaining algorithms were rank-ordered in terms of a performance heuristic. The first step in this process was selecting the performance measures. These measures are represented by the shape of the ROC, warning, and nuisance distributions. To capture their shape, these distributions were evaluated at multiple locations (Figure 58). The true positive rate was evaluated at several points on the warning distribution curve. The true positive rate that corresponded to the favorable (A) and too-late (E) warning points were evaluated. Furthermore, the true positive rate at the first quartile (B), second quartile (C), and third quartile (D) of the region between the favorable and too-late warning points was also obtained. The heuristic also used the false negative rate evaluated at the maximum true positive rate (G) and at a midway point between the zero and the maximum (F).
Once these points were evaluated, the next step was decreasing the precision of these performance measures. The true positive rate was rounded to one decimal place (i.e., a true positive rate of 0.79532 was rounded to 0.8). The false positive rate was rounded to two decimal places (i.e., a false positive rate of 0.023156 was rounded to 0.02). The decrease in precision allowed ordering of the data across multiple performance measures. Leaving the data at full precision would have resulted in ordering determined only by the first variable. The following sequential ordering scheme was performed:

1. Data organized in descending order by the true positive rate at point C.
2. Data organized in ascending order by the false positive rate at point F.
3. Data organized in descending order by the true positive rate at point D.
4. Data organized in descending order by the true positive rate at point E.
5. Data organized in ascending order based on the false positive rate at point G.

With the five-level order scheme above, all algorithms were placed in a unique order from highest performance to lowest performance. There are other ordering heuristics that could be used depending on the relative importance placed on each of the ordering variables. The scheme used above was selected to best fulfill the needs of an ICAS-V system based on the literature reviewed and the authors' experience in this topic area. The scheme aims to maximize the true positives that provide sufficient time for most drivers to stop while minimizing the number of nuisance false positives. This goal is implied or explicitly stated in most ICAS-V documentations (Lee et al., 2004; Neale et al., 2005; Ferlis, 1999).

When applied to the stop sign dataset, the heuristic yielded the following results (Table 15). The table summarizes the top four performing algorithms for the categories of violation threshold and maximum false positive criteria. The orange highlighted rows...
represent the highest performing algorithm for each violation speed by minimum false positive rate combination. The missing cells result from violation thresholds for which none of the algorithms met the minimum requirements.

In addition to the table below, ROC curves, warning distributions, and nuisance distributions are presented for the top two algorithms in each category (Appendix Q). These ROC curves illustrate the selection heuristic which tends to select the algorithm with the highest ability to discriminate. The warning and nuisance distributions are also presented for the best two algorithms which illustrate the remaining strengths of the selection heuristic. For algorithms with a similar ability to discriminate, the heuristic will favor algorithms that provide more appropriately timed alerts while minimizing the level of nuisance.

Table 15: Highest performing four algorithms for each violation threshold at a maximum false positive rate of 0.05 and 0.01.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>TPR</th>
<th>FNR</th>
<th>FPR</th>
<th>TNR</th>
<th>TP</th>
<th>FN</th>
<th>FP</th>
<th>TN</th>
<th>FP : TP</th>
<th>TP : FN</th>
</tr>
</thead>
<tbody>
<tr>
<td>831 - 8</td>
<td>0.59</td>
<td>0.41</td>
<td>0.05</td>
<td>0.95</td>
<td>3,227</td>
<td>2,265</td>
<td>4,705</td>
<td>95,022</td>
<td>1.5 : 1</td>
<td>1.4 : 1</td>
</tr>
<tr>
<td>835 - 8</td>
<td>0.59</td>
<td>0.41</td>
<td>0.05</td>
<td>0.95</td>
<td>3,224</td>
<td>2,269</td>
<td>4,705</td>
<td>95,022</td>
<td>1.5 : 1</td>
<td>1.4 : 1</td>
</tr>
<tr>
<td>631 - 7</td>
<td>0.57</td>
<td>0.43</td>
<td>0.04</td>
<td>0.96</td>
<td>3,119</td>
<td>2,374</td>
<td>4,206</td>
<td>95,550</td>
<td>1.3 : 1</td>
<td>1.3 : 1</td>
</tr>
<tr>
<td>635 - 7</td>
<td>0.57</td>
<td>0.43</td>
<td>0.04</td>
<td>0.96</td>
<td>3,116</td>
<td>2,377</td>
<td>4,206</td>
<td>95,550</td>
<td>1.3 : 1</td>
<td>1.3 : 1</td>
</tr>
<tr>
<td>634 - 12</td>
<td>0.86</td>
<td>0.14</td>
<td>0.05</td>
<td>0.95</td>
<td>525</td>
<td>82</td>
<td>4,853</td>
<td>95,118</td>
<td>9.2 : 1</td>
<td>6.4 : 1</td>
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<tr>
<td>834 - 15</td>
<td>0.88</td>
<td>0.12</td>
<td>0.05</td>
<td>0.95</td>
<td>535</td>
<td>72</td>
<td>4,646</td>
<td>95,326</td>
<td>8.7 : 1</td>
<td>7.4 : 1</td>
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<tr>
<td>234 - 14</td>
<td>0.76</td>
<td>0.24</td>
<td>0.03</td>
<td>0.97</td>
<td>463</td>
<td>144</td>
<td>2,676</td>
<td>97,308</td>
<td>5.8 : 1</td>
<td>3.2 : 1</td>
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<tr>
<td>733 - 14</td>
<td>0.78</td>
<td>0.22</td>
<td>0.04</td>
<td>0.96</td>
<td>473</td>
<td>135</td>
<td>4,196</td>
<td>95,778</td>
<td>8.9 : 1</td>
<td>3.5 : 1</td>
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<tr>
<td>644 - 10</td>
<td>0.98</td>
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<td>0.02</td>
<td>0.98</td>
<td>158</td>
<td>3</td>
<td>1,612</td>
<td>98,385</td>
<td>10 : 1</td>
<td>48 : 1</td>
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<tr>
<td>634 - 10</td>
<td>0.98</td>
<td>0.02</td>
<td>0.03</td>
<td>0.97</td>
<td>158</td>
<td>3</td>
<td>2,689</td>
<td>97,307</td>
<td>17 : 1</td>
<td>48 : 1</td>
</tr>
<tr>
<td>843 - 19</td>
<td>0.98</td>
<td>0.02</td>
<td>0.02</td>
<td>0.98</td>
<td>158</td>
<td>3</td>
<td>2,344</td>
<td>97,652</td>
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<td>48 : 1</td>
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<tr>
<td>833 - 19</td>
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<td>0.02</td>
<td>0.03</td>
<td>0.97</td>
<td>158</td>
<td>3</td>
<td>2,748</td>
<td>97,248</td>
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<td>48 : 1</td>
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<tr>
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<td>0.39</td>
<td>0.01</td>
<td>0.99</td>
<td>371</td>
<td>236</td>
<td>818</td>
<td>99,177</td>
<td>2.2 : 1</td>
<td>1.6 : 1</td>
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<td>0.01</td>
<td>0.99</td>
<td>361</td>
<td>246</td>
<td>834</td>
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<td>1.5 : 1</td>
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<tr>
<td>633 - 13</td>
<td>0.59</td>
<td>0.41</td>
<td>0.01</td>
<td>0.99</td>
<td>358</td>
<td>250</td>
<td>663</td>
<td>99,333</td>
<td>1.9 : 1</td>
<td>1.4 : 1</td>
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<td>433 - 9</td>
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<td>0.99</td>
<td>341</td>
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<td>0.01</td>
<td>0.99</td>
<td>154</td>
<td>7</td>
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<td>99,083</td>
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<td>23 : 1</td>
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<td>0.94</td>
<td>0.06</td>
<td>0.01</td>
<td>0.99</td>
<td>151</td>
<td>10</td>
<td>696</td>
<td>99,303</td>
<td>4.6 : 1</td>
<td>15 : 1</td>
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<tr>
<td>844 - 9</td>
<td>0.98</td>
<td>0.02</td>
<td>0.01</td>
<td>0.99</td>
<td>158</td>
<td>3</td>
<td>946</td>
<td>99,053</td>
<td>6.0 : 1</td>
<td>48 : 1</td>
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<tr>
<td>843 - 15</td>
<td>0.90</td>
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<td>0.01</td>
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<td>16</td>
<td>525</td>
<td>99,474</td>
<td>3.6 : 1</td>
<td>8.8 : 1</td>
</tr>
</tbody>
</table>

- TPR= True Positive Rate
- FNR= False Negative Rate
- FPR= False Positive Rate
- TNR= True Negative Rate
- TP= True Positive
- FN= False Negative
- FP= False Positive
- TN= True Negative
The best true positive rate for the algorithms is 0.98, which occurs at a 20 mph violation threshold combined with the minimum 0.05 false positive criterion. Other high true positive rates are exhibited by the 20 mph violation threshold 0.01 false positive rate and the 15 mph violation threshold 0.05 false positive combinations.

As was demonstrated in the ROC discussion within this chapter, the true positive rate tends to increase with an increasing violation threshold. This suggests that algorithm performance improves with an increasing violation threshold; however, recall the importance of considering the base occurrence rates for the violation vs. compliant approach type at the differing speed thresholds. These base rates are best reflected in the ratio of true negatives to false positives. As the violation threshold increases, the ratio of false positives to true positives is worse. Conversely, the ratio of true positives to false negatives improves with an increasing violation threshold.

Ultimately, as was stated in the beginning of this Chapter, the violation threshold selection should be based on additional research that has not yet been completed. There are two main knowledge gaps that preclude selection of the threshold at this stage. First, we need a better understanding of the stopbar speed at which attentive drivers perceive that warnings are a nuisance. The violation threshold should be set higher than this nuisance speed. Second, we need a better understanding of the stopbar speed at which violations become dangerous. At present, there are no studies that look at the prevalence of violation-related accidents as a function of the stopbar speed. The violation threshold should be set low enough to capture most of the violations that lead to crashes.

Once a violation threshold is objectively determined, the preferred algorithm may be selected from Table 15. The table provides the highest-performing algorithm within each violation threshold. For the purpose of this discussion, consider the stopbar speed and cluster analysis results presented in Chapter 7. Based entirely on the frequency of occurrence, the Chapter 7 results suggested violation thresholds of either 15 mph or 20 mph. Concerns regarding the 20 mph threshold missing some inattentive violations indicated that 15 mph is the best violation criteria. Assuming a 15 mph violation threshold, the best algorithms are 634 and 833. Which of these two algorithms is deemed best depends on selecting the minimum allowable false positive rate of either 0.05 or 0.01.

