

Analytic Assessment of Collision Avoidance Systems
and Driver Dynamic Performance in Rear-End Crashes and Near-Crashes

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ABSTRACT

Collision avoidance systems (CASs) are being developed and fielded to reduce the number and severity of rear-end crashes. Kinematic algorithms within CASs evaluate sensor input and apply assumptions describing human-response timing and deceleration to determine when an alert should be presented. This dissertation presents an analytic assessment of dynamic function and performance CASs and associated driver performance for preventing automotive rear-end crashes. A method for using naturalistic data in the evaluation of CAS algorithms is described and applied to three algorithms. Time-series parametric data collected during 13 rear-end crashes and 70 near-crashes are input into models of collision avoidance algorithms to determine when the alerts would have occurred. Algorithm performance is measured by estimating how much of the driving population would be able to respond in the time available between when an alert would occur and when braking was needed. A sensitivity analysis was performed to consider the effect of alternative inputs into the assessment method. The algorithms were found to warn in sufficient time to permit 50–70% of the population to avoid collision in similar scenarios. However, the accuracy of this estimate was limited because the tested algorithms were found to alert too frequently to be feasible. The response of the assessment method was most sensitive to differences in assumed response-time distributions and assumed driver braking levels. Low-speed crashes were not addressed by two of the algorithms. Analysis of the events revealed that the necessary avoidance deceleration based on kinematics was generally less than 2 s in duration. At the time of driver response, the time remaining to avoid collision using a 0.5g average deceleration ranged from –1.1 s to 2.1 s. In 10 of 13 crashes, no driver response deceleration was present. Mean deceleration for the 70 near-crashes was 0.37g and maximum was 0.72g. A set of the events was developed to measure driver response time. The mean driver response time was 0.7 s to begin braking and 1.1 s to reach maximum deceleration. Implications for collision countermeasures are considered, response-time results are compared to previous distributions and future work is discussed.

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Dr. Thomas Dingus and Dr. Jonathan Hankey provided subject matter expertise, methods review and advising across the entire work. In addition, they were involved in the selection of content and in refining the manuscript for Chapter 2.

Dr. Maury Nussbaum provided methods review and advising across the entire work. He provided specific assistance regarding exploring sensitivity of the algorithms (Chapter 3) and description of distributions (Chapter 4).

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Overview

This dissertation presents an analytic assessment of dynamic function and performance of collision avoidance systems (CASs) and associated driver performance for preventing automotive rear-end crashes. The similarity between parametric data collected in naturalistic driving studies, and sensor data reported to collision avoidance system algorithms, is used to assess the performance of proposed CAS algorithms in actual events. The time-series parametric data collected during rear-end crashes and near-crashes are input into models of collision avoidance algorithms to determine when the alerts would have occurred. Video and kinematic analyses are used to determine the progression of events and when response was required. The severity of the events is described by how early and how hard a deceleration was required to avoid collision. CAS algorithm performance is measured by estimating how much of the driving population would be able to respond in the time available between when an alert would occur and when braking was needed. In addition to considering the performance of proposed CAS algorithms within the events, the events and driver responses are quantified with the intention of providing new details on the timing of events, what responses are necessary for successful avoidance, and what responses drivers achieve.

This dissertation is organized into five chapters. The present chapter introduces the work, describes the rear-end crash problem, and describes previous work related to CASs and driver performance. Chapters 2, 3, and 4 are presented as three standalone but related articles corresponding generally to “methodology,” “results,” and a collection of driver and rear-end scenario measurements. The final chapter summarizes the work and discusses direction for future work.

Chapter 1. Introduction

Rear-end collisions accounted for approximately 25% of collisions nationally in 1995 and approximately 30% of crashes in 2005 (Najm et al., 1995; National Traffic Safety Administration, 2007b). Despite causing fewer fatalities, the rear-end crash type is one of the two most frequent crash types (the second being angled crashes, which is a catchall category). Governmental agencies and automobile manufacturers are looking to collision avoidance systems (CASs) for help in reducing the number of crashes and severity of crash outcomes (National Transportation Safety Board, 2001; Runge, 2005; National Traffic Safety Administration, 2007a).

The term collision avoidance system is used here to describe any system that either warns the driver to assist in avoiding a collision, or potentially controls or assists with vehicle control to avoid a collision or reduce the effects of a collision. A continuum of potential crash avoidance and mitigation countermeasures is presented in Najm et al. (1995). As an initial threat develops during normal driving, the first course of action for a rear-end CAS might be to provide a warning of some kind, such as a visual indicator or auditory tone, but without exerting any control over the vehicle. Adaptive cruise control systems and gas pedal push back are examples of low-level control systems that also provide a warning. Vestibular and haptic stimuli created by these systems provide a warning to the driver. The reduction in vehicle speed assists with avoidance or mitigation. Because more-severe situations tend to generate stronger responses, the systems create a form of graded warning. These systems do not necessarily warn for a stationary target, however, and may be limited to, for example, 0.25g, which is roughly 25% of a typical vehicle's braking capability. Braking assistance systems are currently available on higher-end vehicles (DaimlerChrysler, 2006) and are rapidly becoming more mainstream. Basic braking assistance systems interpret the driver's braking inputs and are intended to assist the driver in achieving maximum braking when desired. More advanced systems use forward-looking radar to interpret the roadway situation. If a hard-braking situation is anticipated, the vehicle's brake system is primed to respond more rapidly once the driver begins braking (Lexus, 2006). Automated full-braking intervention systems are being fielded (DaimlerChrysler, 2006). A system which is capable of full automatic control of braking or steering is expected to operate where other options are no longer available. Among other factors, the timing of this type of

intervention would involve consideration of when the driver is no longer capable of providing an effective response, due to human performance limitations, lack of detection, or incapacity.

Rear-end crashes occur when the front of a following vehicle strikes the rear of a lead vehicle while both vehicles are traveling in the same lane (Martin and Burgett, 2001). Further classification of rear-end collisions can be made by separating those that occur when the lead vehicle is stationary from those that occur when the lead vehicle is moving. Najm et al. (1997) indicate that in 72% of police-reported rear-end crashes, the lead vehicle was decelerating immediately before collision. Rear-end crashes with a stationary lead vehicle typically occur when the lead vehicle has decelerated to a stop, and then is struck by another vehicle. In 28% of police-reported rear-end crashes, the lead vehicle was stationary. How long the vehicle is stationary prior to being hit is not part of the definition and does not appear to be described in the literature.

Lead-vehicle-moving crashes are situations where the lead vehicle is typically decelerating when struck or traveling at some speed slower than the striking vehicle, but it is worth keeping in mind that the lead vehicle may be accelerating when hit. Sixty-four percent of rear-end crashes occur where the speed limit is 30–40 mph (48–64 kph) (Najm et al., 1997). Twenty-three percent of rear-end crashes occur where speed limits are 50 mph (80 kph) or greater. It is difficult from posted speed-limit values to estimate what the initial speeds of the lead and following vehicles were. For example, 18% of police-reported rear-end crashes occur where speed limits are 55 mph (89 kph) or greater. It is reasonable to think that lower speeds within congestion on highways precede many of the rear-end collisions occurring in these speed zones. Approximately 12% of police-reported rear-end crashes occur where speed limits are 25 mph (40 kph) or less. This percentage may be an underestimate. Najm et al. report an estimate of 2 million non-reported crashes in 1994 compared to 1.66 million police-reported rear-end crashes. Knipling et al. (1993) estimated that the number of un-reported rear-end accidents in 1990 was 1.2 times the number of police-reported rear-end accidents. Based on naturalistic driving data (actual video and other recording of driving), Dingus et al. (2006) reported that the number of crashes of all types may be five times the number reported to police. It is likely that lower-speed events go unreported more frequently than high-speed rear-end events.