Additional research will be required to determine which of the minimum false positive rates are acceptable. Studies should be performed to investigate the actual perceived nuisance of the ICAS-V warning. To maximize the true positive rate, the highest maximum false positive rate that does not annoy drivers should be selected. Additional thoughts surrounding the selection of an algorithm for future testing and ICAS-V development are presented in the conclusions chapter below.
CHAPTER 9 – CONCLUSIONS

This dissertation represents the first large-scale naturalistic observation of continuous intersection approach behavior. The database of driver behavior collected during this research was used to systematically formulate threat assessment algorithms for an ICAS-V. The following discussion summarizes the conclusions drawn from the results of this dissertation.

Addressed Research Questions

At the onset of this investigation, a set of research questions was developed to guide the methods and analysis. These research questions were implicitly addressed throughout the results provided in chapters 7 and 8. Concluding remarks for each research question are provided in the following sections.

Question #1: When do violations occur and how can we predict them?

The first research question examined the definition of a violation using the data obtained during the course of the study. The purpose of this question was to learn more about violations in an effort to identify the target population for ICAS-V. Two sub-questions were investigated:

Question #1.1: How often do violations occur?

At the onset of this dissertation, question 1.1 did not appear to represent a major challenge. As the research progressed, the complexities associated with counting violations surfaced. In particular, the very definition of what should constitute an ICAS violation quickly became ambiguous. The legal definition of a violation requires all drivers to stop at the stop sign; however, so few drivers perform this maneuver that most approaches would be classified as violations.

There does not appear to be existing research regarding the type of violations that lead to crashes. A key step in the development of an ICAS-V system is defining the target warning group. The algorithm may then be selected based on its ability to predict this target group. The minimum stopbar speed analysis provides some guidance about where the ICAS-V violation criteria should be set.

The stopbar analysis performed in Chapter 7 established the need for the ICAS-V to deviate from the standard legal definition of a violation. This analysis demonstrated that 36% of the drivers crossing through the intersections never slowed below 3.4 m/s (5 mph). Even with a higher 4.5 m/s (10mph) criteria, nearly six percent of the drivers will violate. Events of this frequency suggested intentional “rolling stops” are being performed by the drivers. Such intentional behavior suggests these drivers are cognizant of the situation and likely do not need or want a warning. Warnings presented to these drivers will likely be perceived as a nuisance alert generating loss of user trust, potentially undermining the purpose of the ICAS-V system (Dingus et al., 1998).
Furthermore, the algorithm analysis demonstrated significantly lower true positive rates for algorithms that used the 3.4 m/s and 4.5 m/s (5 mph and 10 mph) violation thresholds. The outcome of the minimum stopbar speed and algorithm analyses indicated that higher violation criteria are better. In particular, the 6.7 m/s and 8.9 m/s (15 mph and 20 mph) violation thresholds resulted in a more reasonably-sized warning population. At 6.7 m/s, (15 mph) 0.6 % of the drivers would receive an ICAS-V warning followed by just 0.2 % at 8.9 m/s (20 mph). These two higher thresholds also focus on capturing the cluster 3 and 4 groups, which were hypothesized as containing the inattentive drivers.

Although the analyses provided guidance on the selection of the violation threshold, additional research should be performed prior to selecting the final criteria. First, research should be performed to determine the speed at which violations become dangerous. The goal of ICAS-V is to prevent collisions by mitigating the violations that lead to collisions. To succeed at this goal, it would be beneficial to set the violation threshold that would capture the largest portion of the violations that lead to crashes.

The second research need focuses on determining those warning characteristics that result in a perceived nuisance alert. An understanding of nuisance alerts would help to determine the appropriate violation threshold, based on the algorithm performance discussed in Chapter 8. It is unknown if the higher false-positive-to-true-positive ratio at higher violation thresholds will actually result in higher perceived nuisance alerts.

The false positives produced at the higher violation thresholds would be true positives at lower thresholds. As a result, many of these false positives may not be perceived as nuisance. In fact, some proportion of the false positives may actually be appreciated by the driver. This is particularly true for a distracted driver who perceives the intersection late in the approach. While this driver may perform an evasive maneuver to avoid a violation without the ICAS-V warning, they are unlikely to perceive an issued warning as nuisance.

**Question #1.2: What environmental characteristics best predict a pending violation?**

Most of the previous work looking at violation propensity was focused on signalized intersections and was limited to measures available through epidemiological sources. This investigation was the first known opportunity to directly measure violation likelihood as a function of the environmental variables at the time of the event.

At stop sign intersections, the vehicle type did not appear to have an effect on the likelihood of a violation. This finding is counter to previous findings at signalized intersections (Hicks et al., 2005). Perhaps the changing signal phase enticed drivers of certain types of vehicles to violate. For example, Hicks found that trucks were more likely to violate than sports cars. This effect may be the result of the relative effort required to stop a heavy vehicle vs. a light vehicle. When a phase change is not noticed until late in an approach, the driver of the truck may be less likely to exert the effort required for stopping.
Violations were more likely to occur at night rather than during the day or at twilight. It is hypothesized that this effect is due to visibility. In the case of daytime vs. nighttime, the decreased visibility may result in drivers perceiving the intersection late in the approach or not at all. It may also be that drivers can see the headlights of the cross traffic from a greater distance and are more likely to willfully violate in the absence of other vehicles.

Tijerina et al. (1994) found that most intersection crashes occur in clear conditions. Interestingly, this analysis suggested that violations are slightly less likely during clear conditions. However, the effect size is very small, suggesting that this weather is not a major contributor to stop sign violations. The effect found by Tijerina is likely due to exposure, as traffic density is likely higher during clear conditions than during storming conditions.

The largest factor increasing the likelihood of a violation over a near violation is the presence of a lead vehicle that violates. If the lead vehicle violates, the subject vehicle is more than six times as likely to violate as well. Unfortunately, the present data source does not permit an investigation into whether this behavior is intentional or unintentional.

**Question #2: What are the kinematic signatures of intersection approaches?**

The second research question was aimed at describing how drivers approach intersections. Information from this research question provides background to other ICAS researchers and engineers. Furthermore, this research question provided a foundation for the remaining questions and guided the algorithm development and analysis process.

**Question #2.1: What is the best way to operationally classify the approach type?**

Several existing driver approach classifications were presented in the literature review. Two of the systems (Doerzaph et al., 2004a; Milazzo, 2003) were based on driver behaviors which could not be directly observed as part of this dissertation. The other systems (Hicks, 2005; Zimmerman & Bonneson, 2005) contained signal timing as part of their formulation. No existing classifications schemes were found for stop sign intersections.

A cluster analysis was performed to group stop sign intersection approach types with an objective classification system. As expected from the stopbar speed analysis, the two level clustering failed, due to difficulties distinguishing between the common “rolling violations” and more dangerous violation types. The cluster analysis results suggested that a four-level scheme best fit the types of intersection approaches observed.

The first cluster represented drivers who either completed a full stop or who could have easily stopped at any point during their approach. This group represents the conservative stop category. The second cluster contained the remaining drivers who could still typically stop at any point during their approach. These drivers were more aggressive, in
that some portion would have to brake hard if they wanted to completely stop at the stopbar. The second cluster was called rolling violations.

The third and fourth clusters contained the target ICAS-V intersection approaches. Based on the results presented by Doerzaph et al. (2004a), the intersection approaches in these two categories were hypothesized to encompass the inattentive and dangerous willful violations. These groups should be the focus of ICAS-V because they were shown to correspond closely to the 15 mph and 20 mph violation thresholds tested during the algorithm development procedure. The cluster three drivers represent moderate violations, while the fourth cluster represents the highly unusual severe violations.

**Question #2.2: How prevalent are rolling stops and at what speeds do they occur?**
A portion of the cluster one and two groups represents drivers who slowly roll through the intersection without completing a stop. Rolling stops present a significant challenge for ICAS-V at stop signs. Presumably, rolling stops are performed by a driver who is aware of the TCD but feels it is safe to proceed. A driver rolling through the stopbar may appear to be a violator. However, because this driver is aware and likely making a safe maneuver, it may be inappropriate to issue a warning.

The reviewed literature did not include any research regarding typical intersection stopbar speeds. To investigate rolling stops, an analysis looked at the distribution of the minimum stopbar speed across all drivers; it was also viewed as a function of the clusters defined to address the previous research question.

Rolling stops are extremely common, with 50% of the approaches exhibiting a minimum stopbar speed of 2 m/s (5 mph) or higher. Most drivers (90%) did slow down to 4 m/s (9 mph), after which point the distribution flattened out. Approximately four percent of the cluster two drivers, nearly all (99%) of the cluster three drivers, and all the cluster four drivers exceeded a stopbar speed of 6.7 m/s (15 mph). These results were used to imply that a 6.7 m/s (15 mph) violation threshold may be a good choice for ICAS-V.

**Question #2.3: When do drivers begin stopping?**
The studies performed by Horst (1990) suggested that drivers should brake at different locations, depending on the distance at which they perceive the stop sign. This research question examined this possibility by analyzing the braking points of the collected vehicle approaches. It was hoped that a compliant driver would brake earlier than their violating counterparts. Such an effect would have allowed an algorithm based on brake status to eliminate compliant approaches based on brake status.

Horst (1990) found that most drivers applied the brake at a TTI of 2.95 seconds. The data obtained during this dissertation suggested that most drivers initiate braking at a substantially earlier TTI of 6.5 seconds. These differences may be partially due to the data collection techniques and partially due to the location of the data collection.

Like the data collected in this project, the Horst data were collected external to the vehicle. The Horst studies used a manual video reduction technique to measure the vehicle trajectories at a rate of 4 Hz. The update rate used for the present study was five
times that of the Horst study. In addition, the radar likely provided higher resolution measurements than the video technique. The present study also used a sensitive measure to detect the first instant at which the brakes were applied. The technique to identify braking in the Horst studies may not have been as sensitive. Finally, the Horst data were collected in the Netherlands where drivers are expected to yield rather than completely stop. Knowing they may not need to stop may lead drivers to brake later in the approach.

A surprising result was identified in the box plot of brake range. The plot indicated that a late brake onset is not a good predictor of a violation. In fact, the compliant drivers of cluster one actually applied the brakes later in the approach than the more aggressive cluster two and three drivers. This effect was unexpected but may be explained as follows:

Drivers who are attentive to the stop sign and intend to perform a stop will begin reacting to the intersection early in their approach. Rather than actively braking, these drivers release the throttle and coast to toward the intersection. This coasting decreases their velocity so they do not need to brake until much later in the intersection approach. More aggressive drivers maintain higher speeds for a longer period of time, requiring an earlier application of the brakes to slow their vehicle.

The implications of this effect are apparent throughout the results. In the graphical trajectory analysis, the higher clusters did not demonstrate a decrease in speed until later in the approach. Furthermore, algorithms that used brake status as an indicator of whether to warn a driver tended to perform poorly across all conditions.

**Question #2.4: What does the stopping profile look like?**

This research question investigated the kinematic attributes of the vehicle trajectory as a surrogate for how drivers choose to control the vehicle during a stop. This analysis included a graphical inspection of time series measures that included speed, acceleration, RDP, and TTI. Plots were constructed as a function of the clusters created in question 2.1. Viewing the stopping profiles provided valuable information on how to configure algorithms and in what regions of the approach trajectories assessment should be made.

Drivers who exhibited cluster four approach types demonstrated divergence from the other cluster groups across all of the variables. The first cluster drivers also exhibited trends that diverged from the other clusters. The re-occurring challenge was finding separation between the second and third clusters. The trajectories of these two groups tended to look similar across all of the measures for much of the intersection approach.

There are some divergent suggestions about which measures might be best for discriminating violation from compliant behaviors. Work by Horst (1990) suggested that TTI is a good measure for representing the decision criteria used by drivers deciding when to brake. White and Ferlis (2004) demonstrated that both speed and velocity could be used to discriminate stopping drivers from violating drivers. They also suggested that acceleration was superior because it provided additional an earlier indication of the
drivers intent. Previous work by Neale et al., found that RDP and acceleration provided the best two measures for discrimination.

From trajectory plots presented in the graphical analysis, it appeared that RDP was superior to in terms of the distance at which the curves diverged. The trajectories within the acceleration plot were intertwined, indicating that ordering the clusters based on acceleration is not consistent across the approach. This strongly suggested that acceleration may not be the best measure for identifying a violation using a continuous algorithm (acceleration was only evaluated at a single point in the Neale et al. study).

**Question #3: Can driver intent be predicted based on vehicle attributes?**

The focus of the third question is the formulation and testing of a threat assessment algorithm for ICAS-V. Through this research question, the efficacy of ICAS-V at stop signs was demonstrated and recommendations for the ICAS-V algorithm were provided.

**Question #3.1: What algorithms can be developed to predict intent?**

Using the previous ICAS-V and general intersection research presented in Chapter 3, a series of threat assessment algorithms were developed. The algorithms were devised in an iterative fashion, using the results from each simulation as an input into performing enhancements on the algorithm formulas. The end result was eight layer-one algorithm formulas that were combined with four low-speed cutoff and five minimum-braking-level into two warning-suppression algorithms. This resulted in a total of 160 algorithms represented in the performance analysis.

Four of the eight layer-one algorithms were based on the laws of physics. These algorithms used static variables such as TTI and RDP as decision criteria for identifying violators. The other four algorithms used regression techniques to develop warning criteria that changed as a function of the vehicles current state.

A minimum speed threshold was added as a layer-two algorithm component. This second layer suppressed the alert for certain compliant approaches. From the stopbar speed analysis, we learned that many drivers will not completely stop at the stopbar. As such, many of the algorithms would present an alert to drivers rolling through the stop sign. The low speed threshold allows drivers to perform a rolling stop without receiving an alert. Four different levels were tested including 3.4 m/s (5 mph), 4.5 m/s (10 mph), 6.7 m/s (15 mph), and 8.9 m/s (20 mph).

A second problem was also noted when testing the first-layer algorithms. False positive warnings were being issued to drivers in the initial stage of responding to the intersection. A component based on the present braking effort of the driver was added to the second layer of the algorithm. This component suppressed the warning if it detected that the driver was braking above a specified threshold. This threshold was set at five discrete levels: none; status on; minimum of 0.1g; minimum of 0.2g; and braking at or above the present RDP.
The parameters of each algorithm were allowed to vary within a specified range. This specified range permitted a large variety of algorithm instantiations over which the simulation was performed. The simulation procedure allowed efficient testing and evaluation of each of the devised algorithm.

**Question #3.2: What is the performance of the devised algorithms?**
The algorithms devised during question 3.1 were thoroughly tested through simulation, using the vehicle data collected at the test sites. An evaluation method was devised based on the theories of signal detection. With this method, the performance of an algorithm was measured based on the number of true positive and false positive predictions. ROC curves were generated for each of the algorithms to measure and compare the resulting levels of discriminability. The highest-performing algorithms were then evaluated in terms of the timing of the warnings presented for true positives and the level of nuisance resulting from the false positives.

From this analysis, some general performance trends were noted. First, the 2 m/s (5 mph) low speed cutoff of the layer-two algorithm performed poorly across all simulations. This is not surprising, given the results of the cluster and the stopbar speed analyses. A significant portion of compliant drivers rolled through the intersections at speeds above the 2 m/s (5 mph) cutoff. Low speed cutoffs above 4.5 m/s (10 mph) performed much better in the simulations. Indeed, the stopbar speed analysis indicated that most (90%) of the drivers crossed the stopbar below 4 m/s (9 mph). Furthermore, best performance was often achieved when the minimum stopbar speed was set at 8 m/s (15 mph). This speed corresponded to the stopbar behaviors of the third and fourth clusters, which were hypothesized to be the target population.

The minimum braking effort requirement also demonstrated some trends across the ROC plots. The no-braking requirement and the braking at or above RDP requirement often performed similarly. Drivers were rarely meeting the RDP braking requirement; thus, the resulting algorithm performance was not significantly different from not having a braking requirement. Furthermore, these two braking requirements tended to result in the lowest performance.

The highest-performing algorithms tended to use either the 0.1 g or the 0.2 g required braking effort for warning suppression. Which of these two braking requirements performed the best varied from one algorithm to another, depending on the violation threshold used during the evaluation. The final braking measurement only required that braking be active for warning suppression. This criterion typically resulted in a decreased number of true positives, relative to other braking criteria. A portion of the target population was apparently braking while approaching the intersection. The brake status criterion suppresses the warning for this group of violators, resulting in decreased discrimination.

**Question #3.3: What is the most effective algorithm for ICAS-V?**
The threat assessment algorithm is a key component of the ICAS-V system. The algorithm should strive to provide as many warnings to violating drivers as possible,
while minimizing the number of false positives issued. A heuristic was created to systematically order the algorithms from best-to-worst-performing within each of the four violation thresholds and within each of two maximum allowable false positive rates.

A single algorithm was not identified as the one algorithm to use for all future research. Rather, five were identified as the top algorithms, dependent upon the violation threshold selected. Issues surrounding the selection of a violation threshold are presented in research questions 1.1, 2.1, and 2.2. Until these key knowledge gaps can be fulfilled, a single “best” algorithm cannot be identified.

In addition, the allowable maximum false positive rate must also be selected. SDT tells us that it is not possible to simultaneously maximize the true positive rate and minimize the false positive rate. Rather, the number of allowable false positives must be set and the algorithm selected that will maximize the true positives. Algorithms were provided for two possible maximum false positive rates: 0.05 and 0.01.

Across the highest-performing algorithm possibilities, the 600 and 800 series families represent the top performers. These two algorithms are both based on regression techniques with the 600 series algorithm using a prediction of warning distance as a function of velocity and the 800 series algorithm predicting RDP as a function of range. Within the list of highest-performing algorithms, the 200 series non-regression algorithm is also represented. This algorithm uses a static warning RDP to predict violations. For some violation thresholds, the 200 series algorithm performs nearly as well as the top algorithm in the group. The 200 series algorithm is easily explained and may be a good choice if simplicity is desirable.

The top performers for the 4.5 m/s (10 mph) and 6.7 m/s (15 mph) violation thresholds all used the 6.7 m/s (15 mph) speed cutoff. The 6.7 m/s (15 mph) speed cutoff was also represented in the top performing algorithms at the 8.9 m/s (20 mph) violation threshold. These results highlight the conclusion made in the previous research question regarding the appropriateness of the 6.7 m/s (15 mph) speed cutoff.

The conclusions made in the previous research question regarding the best minimum braking suppression criteria are also represented in the highest-performing algorithms. With the exception of the 10 mph violation threshold, all of the highest-performing algorithms used either the 0.01 g or 0.02 g minimum braking requirement.

Combining the algorithm performance results with the violation rate discussion provided as part of questions 1.1, 2.1, and 2.2 above, it appears that the best violation thresholds are either 6.7 m/s (15 mph) or 8.9 m/s (20 mph). The 2 m/s (5 mph) and 4.5 m/s (10 mph) violations occur at such high frequencies that warnings would be issued to a large portion of the drivers. Furthermore, true positive rates and true-positive-to-false-negative rates for these thresholds are low. It is recommended that future research focus on determining whether the 6.7 m/s (15 mph) or the 8.9 m/s (20 mph) is preferable.

The 6.7 m/s (15 mph) threshold will result in a better true-positive-to-false-negative ratio. On the other hand, the 8.9 m/s (20 mph) will result in a better false-positive-to-true-
positive ratio. As discussed previously in question 1.1, additional research is needed to determine the effects of the false positives on driver annoyance.

Depending on the violation criteria and minimum false positive rates selected, the highest-performing algorithms identified will have true positive rates between 0.61 and 0.98. These rates appear to be reasonable, given the low false negative rates. As such, it is believed that ICAS-V systems are feasible at for use at stop signs and should be the focus of continued research efforts.

**Recommendations**

Based on these results, a list of recommendations has been generated. The recommendations are intended for practitioners and researchers who are designing ICAS-V systems. These recommendations represent the key engineering outputs of this research.

- The results of this dissertation suggest that ICAS-V systems can correctly identify most violations at low nuisance alert rates. This outcome provides support for continued research and development for ICAS-V systems.

- The target population for an ICAS-V should not be based on the legal definition of a violation. Although additional research may be required to determine the optimal target population for ICAS-V, this research suggests that the violation threshold should be higher than 4.5 m/s (10 mph).