Detailed investigations of collision databases consistently indicate driver inattention as the leading cause of these crashes (Knipling et al., 1993; Najm et al., 1997). In an investigation

of 74 crashes by Knippling et al. (1993), which were then weighted based on GES data, two-thirds of rear-end crashes were attributed to inattention. Driving-related and non-driving-related tasks can lead to inattention. Knippling et al. (1993) identified rear-end crashes attributed to drivers looking for approaching traffic, looking at vehicles beside the road, watching pedestrians, looking for landmarks, and watching other vehicles. These examples of the driver's focus being away from the forward view could each occur in support of the primary task of driving. Driving-related inattention was a contributing factor in four of 15 rear-end crashes (27%) collected by Dingus et al. (2006). Sources of inattention which are considered secondary to driving (i.e., distractions from the driving task) are found to be contributing causes in crashes more frequently than driving-related inattention (Dingus et al., 2006; McLaughlin et al., 2005). These sources of distraction include eating, picking up objects from the floor, attending to a child, interaction with some object in the vehicle, interaction with a passenger, and interaction with the vehicle audio system (Dingus et al., 2006; Knippling et al., 1993).

Following too closely is the second most common cause of rear-end crashes, but is often found combined with inattention. Following too closely was found as a cause or contributing cause in 27% of the rear-end crashes investigated by Knippling et al. (1993). Though a 2-s headway, or one vehicle length per 10 mph (16 kph) are common recommendations, Fancher et al. (1998) found a 0.8-s headway to be the most likely time headway at speeds greater than 55 mph (89 kph). In short-following situations, two factors are working against drivers. First, the time available to respond is short. It will be difficult for drivers to match the deceleration of a lead vehicle in the time available. This leads to the second factor. As drivers respond late, harder braking is required. The braking required of each subsequent vehicle in a platoon will be higher than that of the preceding vehicle. The level of deceleration required of drivers later in the platoon may exceed the braking capability of their vehicles (Davis and Swenson, 2003). Chain-reaction crashes were found in 44% of rear-end crashes on access roads and 35% of rear-end crashes on highway ramps (McCartt et al., 2004). Congestion was noted in all access road crashes and in 90% of the ramp crashes.

Rear-end CASs are progressing beyond feasibility studies into development and production. As would be expected of a system designed to operate in potentially dangerous conditions, evaluation of the effectiveness of proposed and production systems relies on testing systems in parts and estimations of what occurs in actual crash situations. Many of the sources

describing rear-end crash causation that have been discussed in previous sections also provide approaches for evaluating potential crash countermeasures. Crash problem assessments have been performed on rear-end crashes (Knipling et al., 1993), backing crashes (Tijerina et al., 1993), lane-change crashes (Chovan et al., 1994; Eberhard et al., 1995), roadway departures (Tijerina et al., 1995; Koopmann and Najm, 2001), and intersection crashes (Tijerina et al., 1994; Chovan et al., 1994; Najm et al., 2001). Najm et al. (1995) synthesized much of the crash problem assessment work and use basic CAS models, kinematic analysis, and simulation to estimate how many crashes would be avoided with the introduction of proposed CASs. Eberhard et al. (1995) provided estimates of the fraction of crashes avoided based on simulation of different conditions and CASs.

As production-ready CAS sensors have become available, various developers and original equipment manufacturers (OEM) have been testing potential systems within controlled conditions (Kiefer et al., 1999; Kiefer et al., 2003) or in field operation tests (University of Michigan Transportation Research Institute and General Motors Research and Development Center, 2005). Through iteration and testing of alternatives, warning algorithms are adjusted. Algorithm inputs and terms are included or dropped based on performance with participants on the test track or in the field. Yang et al. (2003) described an alternative approach that combines signal detection theory, specifically Receiver Operating Characteristics (ROCs), and state-space theory to predict effectiveness of a CAS. Their method first considers acceptable false-alarm rates and works backward to determine the coefficients in different terms of warning algorithms. Simulation of kinematic conditions, driver responses, and sensor noise provide probabilities of alerts being issued and crashes being avoided.

In the field, factors such as road geometry, sensor signal continuity, sensor accuracy, or traffic conditions affect the ability of a sensor and system to interpret dynamic conditions. Within the traffic and roadway conditions, further consideration is required to establish whether what is observed is a hazard or something that is within the routine range of driver behaviors and vehicle capabilities. The driver's response time—which includes detecting the potential threat, recognizing the nature of the threat, deciding how to respond, and executing the control inputs necessary for the response—is a large consideration in collision avoidance timing. CASs relying on driver warning must provide sufficient time to accommodate human response. CASs that

intervene with vehicle control will use an estimate of driver response times to determine when time available is insufficient for human response.

A number of controlled studies have been conducted to estimate the driver response time in emergency situations. Olson and Sivak (1986) measured the time required to perceive a yellow foam rubber block (15 cm high by 91 cm wide) and the time to respond to the object by braking. Sixty-four participants were tested. Time from when the object was first visible to brake press provided the total perception response time (PRT) measure. Malaterre et al. (1988) provide discussion of a number of approaches to understanding braking and steering responses in emergency situations, including one approach using kinematic reconstructions of collisions. They found that people tend to use simple responses in emergencies, with braking as the primary response. In a later simulator study in which 49 participants were exposed to an incurring vehicle at an intersection, average time to get to the brake was 1 s (Lechner and Malaterre, 1991). Lerner (1993) released a barrel into the path of participants as they drove their own vehicles on actual roads. PRT was defined as the time from when the barrel became visible to when the brake lights came on. For 56 participants (of 116) whose brake reaction time could be measured, the mean PRT was 1.5 s (*SD* 0.4 s). Measurements of brake response times for 100 drivers were collected in a simulator study by Broen and Chiang (1996) as part of a larger test looking at pedal configurations. Participants were warned during instructions that an obstacle might enter their path. From entry of the obstacle, the mean time to reach the brake pedal was 1.33 s. In a test-track study, time between the beginning of accelerator release and maximum point in brake pedal depression was measured when participants were exposed to a full-size photograph of a vehicle incurring at an intersection (McGehee et al., 2000). Mean brake response time was 2.3 s (*SD* 0.46 s). In a comparable scenario tested in a simulator (Mazzae et al., 1999), the mean response time was 2.2 s (*SD* 0.44 s). In a simulator study looking at an incurring pedestrian (Barrett et al., 1968), brake reaction time appeared to range from approximately 0.8 s to 1.4 s for 11 participants. In a simulator study investigating braking with and without anti-lock braking systems (ABS) during an intersection-incursion scenario similar to those discussed previously, a mean time to brake application of 1.1 s was found (McGehee et al., 2000). Overall, the time between presentation of an event and release of the accelerator in these studies ranged from 0.69 s to 1.28 s. The time between presentation of an event and pressing the brake ranged from 1 s to 2.3 s (Figure 1).