- The highest-performing layer-one algorithms include RDP as a function of range, velocity as a function of range, and static RDP. Depending on the criteria selected, the preferred algorithm for the ICAS-V development is available in Table 15.

- The ICAS-V algorithm should contain the second layer of the algorithm that suppresses warnings when the driver appears to be responding to the intersection. This is necessary to reduce nuisance alerts generated from excessive false positives.

- The low speed cutoff for the second layer of the algorithm should not be set at 2 m/s (5 mph) or 4.5 m/s (10 mph). These two settings resulted in poor performance across all the algorithms tested.

- The braking requirement in the second layer of the algorithm should use braking effort, not just brake status. Using brake status alone results in missing violating drivers who exhibit minimal braking during their approach. In some instances, this braking is part of the speed corrections made by drivers and does not necessarily reflect a response made in reference to an approaching intersection.
Additional Contributions

In addition to the addressed research questions, this dissertation also contains additional contributions to the ICAS development efforts. This section briefly describes the key contributions that will assist in the continued research and development of ICAS.

The methods used throughout this dissertation should apply to all types of ICAS, as well as to some other warning systems. In particular, to the author’s knowledge, the algorithm evaluation procedure based on SDT has not previously been applied in this context. The SDT methods worked well for comparing algorithms and determining the best parameter settings within an algorithm. Furthermore, the methods used to consider the warning timing and nuisance level resulting for a given algorithm instantiation were novel extensions of SDT. These methods ensured that the preferred algorithms considered all the aspects that will affect performance of threat assessment.

The data collection methods and the DAS are also contributions to the ICAS efforts. The data collection methods may be ported to other ICAS research efforts. This includes the site selection method, the sampling strategy, data retrieval and storage protocols. The DAS was developed specifically for the purpose of collecting vehicle trajectory information from the infrastructure. This equipment has many uses beyond ICAS and can be leveraged for a variety of future investigations.

Finally, one of the key contributions of this dissertation is evidence that ICAS-V systems are feasible. Algorithms were developed that correctly identified most violating drivers while not producing an excessive number of false positives. These algorithms use measures that can be captured by in vehicle systems and should not be difficult to incorporate into a production ICAS.

As part of the larger CICAS-V project, this algorithm will be integrated into functional ICAS-V by designers and engineers and subsequently tested in a large scale field operation test. Should the efforts in the larger CICAS-V project prove successful, the algorithm developed here may be integrated into a production ICAS-V eventually available on new vehicles. Widespread deployment of the ICAS-V could result in a substantial increase in intersection safety, providing a societal benefit in the form of reduced loss of life and property damage.

Limitations

As with most research projects, there are certain limitations that need to be considered when interpreting the results. First, the geographic region was limited to southwest Virginia. It is also possible that intersection approach behavior depends on regional differences. Furthermore, the data collection took place over two consecutive months at each site. Thus, the database collected may not reflect seasonal differences in driving behavior.

Placing the DAS at the intersection was required to obtain the volume of data necessary to construct a valid ICAS algorithm. However, placing the data collection equipment at the intersection rather than in the vehicle has certain limitations. This study did not
provide information about the driver actions that led up to the violation. For instance, it is not possible to know for certain whether a violation was intentional or unintentional. Finally, the radar used for this research did not perform at the level anticipated. The radar tended to provide sparse data where continuous data should have been provided. This required a significant post-processing effort to improve the data. During this effort only vehicle tracks that contained sufficient fidelity were carried through to the analysis portion of the study. While there was no direct evidence to suggest that this systematic selection resulted in confounding the data, it is possible that certain types of vehicles or vehicle approach characteristics were prone to degraded radar performance. Thus, a certain type of vehicles or approach types may be unknowingly underrepresented in the data set.

**Future Research**

The research discussed herein is a key step in the development of an ICAS. Nonetheless, future research will be required to bring the ICAS concepts to fruition. The following discussion focuses on the future research needs that were identified during this dissertation.

**Define the ICAS-V target population**

A key research void is the lack of a formal definition of the stopbar speed that constitutes a target ICAS-V violation. Algorithms were tested across several possible definitions. Through this exercise, some recommendations were made regarding the most appropriate threshold from a warning accuracy standpoint; however, the violation threshold should be based on an independent investigation. This investigation should focus on the connection between the stopbar speed and crash risk. The researchers should be careful to only include crashes that result from a violation, as gap-acceptance crashes will confound the results.

**Expanding the data sample**

The methods devised in this research should be applied to a broader set of intersections. First, the data collection and analysis methods will need to be expanded to include signalized intersections. Driver behavior is likely to be different at signalized intersections. The perceived cost of a violation may be higher at a signalized intersection than a stop sign. As such, fewer drivers may violate signalized intersections than stop sign intersections.

Furthermore, for straight and left turn maneuvers the legal definition of a violation may be appropriate at signalized intersections. When performing straight or left turn maneuvers few drivers are expected to roll through at low speeds. This more binary go/no-go decision should result in a separation of behaviors at a further distance from the intersections. Rolling violations are likely for drivers performing right turn maneuvers. Therefore, during right turn maneuvers, the signalized algorithm may require a framework similar to the stop-sign scenario for defining a violation based on stopbar speed.

The traffic signal itself will likely have a large impact on driver behavior during an intersection approach. The inclusion of a traffic signal requires the driver to perform
more complex decisions as they approach the intersection. The increased complexity may lead to more unintended violations from incorrect estimations of future events. The algorithm itself must directly consider the signal phase and timing during violation prediction.

In addition, a more robust algorithm could be devised with a larger sample of intersections. There are intersection geometries that were not considered during this research. For instance, intersections with more than four approaches, multiple lanes, off-angle approaches, grade variations, irregular speed limits, or that only have a stop-sign on one approach were not evaluated.

**Investigate constraints**

ICAS-V is a new technology did not have a large foundation of existing algorithm research to build on. To properly scope this project certain constraints were applied to bound the problem space. These constraints should be further investigation to optimize algorithm performance.

The stop-controlled intersections were selected to include varying site distances; however, sight distance was not directly considered in the algorithm development process. Sight distance is likely to have an impact on the propensity for drivers to willfully violate at higher speeds. Future work should investigate sight distance as a possible factor for predicting violations. It may be possible to make a threat assessment further from the stopbar for intersections with short sight distances in which drivers are more likely to completely stop.

The posted approach speed limit was balanced across the selected sites. Like sight distance, speed limit was not directly considered in the algorithm development process. If the posted speed limit is considered it may be possible to increase algorithm performance. If either speed limit or sight distance is included as a component of the algorithm, care must be taken in a deployed system to maintain the algorithm any time the roadway speed limit is altered or the sight distance is improved (i.e. by cutting down foliage blocking the adjacent lane).

The computational component of the ICAS-V is likely to reside within the vehicle. This makes it possible for the algorithm to consider vehicle type as one of the components of the threat assessment algorithm. Drivers are likely to begin slowing heavy vehicles sooner than light vehicles. Furthermore, the driver of a heavy vehicle may require additional time slow their vehicle. It was cost-prohibitive to measure vehicle type for the present research; however, future research should consider vehicle type as a factor in algorithm development if possible.

The geographic region of this dissertation was limited to Southwest Virginia. Furthermore, the selected intersections primarily resided in rural and suburban areas. A selection bias may have resulted from constraining the regions of investigation. Future research should expand the pool of intersections to include intersections across the country as well as urban areas. The selected intersections should include regions with
adverse weather such that it may also be directly investigated as a component of the algorithm.

For the purpose of the algorithm development for this dissertation, very low false positive rates were assumed. These rates were selected without direct knowledge of the false alert rates that are acceptable to drivers. If the allowable false positive rate constraints are relaxed the algorithm performance would increase. It is prudent to first identify the allowable false positive rate through user acceptance studies and then revisit the algorithm development process if a different false positive rate is identified.

**Evaluate user acceptance**

The first key research void is with regard to our present understanding of annoyance alerts for ICAS-V systems. Algorithm recommendations were made based on assumptions regarding the permissible levels of false positives. These assumptions should be supported with research that provides the allowable types and frequency of nuisance alerts. It is possible that drivers are willing to tolerate more false positives than other collision warning systems.

The warning interface used in the ICAS-V must also be optimized. Studies should be completed to determine the appropriate modalities and physical locations for the driver vehicle interface (DVI). There is an interaction between the algorithm timing and the effectiveness of a DVI. For example, a more effective DVI will allow the driver to be warned later in the approach. DVI tests are planned as part of the CICAS-V project and should eventually be integrated with the results of this research to verify the algorithm feasibility.

**Identify unintended consequences**

As with any system designed to improve safety, researchers must be careful to avoid unintended consequences. For example, automated red light enforcement systems were developed to mitigate crashes by citing drivers who violate traffic signals. An unintended consequence of this has been an increase in rear-end collisions. ICAS-V may have similar unintended consequences that should be identified prior to deployment. Some possible unintended consequences include: increasing rear-end crashes, overwhelming the driver with the alert, driver annoyance, driver reliance on the warning, and miss-use of the alert to determine when to brake.

**Determine ICAS feasibility and plan for deployment**

A cost-benefit analysis should next be performed to ensure that the ICAS-V will provide a measurable benefit and an acceptable cost. Data from the warning interface tests, combined with the results obtained from the naturalistic intersection observations, should provide the data necessary to model the system benefits.

In addition to the human factors work, a significant volume of engineering development must be completed for an ICAS to become reality. Engineers need to develop the on-board equipment, the roadside equipment, and the communications backbone necessary
to support such a system. These systems will need to meet specifications necessary to compute and deliver the warning in a timely and appropriate manner.

Finally, after integrating all the components of the threat assessment algorithms, the warning interface, and the hardware/software, the entire system must be validated. This validation should include a large scale field operational test to demonstrate the system’s effectiveness on the open roadway under natural conditions.
CHAPTER 10 – REFERENCES


APPENDIX A: INTERNAL REVIEW BOARD AUTHORIZATION TO PROCEED

Virginia Tech

Office of Research Compliance
Institutional Review Board
1880 Pratt Drive (0497)
Blacksburg, Virginia 24061
540/231-4991 Fax: 540/231-0959
E-mail: moored@vt.edu
www.irb.vt.edu
丝印日期: 5/24/2007

DATE: July 25, 2006

MEMORANDUM

TO: Vicki Neale
  Zachary Doerzaph
  Tye Tuckmyr

FROM: David M. Moore


This memo is regarding the above-mentioned protocol. The proposed research is eligible for expedited review according to the specifications authorized by 45 CFR 46.110 and 21 CFR 56.110. As Chair of the Virginia Tech Institutional Review Board, I have granted approval to the study for a period of 12 months, effective July 25, 2006.

As an investigator of human subjects, your responsibilities include the following:

1. Report promptly proposed changes in previously approved human subject research activities to the IRB, including changes to your study forms, procedures and investigators, regardless of how minor. The proposed changes must not be initiated without IRB review and approval, except where necessary to eliminate apparent immediate hazards to the subjects.
2. Report promptly to the IRB any injuries or other unanticipated or adverse events involving risks or harms to human research subjects or others.
3. Report promptly to the IRB of the study's closing (i.e., data collecting and data analysis complete at Virginia Tech). If the study is to continue past the expiration date (listed above), investigators must submit a request for continuing review prior to the continuing review due date (listed above). It is the researcher's responsibility to obtained re-approval from the IRB before the study's expiration date.
4. If re-approval is not obtained (unless the study has been reported to the IRB as closed) prior to the expiration date, all activities involving human subjects and data analysis must cease immediately, except where necessary to eliminate apparent immediate hazards to the subjects.

Important: If you are conducting federally funded non-exempt research, this approval letter must state that the IRB has compared the OSP grant application and IRB application and found the documents to be consistent. Otherwise, this approval letter is invalid for OSP to release funds. Visit our website at http://www.irb.vt.edu/pages/newstudy.htm#OSP for further information.

As indicated on the IRB application, this study is receiving federal funds. The approved IRB application has been compared to the OSP proposal listed above and found to be consistent. Funds involving procedures relating to human subjects may be released. Visit our website at www.irb.vt.edu for further information.

cc: File
  Department Reviewer: Suzanne E. Lee
APPENDIX B: VIOLATION TRIGGER DEVELOPMENT PROCESS

The data needs identified in the Chapter 5 required the validation of aggressive intersection approaches. In particular, it was necessary to identify approaches in which drivers either committed a violation or performed a stop (or near stop) in such a way that their behavior would make it difficult for the algorithm to discriminate. Thus, the trigger development focused on finding a metric that would identify aggressive stopping behaviors.

In addition, a second important criterion was to identify a trigger that functioned on sparsely populated data. As discussed in the methods and results section, the radar used for this study did not reliably return a measurement for every collection frame. Thus, the trigger could not operate at a single location as it would miss vehicles that were not reported by the radar in that location.

Several possible trigger strategies were considered with the goal of identifying violations. In particular, triggers evaluating the stopbar speed, average deceleration, peak deceleration, and minimum speed were assessed. However, a measure of the average deceleration required to stop at the stopbar was identified as the appropriate triggering variable.

The required deceleration parameter (RDP) is a calculated value computed at each frame of data. RDP is the kinematic relationship between instantaneous velocity and distance to the stopbar as described by Equation 16.

\[
\text{Equation 16}
\]

\[
RDP = \frac{V^2}{2 \cdot R \cdot g}
\]

Where:
- \(V\) = Instantaneous velocity
- \(R\) = Instantaneous range from stopbar
- \(G\) = Gravitational constant

RDP has several advantageous characteristics that make it a particularly good metric for triggering the data reduction. First, RDP uses velocity and range which are frequently measured by the radar. This has the advantage of not relying on a derived measure such as acceleration, which is prone to amplified noise. Second, RDP is easily interpreted in the context of stopping behavior. A driver who performs an aggressive intersection approach would have to brake hard to stop before the stopbar. Thus, this driver would also exhibit a high RDP. If that driver did not stop, the RDP would likely exceed the capabilities of the vehicle as the stopbar neared. On the other hand, a conservative driver would exhibit a low required deceleration. Furthermore, unlike evaluating velocity at a particular point, RDP can be evaluated at any point along the intersection approach and remain valid. For instance, a driver who initially approached the intersection at a high
speed followed by a hard brake will be missed by a stopbar speed trigger. A RDP trigger, on the other hand, will catch the high deceleration that was required to slow that vehicle upstream of the stopbar.

To develop an effective trigger, there are some additional criteria that must be considered during the RDP computation. First, RDP tends towards infinity as the vehicle nears the stopbar. This tendency will have a negative impact on the sensitivity of the measure to segregate stopping behaviors. Investigation of RDP indicated that the tendency does not exist for typical approaches until the vehicle was within 1 m from the stopbar. Thus, RDP was only evaluated at distances greater than 1 m.

In addition, RDP is a continuous measure existing over the entire time period in which the vehicle was tracked. Thus, to enable a simple trigger comparison the maximum RDP was extrapolated and compared to a trigger threshold. The maximum RDP over the entire vehicle approach represents the highest rate at which the driver would have needed to stop. For a violating driver, the maximum RDP will exist near the stopbar. However, for an aggressive driver, that stops rapidly. The maximum RDP may exist at some point upstream prior to the high deceleration stop. This makes the trigger particularly advantageous because it is sensitive to violators and aggressive drivers; these are the groups of primary interest for the algorithm.

With the triggering metric identified, the next step was to set a threshold for separating the reduction events from the non-reduction events. To identify the trigger threshold, the maximum RDP was calculated for each vehicle approach in the dataset. The distribution of maximum RDP was then analyzed to determine an appropriate threshold. This analysis will be described through the subsequent figures.

First, in light of time and budget constraints it was important to select a threshold that provided a reasonable number of reducible events. The number of events was evaluated as a function of the threshold selected (Figure 59). As the RDP threshold is lowered, the number of events rises sharply. Based on the constraints, a cap was set at 10,000 events, with a desire to reduce the number of events to a lower number if possible. This criterion suggested a threshold in the region of 0.8 g to 1.2 g. While initially these values may appear high, they are actually well within the region that provides the data of interest. Additional details will be provided with the figures below as well as during the stopping behavior analysis discussed in the results section.
In conjunction with the results shown above, the average stopbar speed, as a function of the RDP threshold, was also considered (Figure 60). Stopbar speed provides an indication of the severity of a violation that can be readily understood. Furthermore, results discussed during the introduction indicated that a stopbar speed of 4.47 m/s (10 mph) appeared to separate intentional “rolling stops” from a violation resulting from some form of inattention. Considering the stopbar speed, it appeared that an RDP threshold of approximately 1.2 g was appropriate as it corresponded to a stopbar speed of 4.47 m/s (10 mph). To ensure that these approaches were obtained, a cutoff closer to 1 g looked more feasible.

Figure 59: Number of events that would be reduced as a function of the RDP threshold selected.
Finally, the empirical distribution of RDP across the entire sample of drivers was evaluated (Figure 61). With warning systems, such as the ICAS, researchers are interested primarily in the tail of a distribution which represents uncommon behavior. In this context, these behaviors belong to dangerous violators. Considering the distribution, a 1 g RDP threshold addresses 5% of the sample. Focusing on the top 5% of the population provides a convenient and logical cutoff for investigation. Furthermore, this cutoff should be conservative, as ICAS developers are aiming for warning rates significantly lower than 5% to avoid excessive nuisance alarms. Setting the reduction threshold for RDP at 1 g provides a conservative cutoff that will include nearly all of the severe violations as well as a sample of the more aggressive intersection approaches.
Based on the data presented above, a trigger threshold of 1 g was selected for identifying the approaches for reduction. This resulted in the reduction of 6,171 events. Considering that a typical braking maneuver occurs around 0.3 g, the 1g threshold may appear larger than one might expect. There are a few reasons for this.

First, as discussed in the results section, most drivers do not come to a complete stop. Thus, even the drivers performing a slow rolling stop will exhibit an elevated RDP; however, these slow rolling cases occur with such frequency that it would be a mistake to issue a warning. Such a low threshold warning system would have an impact on driver acceptance and would not be implemented by the automotive manufacturers. Furthermore, the purpose of the ICAS system is to mitigate crashes through a violation warning. In general, drivers who perform a slow rolling stop are as attentive as a driver that completely stops. This suggests no increase in crash likelihood.
### Table 16: Stop sign post processing and radar-induced error.

<table>
<thead>
<tr>
<th>Range</th>
<th>Speed</th>
<th>Acceleration</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Standard</td>
</tr>
<tr>
<td>45 mph</td>
<td>0.506</td>
<td>0.164</td>
</tr>
<tr>
<td></td>
<td>2.446</td>
<td>1.520</td>
</tr>
<tr>
<td>35 mph</td>
<td>1.061</td>
<td>0.076</td>
</tr>
<tr>
<td></td>
<td>-6.207</td>
<td>-0.085</td>
</tr>
<tr>
<td>25 mph</td>
<td>0.833</td>
<td>0.034</td>
</tr>
<tr>
<td></td>
<td>-6.292</td>
<td>-0.278</td>
</tr>
<tr>
<td>Overall</td>
<td>0.829</td>
<td>0.062</td>
</tr>
<tr>
<td></td>
<td>-6.579</td>
<td>-0.278</td>
</tr>
</tbody>
</table>
APPENDIX D: DECELERATION THRESHOLD AND DRIVER REACTION TIME

Introduction
The following study was performed to determine the relationship between brake pedal status and acceleration for drivers approaching a stop-controlled intersection. The goal of the analysis was to predict driver-induced brake status (on/off), based on the vehicle’s instantaneous rate of deceleration. This relationship was used to infer brake status, using radar data which does not natively contain brake information. The primary measures evaluated in this study included the deceleration level at which the brake was initially pressed and the time from brake press to various pre-determined deceleration levels. The outputs of this task included a threshold, below which the brakes will be considered active, and the corresponding delay, to determine the initial point at which the brakes were applied. This information was used to determine the point of brake activation.

Methods
The 100-car database was mined for the desired braking information (Dingus et al., 2006). This database includes naturalistic continuous in-vehicle data for over 100 participants who drove a personal or leased vehicle for one full year. The parametric data included a variety of kinematic and environmental variables collected at 10 Hz. This parametric data were accompanied by a digital video feed containing images of the driver and vehicle environment collected at 30 Hz. The 100-car database was accessed and analyzed using the VTTI Data Analysis and Reduction Tool.