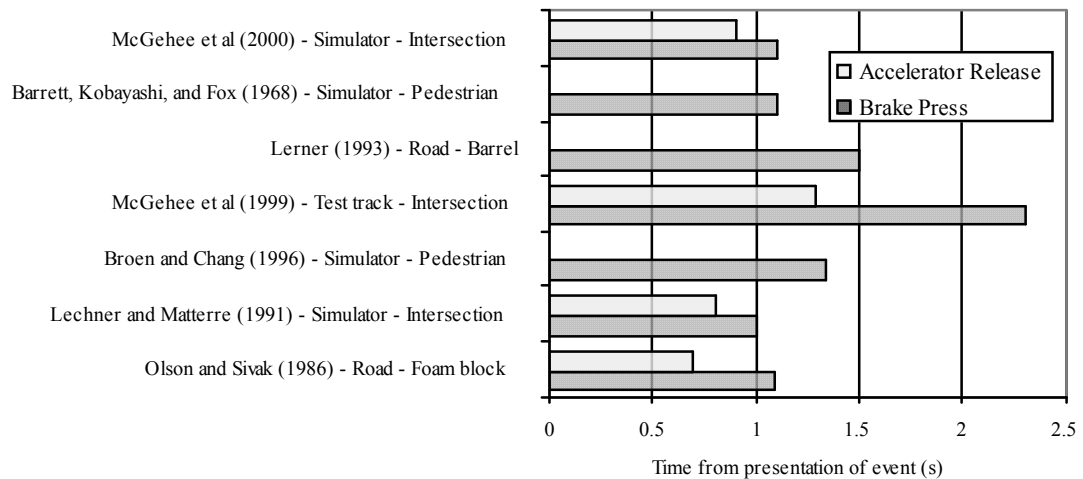


Figure 1. Response time comparison across studies (reported means or medians).

Sohn and Stepleman (1998) provide a meta-analysis of total brake time from studies involving both emergency- and normal-braking situations. They used log-normal and normal models to fit the findings of the previous studies. With both approaches, mean total brake times were found to be higher when the driver was unaware of the need to brake. At longer distances, and when the object ahead was a car, rather than some other object, the variance in total brake time was greater. The magnitude of a driver’s deceleration dictates both the distance and time required to avoid a collision, with lesser available times and distances resulting in crash-severity reduction rather than complete crash avoidance. In warning systems, the time to decelerate will need to be accommodated. In CASs incorporating vehicle control, understanding the nature of driver-controlled decelerations is desirable for:

- establishing boundaries defining when required deceleration is beyond the norm of drivers,
- determining when driver braking inputs are representative of emergency response, and
- for evaluating the performance of automated braking versus manual braking.

Simulator and test-track studies have been used to measure decelerations in response to an intersection incursion and in various following situations. In the intersection-incursion scenarios described previously, Mazzae et al. (1999) recorded a mean maximum deceleration in the test-track study of 0.65g, and in the simulator 0.8g. In studying lead-vehicle deceleration scenarios on the test track, Kiefer et al. (1999) recorded maximum decelerations of 0.9g and average of 0.42g when participants were instructed to brake at the last second. In a review of

driver responses in lead-vehicle-moving and lead-vehicle-stationary scenarios on the test track, Smith et al. (2003) indicate average median decelerations of 0.27g and 0.37g respectively.

Driving style is also a consideration in CAS design. While some individuals are comfortable executing higher-level braking maneuvers or driving with shorter separation, other drivers may seek to avoid these types of maneuvers and may be uncomfortable or unpracticed with them. A CAS designed to accommodate a more conservative driver, for example, may trigger more frequently for a more aggressive driver. Additionally, warning systems must not annoy attentive drivers, but need to be early enough to assist the inattentive driver. The trade-off between false alarms and potential missed alerts is a difficult one for system designers. Wilson (1994) provides a review of previous studies in which the false-alarm rates of various systems were identified. One study looked at a system developed by Nissan (Stien et al., 1989 as cited in Wilson, 1994) and identified an 80% false-alarm rate. In a prototype radar-based system, a false-alarm rate of 60% was found. In more recent work, a ten to one difference was found in the frequency of alerts occurring across drivers (National Highway Traffic Safety Administration, 2002). The challenge for CAS designers is first to develop a system that can identify the necessary variables and variable states to identify a hazard, and second, to make appropriate assessment of when the driver will benefit from an alert and when the alert is unnecessary or undesirable. The goal is not necessarily to minimize the false-alarm rate, but rather to maintain an acceptable false-alarm rate while maximizing crash reduction.

Existing work that has been described identified causal factors and provided guidance as to what potential countermeasures appear to provide the greatest crash-reduction potential based on accident database information. More recent CAS work has begun the transition from theoretical systems into prototypes, and evaluation of the prototypes in field tests. This document includes three related investigations, describing an assessment of CASs, events in which rear-end CASs would operate, and driver braking performance within these events. A unique aspect of the work is the use of actual, naturalistic driving data in the investigation. In previous efforts to describe human performance in collision avoidance situations, measurements and approximations are based on partial scenarios or simulations, rather than whole task, real events. Based on these previous approaches, it is difficult to be certain if the test events successfully replicate actual events and if a CAS would provide sufficient warning in actual events. Additionally, measurements of driver performance in unstaged events have not been

available. Chapter 2 describes a generic method for evaluating CASs using naturalistic driving data. Chapter 3 uses this method to evaluate three rear-end collision avoidance systems. Using actual crashes and near-crashes, Chapter 4 provides several measurements of the conditions present and timing of the rear-end crash scenario and driver performance during these events. The final chapter summarizes the work.

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Chapter 2. A Method for Evaluating Collision Avoidance Systems Using Naturalistic Driving Data*

Abstract

This paper describes a method for use in evaluating the performance of collision avoidance systems (CASs) using naturalistic driving data collected during real crashes and near-crashes. The method avoids evaluation of algorithms against specific assumptions of reaction times or response inputs. It minimizes interpretation of the involved driver's perception and response levels which permits generalizing findings beyond the performance of the involved driver. The method involves four parts: input of naturalistic crash data into alert models to determine when alerts would occur, kinematic analysis to determine when different responses would be required to avoid collision, translation of the time available into an estimate of the percentage of the population able to avoid the specific event, and an evaluation of the frequency of alerts that would be generated by the CASs. The method permits comparison of CAS performance and provides guidance for CAS development. The method is described primarily in the context of Forward Collision Warning CASs, but is applicable to other CAS types.

Keywords

Collision countermeasure; crash avoidance; alert algorithm; kinematic; naturalistic driving

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Introduction

In 2005, the administrator of the National Highway Traffic Safety Administration (NHTSA) indicated that while focusing on vehicle crash worthiness in the past has reduced the number of crash-related fatalities and injuries, an emphasis on crash-avoidance technologies is now necessary to break through a plateau in fatality and injury statistics (Runge, 2005). Collision avoidance systems (CASs) for automotive applications have been in development for some time, and are currently being fielded by manufacturers. CASs use various types of sensors including radar, infrared laser, ultrasonic, and machine vision, to monitor the area around a vehicle, or in the path of a vehicle. Data from the host vehicle, such as speed, yaw, acceleration, the state of different controls (e.g., brake pedal, turn signals), or measures of driver attention are also collected. These inputs are processed within a CAS algorithm to determine when driver warning or active vehicle control (e.g., braking) should occur. All of the algorithms interpret the observed position and speed information to predict a possible collision. An expected driver response is also incorporated into the algorithms, usually based on expected reaction times and amplitude of expected reaction inputs. This anticipated driver behavior provides the limits at which a warning is necessary. The details of how these general algorithm components are implemented, and the assumptions made, are what create the differences in performance from one algorithm to another.