To extract the relevant data samples, a query was created to identify regions in which drivers would approach stop-controlled intersections. From the 1,400 resulting observations, 10 approaches were selected at random for each of five different vehicle models, providing a total of 60 observations. Only intersection approaches that contained straight and flat geometry were considered in the evaluation. The task was to determine the threshold values and time offsets for each of the approaches. The parameters that were collected from the database were:

- Trigger ID for each vehicle
- Vehicle type (e.g. Ford Explorer, Ford Taurus, Chevy Malibu, etc.)
- Time sync and deceleration values at which time the driver initiated braking; similarly, the sync and deceleration values when the car reached -0.05g, -0.075g, -0.10g, -0.12g.
- Time elapsed before abovementioned deceleration values were calculated. This was obtained by subtracting the sync numbers from the start of braking to the sync number when the deceleration reached the specified levels.

Results
Based on the method described above Table 17 provides the average deceleration thresholds determined for each vehicle. The table also contains the time it took each vehicle to reach pre-determined deceleration values.
Table 17: Deceleration thresholds and pre-determined deceleration values from 100-car data

<table>
<thead>
<tr>
<th>Threshold deceleration when braking starts (g)</th>
<th>CAR TYPE</th>
<th>Chevy Malibu</th>
<th>Toyota Corolla</th>
<th>Toyota Camry</th>
<th>Leased Cavalier</th>
<th>Ford Taurus</th>
<th>Ford Explorer</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average</td>
<td></td>
<td>-0.042</td>
<td>-0.040</td>
<td>-0.012</td>
<td>-0.025</td>
<td>-0.052</td>
<td>-0.007</td>
</tr>
<tr>
<td>Std Dev</td>
<td></td>
<td>0.034</td>
<td>0.038</td>
<td>0.022</td>
<td>0.034</td>
<td>0.022</td>
<td>0.017</td>
</tr>
<tr>
<td>Min</td>
<td></td>
<td>-0.11</td>
<td>-0.05</td>
<td>-0.04</td>
<td>-0.07</td>
<td>-0.04</td>
<td>-0.04</td>
</tr>
<tr>
<td>Max</td>
<td></td>
<td>0.01</td>
<td>0.07</td>
<td>0.03</td>
<td>0.04</td>
<td>0.03</td>
<td>0.02</td>
</tr>
<tr>
<td>-0.05g</td>
<td></td>
<td>0.257</td>
<td>0.600</td>
<td>1.450</td>
<td>0.778</td>
<td>1.778</td>
<td>0.840</td>
</tr>
<tr>
<td>Std dev</td>
<td></td>
<td>0.257</td>
<td>0.644</td>
<td>2.514</td>
<td>1.180</td>
<td>1.300</td>
<td>0.609</td>
</tr>
<tr>
<td>Min</td>
<td></td>
<td>0</td>
<td>0</td>
<td>0.1</td>
<td>0</td>
<td>0.6</td>
<td>0.1</td>
</tr>
<tr>
<td>Max</td>
<td></td>
<td>0.6</td>
<td>2.1</td>
<td>8.5</td>
<td>2.9</td>
<td>4</td>
<td>1.7</td>
</tr>
<tr>
<td>-0.075g</td>
<td></td>
<td>1.600</td>
<td>1.230</td>
<td>2.180</td>
<td>1.200</td>
<td>2.289</td>
<td>1.120</td>
</tr>
<tr>
<td>Std dev</td>
<td></td>
<td>3.090</td>
<td>0.979</td>
<td>2.785</td>
<td>1.217</td>
<td>1.274</td>
<td>0.890</td>
</tr>
<tr>
<td>Min</td>
<td></td>
<td>0.1</td>
<td>0.5</td>
<td>0.2</td>
<td>0.1</td>
<td>0.8</td>
<td>0.3</td>
</tr>
<tr>
<td>Max</td>
<td></td>
<td>9.8</td>
<td>3.4</td>
<td>9.3</td>
<td>3.4</td>
<td>4.2</td>
<td>3.1</td>
</tr>
<tr>
<td>-0.10g</td>
<td></td>
<td>1.840</td>
<td>1.730</td>
<td>2.520</td>
<td>1.290</td>
<td>2.844</td>
<td>1.3</td>
</tr>
<tr>
<td>Std dev</td>
<td></td>
<td>3.769</td>
<td>1.636</td>
<td>3.134</td>
<td>1.251</td>
<td>1.455</td>
<td>0.885</td>
</tr>
<tr>
<td>Min</td>
<td></td>
<td>0</td>
<td>0.6</td>
<td>0.3</td>
<td>0.1</td>
<td>1.3</td>
<td>0.5</td>
</tr>
<tr>
<td>Max</td>
<td></td>
<td>12.5</td>
<td>6</td>
<td>10.7</td>
<td>3.7</td>
<td>4.9</td>
<td>3.1</td>
</tr>
<tr>
<td>-0.12g</td>
<td></td>
<td>2.660</td>
<td>2.440</td>
<td>2.810</td>
<td>1.640</td>
<td>3.712</td>
<td>1.460</td>
</tr>
<tr>
<td>Std dev</td>
<td></td>
<td>4.884</td>
<td>2.872</td>
<td>3.252</td>
<td>1.510</td>
<td>1.726</td>
<td>0.916</td>
</tr>
<tr>
<td>Min</td>
<td></td>
<td>0.1</td>
<td>0.7</td>
<td>0.4</td>
<td>0.2</td>
<td>1.7</td>
<td>0.6</td>
</tr>
<tr>
<td>Max</td>
<td></td>
<td>16.2</td>
<td>10.3</td>
<td>11.3</td>
<td>4.1</td>
<td>6.2</td>
<td>3.2</td>
</tr>
</tbody>
</table>

**Conclusion**

The purpose of this study was to determine: 1) the deceleration threshold at which it may be stated that a vehicle is actively braking; and 2) the corresponding time from initiation of braking to the selected threshold deceleration value. Rather than selecting an average threshold deceleration value, the 95% value was selected for three primary reasons.

First, the vehicle data collected for this study was measured by radar. As radar does not directly measure acceleration, the acceleration had to be derived from the velocity. As a derivative, any noise inherent in the velocity data were amplified in the acceleration data. Thus, a more strident threshold would minimize early identification of braking.

Second, drivers initiate braking at a variety of initial levels of acceleration. It was not unusual for the acceleration at the brake onset to be positive (i.e., driver accelerating just prior to pressing the brakes). This explains a number of the low average threshold values displayed in the table above. Given the safety application of an ICAS system, it is desirable to select a threshold in which a majority of drivers will have applied the brake.

Third, the braking points were determined by identifying the threshold deceleration level and subsequently subtracting the average time elapsed from the onset of braking until the
threshold is reached. Thus, the time measure will take into account the differences in the actual brake onset described in the table above.

The overall average threshold value for the 60 observations was -0.015 g with a standard deviation of -0.031 g. Thus, the 95th percentile driver has initiated braking at a threshold of approximately -0.077 g. From the table above, this corresponds closely to the -0.075 g threshold suggesting an average response time value of 1.60 s with a standard deviation of 1.89 s. Thus, the brake onset will be identified at 1.60 s before the vehicle acceleration reaches -0.075 g.
APPENDIX E: OPERATIONAL DEFINITION FOR REDUCTION MEASURES

I. Question Reduction Operational Definitions

1. Is the video operational?
   a. Yes, present and usable
      i. This is referring to quality video that is operating properly. In general most videos should fall into this category.
   b. Yes, poor video quality
      i. Video operates, but the video quality is low (blurry, out of focus, water or condensation on lens), and it is difficult to view the intersection. Use this option only if there appears to be a problem with the camera. (Note: Night video does NOT qualify unless it is also poor video.)
   c. Segments of video missing
      i. This is referring to video files where the screen either blacks out or skips the range of frame numbers that correspond to the parametric data.
   d. No video present
      i. There is no video file that corresponds to the parametric data

2. Is the video aligned?
   a. Yes- This is referring to the video alignment tool in DART that aligns parametric and video data by sync and frame number respectively. This may occasionally occur if the sync number is same as the frame number.
   b. Cannot align video - This is referring to the video alignment tool in DART that aligns parametric and video data by sync and frame number respectively. This may occasionally occur if the required alignment is more than the alignment tool will allow.
   c. Uncertain- Default option when the reductionist is not able to determine the actual aligned

3. Has this event been spot checked?
   a. Yes. This means the event is spot checked.
   b. No. This means the event is not spot checked.

4. Vehicle Type?
   a. Select the appropriate vehicle from the options given.
5. **Turn Intent?**
   a. Select the turn behavior that the vehicle performs as it passes through the intersection.

6. **Stopping behavior (See sample video clips)**
   a. Violation without caution – Vehicle goes through stop sign with little or no slowing.
   b. Violation with caution – Vehicle moderately slows down while going through the stop sign. The vehicle is going faster than a rolling violation; thus, a hard brake would be required to completely stop.
   c. Rolling violation – Vehicle does not come to a complete stop, but cautiously rolls through the intersection.
   d. Stopped behind leading vehicle but not at the stop sign - Vehicle stops behind the leading vehicle but subsequently follows the leading vehicle without performing an independent stop at the stop sign.
   e. No violation - Vehicle comes to a complete stop at the stop sign.
   f. Unable to determine - The reductionist uses this option when the visual cues from the video and parametric data are not enough to determine the stopping behavior.

7. **Is lead vehicle present? (See sample video clips)**
   a. Consider lead vehicles when, the headway between coupled vehicles is 3 seconds or less while the vehicles are in motion.

8. **Lead vehicles stopping behavior?**
   a. See “Stopping Behavior” (item 6 above) and answer this question using the same responses.

9. **Is a following vehicle present? (See sample video clips)**
   a. Consider following vehicles when the headway between coupled vehicles is 3 seconds or less while the vehicles are in motion.

10. **Following vehicles stopping behavior?**
    a. See “Stopping Behavior” (item 6 above) and answer this question using the same responses.