CASs include systems with varying degrees of warning and control authority, ranging from advisory systems to systems that take control of the vehicle (Najm, et al., 1995), and are intended to address different driving scenarios. Parking-assistance systems generally include auditory or visual warnings indicating distance from bumpers to an obstacle. Forward collision warning (FCW) systems, also known as rear-end CASs, attempt to recognize a developing conflict and warn the driver in time to avoid or mitigate the effects of a collision. Similarly, lane change/merge warning systems are intended to monitor the areas to the side and rear of a vehicle and warn the driver if another vehicle is present. Lane or roadway departure warnings evaluate the path of the vehicle and attempt to warn the driver in sufficient time to avoid roadway departures or encroaching on other lanes.

A number of approaches have been used for evaluation of CASs, or more specifically, the estimation of possible benefits of CAS systems. Data describing vehicle speeds, ranges, driver

decelerations, and even driver reaction time have been estimated from crash databases and input into models to guide alert design or to predict CAS benefits (Knipling et al., 1993; Chovan et al., 1994; Najm et al., 1997; Tijerina et al., 1993; Eberhard et al., 1995; Smith et al., 2003; Najm and Smith, 2004). Though these approaches predict possible benefits from a macroscopic level, to provide more microscopic understanding necessary for design, CAS researchers have had to assemble descriptions of crashes from partial sources of data. The Collision Avoidance Metrics Partnership developed CAS system requirements based on measurements of driver performance in test-track studies (Kiefer et al., 2003; Kiefer et al., 1999). Prototype systems were later tested by releasing vehicles to drivers for several weeks, and algorithm alternatives were compared in terms of their effect on driving conflict frequency (FERENCE and Najm, 2005). Large scale processing of naturalistic data was used to estimate alert frequencies based on different algorithm operating restrictions (Kiefer et al., 2003; Kiefer et al., 1999). Accident reconstructions (Tumbas et al., 1997; Ferrandez, et al., 1984 as reported in Malaterre et al., 1988) or simulator studies (McGehee et al., 2000a; McGehee et al., 2000b) have been used to estimate the effectiveness of some design alternatives. These approaches provide valuable guidance both in design and evaluation, but until recently, it has not been possible to know how well these efforts approximate what actually occurs during accidents. Whether or not a proposed system would provide warnings at a time when drivers could effectively respond has been uncertain, and predictions are largely influenced by assumptions of reaction time and braking levels. Recently, time-series data describing actual crashes have become available (Dingus et al., 2006) and will continue to accumulate from ongoing and future research and from OEM-installed event data recorders. These data describe events in greater detail than has ever been available. The data can be used to further understand crashes and near-crashes and to evaluate the benefits of various CAS systems using actual crash data. This paper describes a methodology developed for evaluating proposed CASs using time-series data recorded in crashes and near-crashes. The method avoids reliance on a single reaction-time estimate or specification of a single expected driver response. The method also permits generalizing beyond the limited numbers of involved drivers by determining how much time would be available to respond, and then estimating the percentage of drivers expected to respond in the available time. The evaluation method described in this paper is applicable to different types of CASs (including both driver warning

and vehicle control) and different collision types, but is illustrated here through application to FCW algorithms that solely rely on driver warning for collision avoidance.

Event Timing in Naturalistic Crash and Near-Crash Data

The effectiveness of a CAS depends on the ability of the system to make the driver aware of a risk earlier than if the alert had not been present. The sequence of events that occurs in the avoidance of a crash or near-crash is shown in Figure 2.

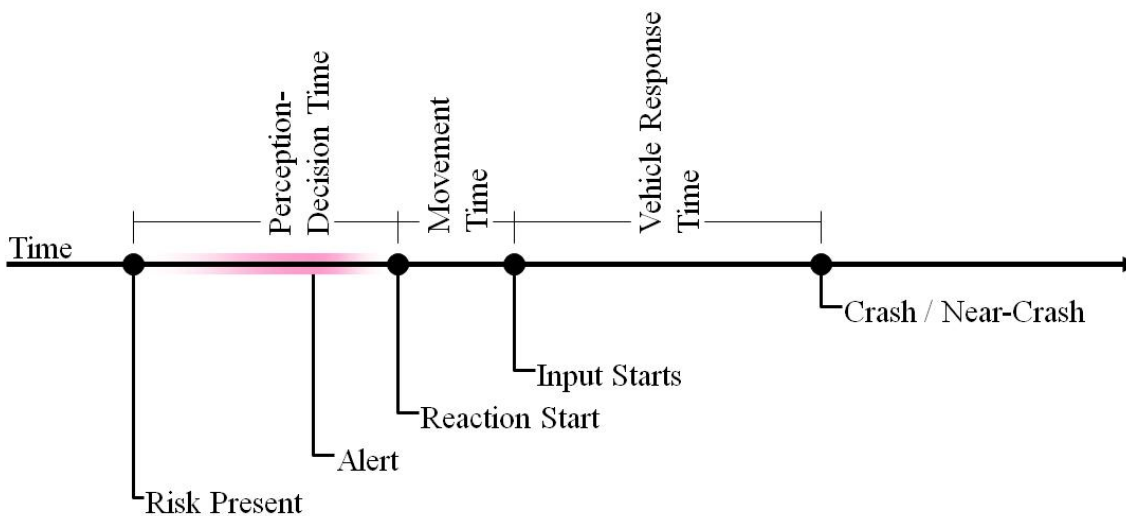


Figure 2. Sequence of events during a crash or near-crash.

During a drive, some potential risk develops. Time is required to perceive this risk, identify it as a valid threat, decide on an action, and move to the control for the action (e.g., move from accelerator to the brake). Once input starts (e.g., braking), time is required for the control input to translate into a sufficient change in vehicle path or speed to avoid a crash. Ignoring false alarms for the moment, in the development of an alert, if the alert occurs earlier than the driver's reaction would have been without the alert, the proposed alert should be successful in avoiding or mitigating collisions. In experimental studies, either in simulators or on the test track, it is possible to control the presentation of a risk, measure the timing of each stage, and compare performance of many subjects under different alert conditions. Naturalistic crash and near-crash data have some unique characteristics, however, that create the need for alternative methods.

First, until more time-series records of crashes and near-crashes are accumulated, only relatively low numbers of events are available for analysis. The observed perceptual capabilities,

movement time, decision making, and vehicle-control capabilities are known for only a few drivers, potentially limiting the ability to generalize findings to a broader population. The vehicle control achieved during the event is only one outcome. The involved driver may not have executed the optimal input. The amount of braking or steering achieved might have been different for another driver or another vehicle.

Second, in real world data, it is difficult to identify the timing of different response stages during a crash or near-crash. It is sometimes difficult in a crash or near-crash to define when a risk is first present. A lead vehicle may be braking, for example, but what level of lead-vehicle braking poses a risk? When reviewing crash or near-crash video, it is sometimes difficult to define when a driver recognizes a threat, or even when the driver's response begins. For example, movement toward a control is not necessarily indicative of a response to a risk. A driver may already be changing lanes, or may already be braking or moving to brake at the time a risk becomes apparent. Part of a driver's movement may involve normal driving behavior, and part may follow recognition of a threat. In other cases, the driver demonstrates a gradual increase in readiness to respond. For example, as events develop ahead, the driver might sit more upright and gradually move a foot closer to a brake pedal. This may happen anytime a driver approaches an intersection, whether a threat develops or not. This makes it challenging to discern when the driver first perceived the potential threat.

Generalizable Evaluation Method Overview

A CAS evaluation method was developed based on earlier countermeasure benefit estimation work (Najm et al., 1995). The method avoids evaluation of algorithms against specific assumptions of response times or response inputs, permits generalizing findings beyond the performance of the involved driver, and minimizes interpretation of the driver's perception and response levels. The first three parts of this method are illustrated in Figure 3.

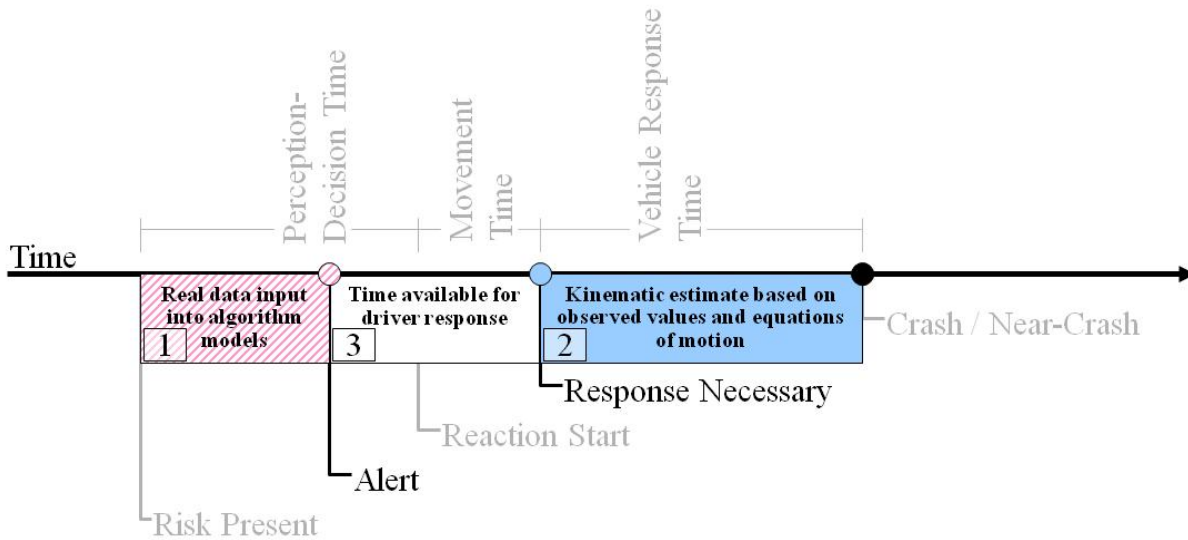


Figure 3. Evaluation method parts 1, 2 and 3.

The first part (labeled with a 1 in Figure 3) uses algorithm models processing time-series crash and near-crash data to determine if and when CAS algorithms will alert in actual collision situations. The second part (labeled with a 2 in Figure 3) of the analysis is a kinematic analysis of the events. The kinematic analysis determines when vehicle response must begin to avoid collision in each event. Multiple response alternatives are considered in this step. The third part (labeled with a 3 in Figure 3) is to estimate how much time is available for the driver to respond in each event and estimate the percentage of the population who could respond successfully. That is to say, subtracting the time when alerts will be given in each of the events from the time when vehicle response needs to begin in each of the events indicates the time available for the driver to respond. Using a distribution of driver response times estimated in other research, the time available to respond to an alert in each of the events will be generalized to an estimate of how many drivers could respond in the available time given the event observed.

The final part of the evaluation (not in the figure) estimates the frequency with which the tested algorithms would generate an alert during normal driving. Figure 4 illustrates the overall approach to implementing this evaluation method with naturalistic data, including organization of the software and the analysis approach.

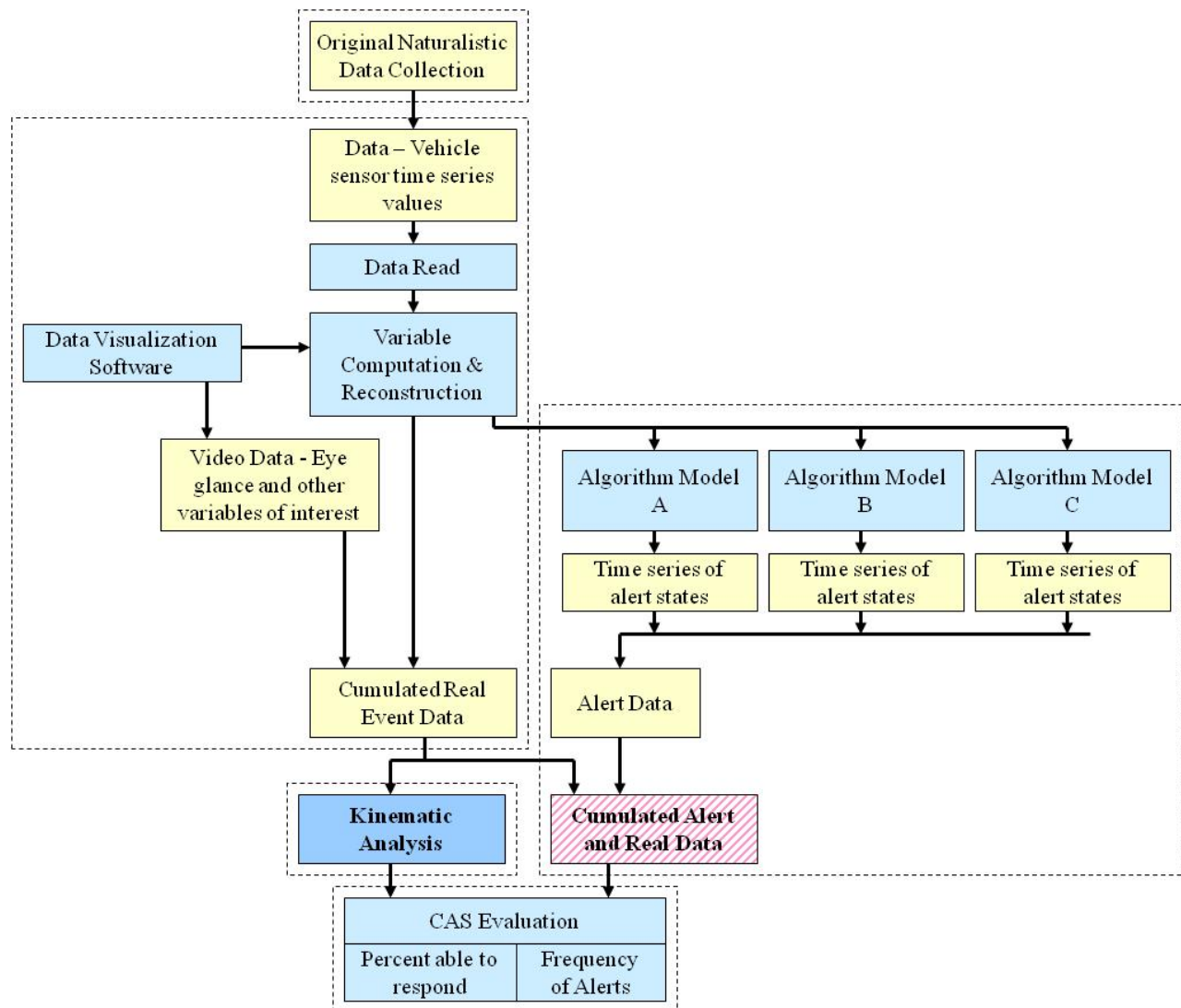


Figure 4. Overview of the evaluation method.