11. **Event Classification (See sample video clips)**
a. Non-conflict – This is an event where there was not another vehicle (crossing traffic) present at the intersection and thus no possibility of a crash.
b. Crash – Any impact between the vehicle and any other object occurred at the intersection (i.e. other vehicle, pedestrian, guard rail, etc).
c. Near Crash – This is an event where the driver performed an evasive maneuver to avoid a crash. An evasive maneuver is any action taken by the driver to avoid a crash with another vehicle (e.g. Hard braking, swerving, etc). An evasive maneuver does not include normal braking. Hard braking can be diagnosed by observing the front of the vehicle dipping, dust/smoke behind the tires, a rapid decrease in velocity, or other similar observations.
d. Possible Conflict – This is an event where there was no crash or evasive maneuver, however, there was potentially conflicting cross traffic present such that it would have been possible for a crash to occur if the driver had not slowed.
e. Unable to Determine - This option is selected when the reductionist is not sure of the vehicle behavior at the stop sign.

12. Weather
a. Select the appropriate option based on the information available from the video.
b. Unknown- When video data has insufficient information to determine the weather condition.

13. Roadway Surface Condition
a. Select the appropriate option based on the information available from the video.
b. Unknown- When video data has insufficient information to determine the weather condition.

14. Daytime or Nighttime?
   a. Dawn
   b. Daylight
   c. Dusk
   d. Nighttime
   e. Unable to Determine

15. Does this event need to be reviewed by a project manager?
   a. No - The reductionist chooses this option when he/she is absolutely sure about the reduction performed.
b. Yes - When the reductionist is unsure of the reduction, or if there is an event in the video that the reductionist wishes the project manager to have a look at.

16. Comments or Issues?
   a. In case the reductionist observed some event or peculiar vehicle behavior, he/she has to use this section to write a small note about it.

II. Invalidation Menu Definitions

1. **No subject vehicle present:** There is not a subject vehicle present in the video during the trigger. That is, the trigger was essentially noise, possibly created by objects such as a bird, bicycle, or other non-vehicular object.

2. **False alarm from specialty vehicle:** Select this option if the event was created by a secondary radar return. For instance, trucks pulling trailers may return the trailer as a new vehicle. The trailer may appear to DART as a violator thus creating a trigger. This appears to be common for vehicles pulling trailers and busses. Typically the vehicle will make a complete stop and the trigger will fire as the vehicle is pulling away from the stop bar.

3. **Insufficient data:** There is not enough data to answer any of the questions. This would happen if the video is missing AND the parametric data contains insufficient data to make a clear violate/no violate decision. Both criteria (missing video and bad parametric data) must be met to use this option.
### Table 18: results from the performed cluster analysis

<table>
<thead>
<tr>
<th>Cluster</th>
<th>Overall Cluster Information</th>
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<th></th>
<th></th>
<th>Clusters</th>
<th>Silhouette Width</th>
<th>Sum of Differences</th>
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<td>2.152</td>
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<td></td>
<td></td>
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APPENDIX F: SUMMARY OF RESULTS FOR THE CLUSTER ANALYSIS
### APPENDIX G: SUMMARY TABLE OF RESULTS FOR THE GEV FITS AND THE KOLMOGOROV-SMIRNOV GOODNESS OF FIT TEST

#### Table 19: Summary of GEV fits and the KS test

<table>
<thead>
<tr>
<th>Generalized Extremely Value Fit Information</th>
<th>Overall Max RDP GEV Fit</th>
<th>Four Partition Within Cluster GEV Fit</th>
<th>Parameters</th>
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</tr>
<tr>
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APPENDIX H: STOPBAR VELOCITY FIT INFORMATION

Table 20: Summery of GEV fit and KS test for Cluster 1.

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<td>H</td>
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Table 21: Summery of Normal Fits and KS test for Cluster 2 through Cluster 4.

<table>
<thead>
<tr>
<th>Normal Fit Information</th>
<th>Cluster 2</th>
<th>Cluster 3</th>
<th>Cluster 4</th>
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<tr>
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<td>0</td>
<td>0</td>
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# Appendix I: Brake Onset Fit Information

Table 22: Summary of normal fit and KS test for brake onset

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Warning timing is an important consideration in the development of the threat assessment algorithm. The likelihood of a driver stopping in response to an ICAS warning decreases as the required deceleration to stop increases. Ongoing work at VTTI is developing the DVI as part of the CICAS-V project. During the DVI development, several potential warning timings were investigated.

The probability of stopping is plotted below (Figure 62) for each of the warning timings tested to date. A normal probability function was assumed which allowed a sigmoid curve fit to the data. The following equation was used in the model:

**Equation 17**

\[
\frac{1}{1 + \exp\left(-\frac{x - a}{b}\right)}
\]

Where:

\[a = -0.417\]
\[b = 0.025\]

Figure 62: Model of the probability of stopping by the stopbar based on the required constant deceleration at the warning onset
Appendix K: Regression of Minimum RDP as a Function of Minimum Stopbar Velocity

To relate the minimum RDP to stopbar velocity a series of regression fits were performed. For the purpose of the analysis, a fourth order polynomial fit was found to produce the best regression of stopbar velocity as a function of RDP. This regression resulted in the following:

Velocity = RDP^a + RDP^b + RDP^c + RDP^d + e

Coefficients:
- a = -0.0012
- b = 0.0506
- c = -0.7336
- d = 5.4488
- e = 0.5191

Goodness of fit:
- sse = 25571
- rsquare = 0.6403
- dfe = 30437
- adjrsquare = 0.6403
- rmse = 0.9166

Figure 63: Regression line relating the maximum stopbar RDP to the minimum stopbar speed.
## APPENDIX L: REGRESSION BASED ALGORITHM FIT INFORMATION

Table 23: Summary of fits used in the regression based threat assessment algorithms

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<th>b</th>
<th>c</th>
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<th>Rsquare</th>
<th>dfe</th>
<th>adjRsqure</th>
<th>RSME</th>
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<td>0.9990</td>
<td>47</td>
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</table>
**APPENDIX M: ROC CURVES FOR TESTED ALGORITHMS**

Figure 64: ROC curve for the 100 series algorithm family using a violation threshold of 5mph.

Figure 65: ROC curve for the 200 series algorithm family using a violation threshold of 5mph.
Figure 66: ROC curve for the 300 series algorithm family using a violation threshold of 5mph.

Figure 67: ROC curve for the 400 series algorithm family using a violation threshold of 5mph.
Figure 68: ROC curve for the 500 series algorithm family using a violation threshold of 5mph.

Figure 69: ROC curve for the 600 series algorithm family using a violation threshold of 5mph.
Figure 70: ROC curve for the 700 series algorithm family using a violation threshold of 5mph.

Figure 71: ROC curve for the 800 series algorithm family using a violation threshold of 5mph.
Figure 72: ROC curve for the 100 series algorithm family using a violation threshold of 10mph.

Figure 73: ROC curve for the 200 series algorithm family using a violation threshold of 10mph.
Figure 74: ROC curve for the 300 series algorithm family using a violation threshold of 10mph.

Figure 75: ROC curve for the 400 series algorithm family using a violation threshold of 10mph.
Figure 76: ROC curve for the 500 series algorithm family using a violation threshold of 10mph.

Figure 77: ROC curve for the 600 series algorithm family using a violation threshold of 10mph.
Figure 78: ROC curve for the 700 series algorithm family using a violation threshold of 10mph.

Figure 79: ROC curve for the 800 series algorithm family using a violation threshold of 10mph.
Figure 80: ROC curve for the 100 series algorithm family using a violation threshold of 15mph.

Figure 81: ROC curve for the 200 series algorithm family using a violation threshold of 15mph.
Figure 82: ROC curve for the 300 series algorithm family using a violation threshold of 15mph.

Figure 83: ROC curve for the 400 series algorithm family using a violation threshold of 15mph.
Figure 84: ROC curve for the 500 series algorithm family using a violation threshold of 15mph.

Figure 85: ROC curve for the 600 series algorithm family using a violation threshold of 15mph.
Figure 86: ROC curve for the 700 series algorithm family using a violation threshold of 15mph.

Figure 87: ROC curve for the 800 series algorithm family using a violation threshold of 15mph.
Figure 88: ROC curve for the 100 series algorithm family using a violation threshold of 20mph.

Figure 89: ROC curve for the 200 series algorithm family using a violation threshold of 20mph.
Figure 90: ROC curve for the 300 series algorithm family using a violation threshold of 20mph.

Figure 91: ROC curve for the 400 series algorithm family using a violation threshold of 20mph.
Figure 92: ROC curve for the 500 series algorithm family using a violation threshold of 20mph.

Figure 93: ROC curve for the 600 series algorithm family using a violation threshold of 20mph.
Figure 94: ROC curve for the 700 series algorithm family using a violation threshold of 20mph.

Figure 95: ROC curve for the 800 series algorithm family using a violation threshold of 20mph.
Warning Timing Distribution for Tested Algorithms

Figure 96: Cumulative distribution of the warning timing for true positives produced by the 100 series algorithm at a false positive rate of .01 using a violation threshold of 15mph.

Figure 97: Cumulative distribution of the warning timing for true positives produced by the 200 series algorithm at a false positive rate of .01 using a violation threshold of 15mph.
Figure 98: Cumulative distribution of the warning timing for true positives produced by the 300 series algorithm at a false positive rate of .01 using a violation threshold of 15mph.

Figure 99: Cumulative distribution of the warning timing for true positives produced by the 400 series algorithm at a false positive rate of .01 using a violation threshold of 15mph.
Figure 100: Cumulative distribution of the warning timing for true positives produced by the 600 series algorithm at a false positive rate of .01 using a violation threshold of 15mph.

Figure 101: Cumulative distribution of the warning timing for true positives produced by the 700 series algorithm at a false positive rate of .01 using a violation threshold of 15mph.
Warning Timing Distributions using a FPR of 0.01 and a 15 mph Violation Threshold

Figure 102: Cumulative distribution of the warning timing for true positives produced by the 800 series algorithm at a false positive rate of .01 using a violation threshold of 15mph.
Figure 103: Cumulative distribution of the warning timing for true positives produced by the 100 series algorithm at a false positive rate of .01 using a violation threshold of 20mph.

Figure 104: Cumulative distribution of the warning timing for true positives produced by the 200 series algorithm at a false positive rate of .01 using a violation threshold of 20mph.
Figure 105: Cumulative distribution of the warning timing for true positives produced by the 300 series algorithm at a false positive rate of .01 using a violation threshold of 20mph.

Figure 106: Cumulative distribution of the warning timing for true positives produced by the 400 series algorithm at a false positive rate of .01 using a violation threshold of 20mph.
Figure 107: Cumulative distribution of the warning timing for true positives produced by the 500 series algorithm at a false positive rate of .01 using a violation threshold of 20 mph.