Software was developed that would present time-series data to independent alert algorithm models which would then generate a time-series output indicating when the alerts would have occurred. The output of the alert models, kinematic analysis of the events, and an alert frequency analysis, were combined as described in the previous sections, to provide side-by-side comparison of the alert performance during crashes and near-crashes. Inputting the naturalistic data from “normal” driving into the algorithm models also provided an estimate of the expected frequency of alerts. The performance of the alerts in crashes and near-crashes, as well as the estimate of the number of alerts occurring during drives, provided the summary CAS evaluation. Additional details on applying this evaluation methodology are described in the following sections.

Data Review and Preparation

The first step in the analysis method involved readying the data for subsequent analysis steps. In-house data visualization software was used to review 13 rear-end striking crashes and 60 rear-end striking near-crashes in detail. This software permits frame-by-frame review of five video views along with numeric data collected during the event. Some events were missing certain variables of interest and there were some data streams that had discontinuous data. Due to the range of sensors available on the vehicle, and the short epoch length needed for this analysis, it was possible to reconstruct missing segments when necessary using data fill techniques, alternate sensors, video, and/or equations of motion. Reconstructed values were checked by comparing them to original data from alternative sources. Additional variables of interest were also collected from video review. These included position of encroaching vehicles, brake-light state of a forward vehicle, and glance location of the subject-vehicle (SV) driver.

The 73 events used to date were collected during actual driving and provide both data on which to test the method and a starting point for a set of events for testing algorithms. The following-vehicle speeds represented in the set ranged from 1.4 mph (2.3 kph) to 60.3 mph (97.0 kph). These measures were collected just prior to the response of the driver of the following vehicle. The relative speed at this time ranged from -30.2 mph (-48.6 kph) to 2.4 mph (3.9 kph). In all of the events, the range at the time of driver response was 100 ft (30.5 m) or less. The headway ranged from 0.3 s to 3.3 s. As data from additional events are collected, they will be incorporated into the testing.

Algorithm Modules

Three FCW algorithms were modeled (McLaughlin et al., 2005) and will be presented generically here to demonstrate application of the evaluation method. Algorithms were selected that included a range of characteristics including alert logic approaches, scenario assumptions, driver monitoring (e.g., brake pedal state), operating ranges, alert stages, and sensitivity settings. None of the algorithms tested here included active vehicle control (e.g., brake pulse or full braking) as part of its response. The function and characteristics of each of the algorithms were coded in the MATLAB[®] programming language. Software tools were developed to review the alert state of each algorithm simultaneously over the course of the time-series crash and near-

crash data. Figure 5 illustrates time-series data from one event and the output of the algorithm models for the event.

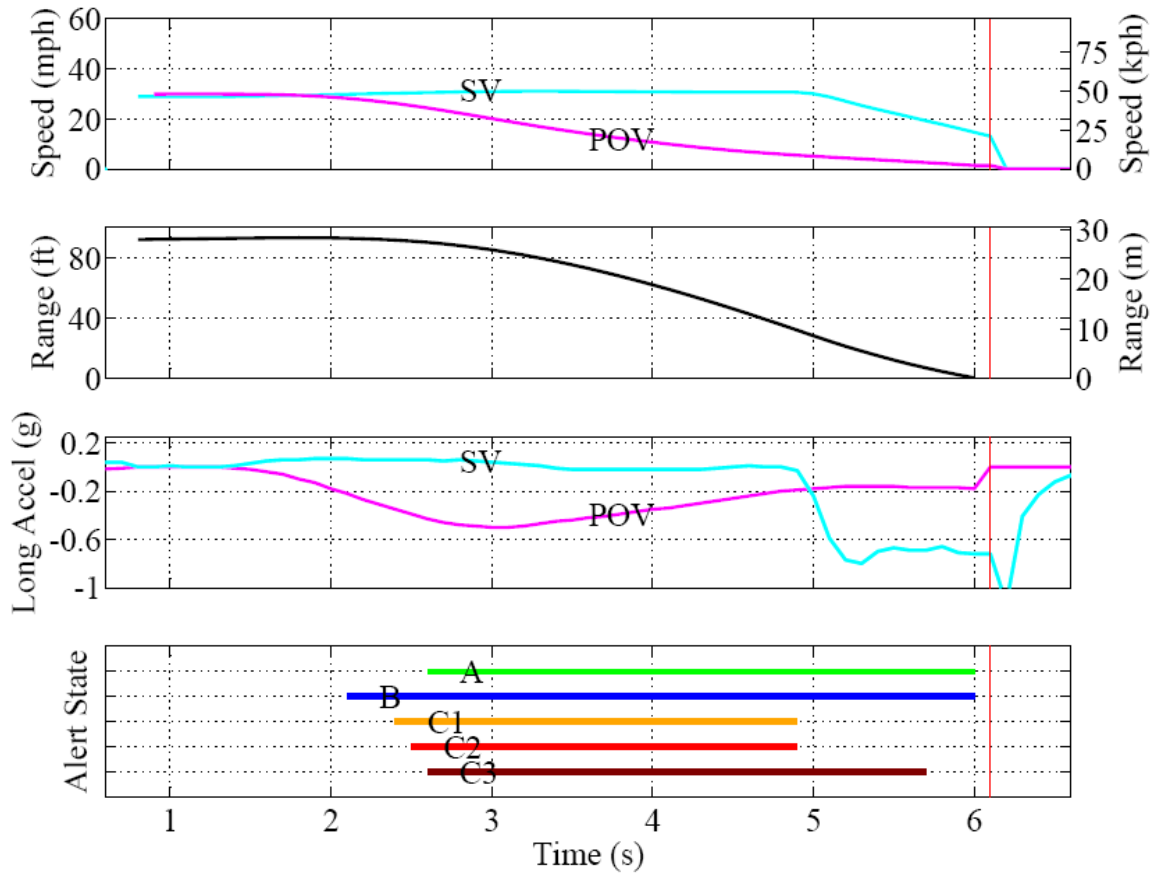


Figure 5. Illustration of values of various event related variables and algorithm model output.

The bottom plot in Figure 5 indicates the alert state. Where a solid line is present, the alert is active. Algorithms A and B could be either on or off. Algorithm C included three warning levels which are presented as C1, C2, and C3 in Figure 5. The alert state time-series data was also ported back into the data visualization software. The alert states could then be reviewed beside the video views and other numeric data. In addition to observing the alert state that would be presented to the driver, it is also possible to monitor the state of intermediate values used in each of the alerts. This provides a diagnostic tool helpful in understanding why an alert may or may not be active at certain times and what algorithm adjustments might be helpful.

Kinematic Modeling

Kinematic analysis was used to identify where in time vehicle response would need to occur to avoid collision in the 13 rear-end striking crashes and 60 rear-end striking near-crashes. The kinematic modeling portion of this method is applicable to any crash type where measuring and predicting position trajectories is possible using naturalistic data.

In rear-end striking crashes, SV driver response is either not present, too late, or not of a sufficient level to avoid collision. Near-crashes in the original naturalistic data set were defined as “[a]ny circumstance that requires a rapid, evasive maneuver by the subject vehicle, or any other vehicle, pedestrian, cyclist, or animal to avoid a crash” (Dingus et al., 2006, p. 65). In near-crashes, when present, the SV driver’s response tends to be more than the minimum necessary and is typically earlier than the last instant necessary to avoid a crash. Kinematic analysis was used to determine the time boundaries when vehicle response had to occur to avoid collision. In the naturalistic data, at each instant, the speeds, accelerations, and separation of the vehicles are changing. Software routines were written that used the speed and acceleration values of the principal other vehicle (POV) at each time sample to determine its position over time. The performance of the SV was then varied to model alternative responses and the necessary timing of response to avoid collision. In this way, the POV is located in a coordinate system over time, and then the SV is located in the same coordinate system. The separation, relative speeds, and time of collision can then be computed for different response alternatives.

The first step in this part of the analysis is to locate the start of an observable response point in the naturalistic data. Graphs of variables such as acceleration, throttle level, and SV brake state were visually inspected with the coinciding video to locate the start of vehicle response which was indicative of a driver’s avoidance input. Event videos were reviewed to determine factors, such as when the driver was looking ahead, what events were occurring ahead, and particularly, what changes were occurring and where the timing of these changes was shortly followed by a sharp change, or “knee,” in acceleration. The point where the “knee” occurred in accelerometer data, which agreed with contextual information from video, was selected as the observed response point. This point is illustrated in Figure 6.

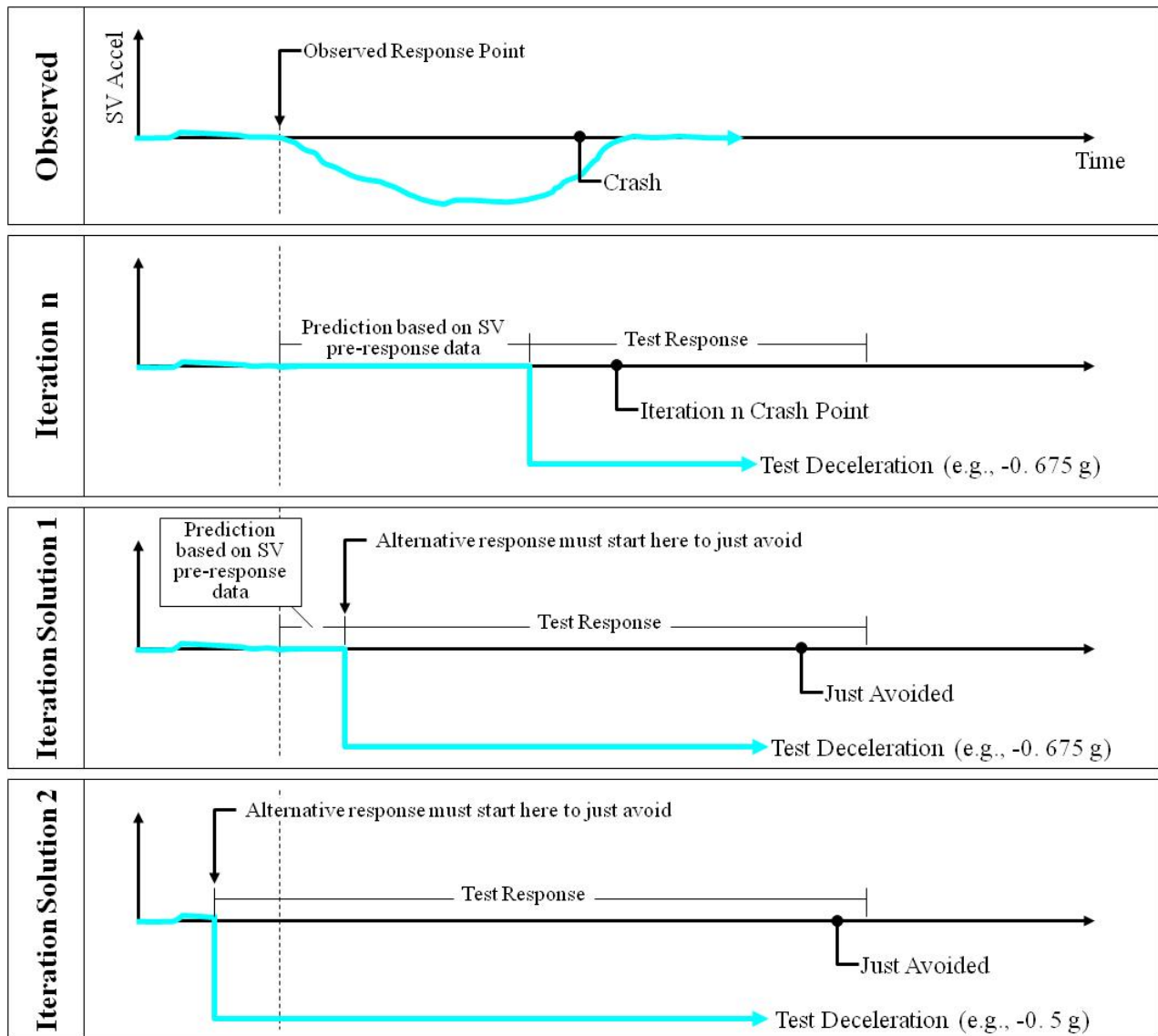


Figure 6. Iterations to determine when a given response needed to begin to just avoid collision.

Once the observed response point was located, the first response alternative to explore is the no-response alternative. The SV speed and average acceleration level at a point just before the observed response point were input into equations of motion to project SV position and speed forward in time. This approximates the outcome had the SV driver not responded to the forward event. This also provides a prediction of SV speed and position relative to the lead vehicle at each time interval.