Figure 108: Cumulative distribution of the warning timing for true positives produced by the 600 series algorithm at a false positive rate of .01 using a violation threshold of 20 mph.
Figure 109: Cumulative distribution of the warning timing for true positives produced by the 700 series algorithm at a false positive rate of .01 using a violation threshold of 20mph.

Figure 110: Cumulative distribution of the warning timing for true positives produced by the 800 series algorithm at a false positive rate of .01 using a violation threshold of 20mph.
Figure 111: Cumulative distribution of the warning timing for true positives produced by the 200 series algorithm at a false positive rate of .05 using a violation threshold of 10mph.

Figure 112: Cumulative distribution of the warning timing for true positives produced by the 600 series algorithm at a false positive rate of .05 using a violation threshold of 10mph.
Figure 113: Cumulative distribution of the warning timing for true positives produced by the 800 series algorithm at a false positive rate of .05 using a violation threshold of 10mph.
Figure 114: Cumulative distribution of the warning timing for true positives produced by the 100 series algorithm at a false positive rate of .05 using a violation threshold of 15mph.

Figure 115: Cumulative distribution of the warning timing for true positives produced by the 200 series algorithm at a false positive rate of .05 using a violation threshold of 15mph.
Figure 116: Cumulative distribution of the warning timing for true positives produced by the 300 series algorithm at a false positive rate of .05 using a violation threshold of 15mph.

Figure 117: Cumulative distribution of the warning timing for true positives produced by the 400 series algorithm at a false positive rate of .05 using a violation threshold of 15mph.
Warning RDP (g)
Cumulative Probability

Figure 118: Cumulative distribution of the warning timing for true positives produced by the 500 series algorithm at a false positive rate of .05 using a violation threshold of 15mph.

Warning RDP (g)
Cumulative Probability

Figure 119: Cumulative distribution of the warning timing for true positives produced by the 600 series algorithm at a false positive rate of .05 using a violation threshold of 15mph.
Warning Timing Distributions using a FPR of 0.05 and a 15 mph Violation Threshold

Figure 120: Cumulative distribution of the warning timing for true positives produced by the 700 series algorithm at a false positive rate of .05 using a violation threshold of 15mph.

Figure 121: Cumulative distribution of the warning timing for true positives produced by the 800 series algorithm at a false positive rate of .05 using a violation threshold of 15mph.
Figure 122: Cumulative distribution of the warning timing for true positives produced by the 100 series algorithm at a false positive rate of .05 using a violation threshold of 20mph.

Figure 123: Cumulative distribution of the warning timing for true positives produced by the 200 series algorithm at a false positive rate of .05 using a violation threshold of 20mph.
Figure 124: Cumulative distribution of the warning timing for true positives produced by the 300 series algorithm at a false positive rate of .05 using a violation threshold of 20mph.

Figure 125: Cumulative distribution of the warning timing for true positives produced by the 400 series algorithm at a false positive rate of .05 using a violation threshold of 20mph.
Figure 126: Cumulative distribution of the warning timing for true positives produced by the 500 series algorithm at a false positive rate of .05 using a violation threshold of 20mph.

Figure 127: Cumulative distribution of the warning timing for true positives produced by the 600 series algorithm at a false positive rate of .05 using a violation threshold of 20mph.
Figure 128: Cumulative distribution of the warning timing for true positives produced by the 700 series algorithm at a false positive rate of .05 using a violation threshold of 20mph.

Figure 129: Cumulative distribution of the warning timing for true positives produced by the 800 series algorithm at a false positive rate of .05 using a violation threshold of 20mph.
Figure 130: Cumulative distribution of the stopbar speed for false positives produced by the 100 series algorithm at a false positive rate of 0.01 using a violation threshold of 15mph.

Figure 131: Cumulative distribution of the stopbar speed for false positives produced by the 200 series algorithm at a false positive rate of 0.01 using a violation threshold of 15mph.
Figure 132: Cumulative distribution of the stopbar speed for false positives produced by the 300 series algorithm at a false positive rate of 0.01 using a violation threshold of 15mph.

Figure 133: Cumulative distribution of the stopbar speed for false positives produced by the 400 series algorithm at a false positive rate of 0.01 using a violation threshold of 15mph.
Figure 134: Cumulative distribution of the stopbar speed for false positives produced by the 600 series algorithm at a false positive rate of 0.01 using a violation threshold of 15mph.

Figure 135: Cumulative distribution of the stopbar speed for false positives produced by the 700 series algorithm at a false positive rate of 0.01 using a violation threshold of 15mph.
Figure 136: Cumulative distribution of the stopbar speed for false positives produced by the 800 series algorithm at a false positive rate of 0.01 using a violation threshold of 15mph.
Figure 137: Cumulative distribution of the stopbar speed for false positives produced by the 100 series algorithm at a false positive rate of 0.01 using a violation threshold of 20mph.

Figure 138: Cumulative distribution of the stopbar speed for false positives produced by the 200 series algorithm at a false positive rate of 0.01 using a violation threshold of 20mph.
Stopbar Velocity Distributions using a FPR of 0.01 and a 20 mph Violation Threshold

Figure 139: Cumulative distribution of the stopbar speed for false positives produced by the 300 series algorithm at a false positive rate of 0.01 using a violation threshold of 20mph.

Figure 140: Cumulative distribution of the stopbar speed for false positives produced by the 400 series algorithm at a false positive rate of 0.01 using a violation threshold of 20mph.
Figure 141: Cumulative distribution of the stopbar speed for false positives produced by the 500 series algorithm at a false positive rate of 0.01 using a violation threshold of 20mph.

Figure 142: Cumulative distribution of the stopbar speed for false positives produced by the 600 series algorithm at a false positive rate of 0.01 using a violation threshold of 20mph.
Figure 143: Cumulative distribution of the stopbar speed for false positives produced by the 700 series algorithm at a false positive rate of 0.01 using a violation threshold of 20mph.

Figure 144: Cumulative distribution of the stopbar speed for false positives produced by the 800 series algorithm at a false positive rate of 0.01 using a violation threshold of 20mph.
Figure 145: Cumulative distribution of the stopbar speed for false positives produced by the 200 series algorithm at a false positive rate of 0.05 using a violation threshold of 10 mph.

Figure 146: Cumulative distribution of the stopbar speed for false positives produced by the 600 series algorithm at a false positive rate of 0.05 using a violation threshold of 10 mph.
Stopbar Velocity Distributions using a FPR of 0.05 and a 10 mph Violation Threshold

Figure 147: Cumulative distribution of the stopbar speed for false positives produced by the 800 series algorithm at a false positive rate of 0.05 using a violation threshold of 10mph.
Figure 148: Cumulative distribution of the stopbar speed for false positives produced by the 100 series algorithm at a false positive rate of 0.05 using a violation threshold of 15mph.

Figure 149: Cumulative distribution of the stopbar speed for false positives produced by the 200 series algorithm at a false positive rate of 0.05 using a violation threshold of 15mph.
Figure 150: Cumulative distribution of the stopbar speed for false positives produced by the 300 series algorithm at a false positive rate of 0.05 using a violation threshold of 15mph.

Figure 151: Cumulative distribution of the stopbar speed for false positives produced by the 400 series algorithm at a false positive rate of 0.05 using a violation threshold of 15mph.
Figure 152: Cumulative distribution of the stopbar speed for false positives produced by the 500 series algorithm at a false positive rate of 0.05 using a violation threshold of 15mph.

Figure 153: Cumulative distribution of the stopbar speed for false positives produced by the 600 series algorithm at a false positive rate of 0.05 using a violation threshold of 15mph.
Figure 154: Cumulative distribution of the stopbar speed for false positives produced by the 700 series algorithm at a false positive rate of 0.05 using a violation threshold of 15mph.

Figure 155: Cumulative distribution of the stopbar speed for false positives produced by the 800 series algorithm at a false positive rate of 0.05 using a violation threshold of 15mph.
Figure 156: Cumulative distribution of the stopbar speed for false positives produced by the 100 series algorithm at a false positive rate of 0.05 using a violation threshold of 20mph.

Figure 157: Cumulative distribution of the stopbar speed for false positives produced by the 200 series algorithm at a false positive rate of 0.05 using a violation threshold of 20mph.
Figure 158: Cumulative distribution of the stopbar speed for false positives produced by the 300 series algorithm at a false positive rate of 0.05 using a violation threshold of 20mph.

Figure 159: Cumulative distribution of the stopbar speed for false positives produced by the 400 series algorithm at a false positive rate of 0.05 using a violation threshold of 20mph.
Figure 160: Cumulative distribution of the stopbar speed for false positives produced by the 500 series algorithm at a false positive rate of 0.05 using a violation threshold of 20mph.

Figure 161: Cumulative distribution of the stopbar speed for false positives produced by the 600 series algorithm at a false positive rate of 0.05 using a violation threshold of 20mph.
Figure 162: Cumulative distribution of the stopbar speed for false positives produced by the 700 series algorithm at a false positive rate of 0.05 using a violation threshold of 20mph.

Figure 163: Cumulative distribution of the stopbar speed for false positives produced by the 800 series algorithm at a false positive rate of 0.05 using a violation threshold of 20mph.
APPENDIX P: ROC CURVES, WARNING DISTRIBUTIONS, AND NUISANCE DISTRIBUTIONS FOR THE TOP TWO ALGORITHMS WITHIN THE VIOLATION THRESHOLD AND FALSE POSITIVE LEVELS

Figure 164: ROC curve for the best four algorithms at a violation threshold of 10 mph

Figure 165: ROC curve for the best four algorithms at a violation threshold of 15 mph
Figure 166: ROC curve for the best four algorithms at a violation threshold of 20mph

Figure 167: Cumulative distribution of the warning timing for true positives produced by the four best performing algorithms at a false positive rate of 0.05 using a violation threshold of 15mph.
Figure 168: Cumulative distribution of the stopbar speed for false positives produced by the four best performing algorithms at a false positive rate of 0.05 using a violation threshold of 15mph.

Figure 169: Cumulative distribution of the warning timing for true positives produced by the four best performing algorithms at a false positive rate of 0.01 using a violation threshold of 15mph.
Figure 170: Cumulative distribution of the stopbar speed for false positives produced by the four best performing algorithms at a false positive rate of 0.01 using a violation threshold of 15mph.