Next, three alternative deceleration responses were investigated to determine when the responses would need to begin to avoid colliding with the POV. An analysis routine was

developed to iterate the time at which a response alternative would start, and used equations of motion to determine if a collision would result. By working backward (earlier in time) from the crash or near-crash, this iteration routine located the point in time where the alternative response needed to start to just avoid impacting the POV. Determination of where an alternate response needed to begin required evaluating three segments of time-series data. The analysis routine retained the SV time-series data up to the observed response point. After the observed response point, the no-response position and speed predictions were used up to the time sample being tested as an alternative response start point. From the alternative response start point forward, the iteration input the alternate response (e.g., 0.675g deceleration) into equations of motion to determine an alternate SV position and speed at each time interval. If an iteration resulted in a crash, the next iteration started the alternate response one time sample earlier, and again evaluated the outcome. Figure 6 illustrates the iteration to find a solution. In the illustrated example, a 0.675g deceleration response alternative is being tested. The first graph (Observed) illustrates the acceleration recorded in the event. The observed response point is indicated where the “knee” in SV acceleration occurs. The point in time where the real crash occurred is also indicated. An example of an iteration is shown in the second graph (Iteration n). In this iteration, the alternative response (deceleration) does not start early enough to avoid collision, though it does make the crash occur later in time. Note that the alternate response point moves earlier in time with each successive iteration, while the iteration crash point moves later in time. In the third graph (Iteration Solution 1), the point where the alternative response must begin to just avoid collision is located. In this solution, the iteration routine arrived at a solution point indicating the response alternative could occur later in time than the driver responded. This type of solution would be expected, for example, when a high- g braking alternative is being tested. The braking level tested was higher than the average deceleration achieved by the driver, and so could have started later. In other events, however, and for specific response levels, the solution point occurred earlier in time than the vehicle response was observed. An example of this is illustrated in the fourth graph (Iteration Solution 2). In the rear-end striking scenario, this type of solution will arise, for example, if a low SV deceleration alternative is being tested. In a steering response alternative, this type of solution would arise where the effect of a small steering response is being evaluated. In iterations resolving in this manner, the observed SV speed and

acceleration values were used up to the point where the tested alternative response began. In this case, the no-response prediction values are not necessary.

For each event, the kinematic analysis identifies a set of times within the time-series data at which a response is necessary. In this example, three points in time were identified where three levels of deceleration must occur to just avoid collision. In a FCW CAS investigation considering steering, various levels of steering input or some combination of steering and braking could be used in a similar manner.

Evaluation of Time Available for Driver Response

Having identified when alerts would occur in each event and having determined when different responses are necessary given the observed behavior of the POV, it is now possible to estimate the outcome of the event. To avoid building an assumption of a specific driver response time into the evaluation of the CAS alerts, development of a distribution of response times was necessary. There have been a number of studies that measure the response time of drivers to different events or stimuli. Simulator studies have looked at intersection incursions (Mazzae et al., 1999; Lechner and Malaterre, 1991) and pedestrian incursion (Barrett et al., 1968; Broen and Chiang, 1996) for example. On-road or test-track studies have measured responses to intersection incursions (McGehee et al., 2000a, Mazzae et al., 2003), rolling barrels (Lerner, 1993; Shutko, 1999), and blocks in the path of travel (Olson and Sivak, 1986). Response to visual, auditory, and haptic warning systems have also been measured (Shutko, 1999; Harpster et al., 1996). Though response times are skewed to the right, measured response times are often reported in the literature as mean values, making it difficult to estimate values away from the mean. A few authors have presented response times as a distribution. For example, Taoka (1989) describes a distribution of brake reaction times based on work by Sivak et al. (1982), and Eberhard et al. (1995) provide a summary of different distributions. Figure 7 illustrates how a cumulative reaction-time distribution was used to estimate the percentage of the population able to respond within the time available.

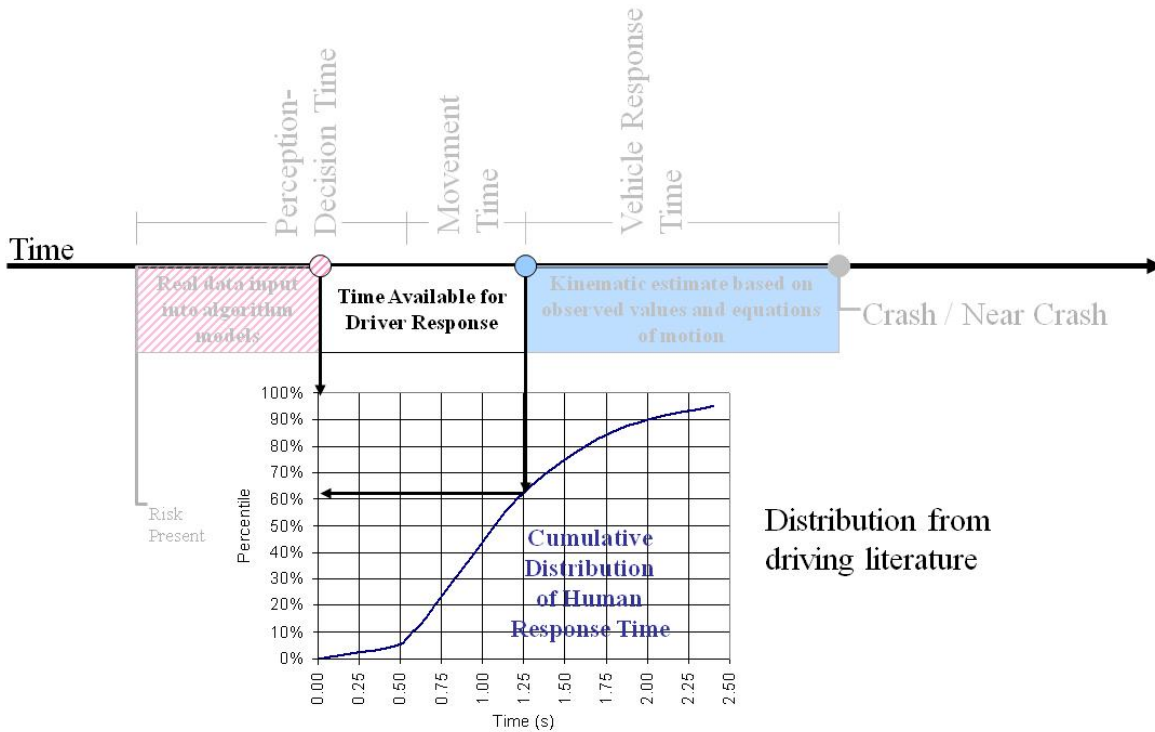


Figure 7. Use of response-time distributions in evaluation.

In Figure 7, 1.25 s are available to respond. This translates to an estimate of just over 60% of the population being able to avoid collision. In Figure 8, application of this process is illustrated with the output of the kinematic analysis and the timing of the alerts generated by the alert models (see Figure 5).

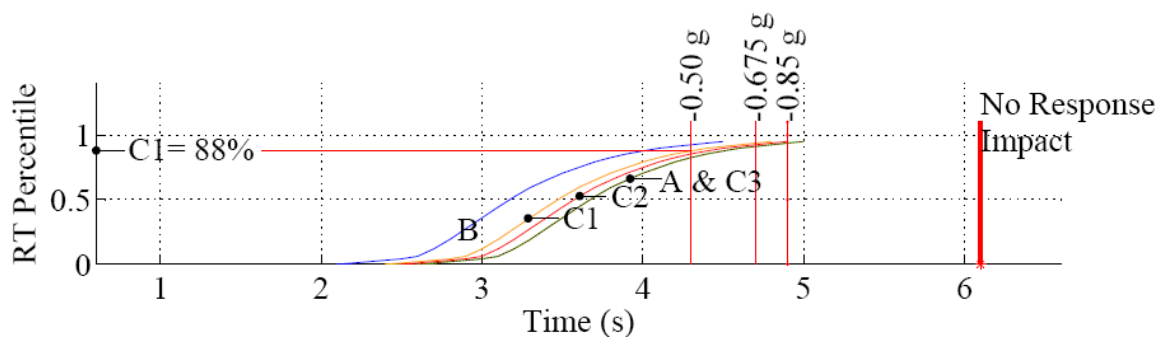


Figure 8. Illustration of output from kinematic modeling, timing of alerts, and evaluation of available driver response time for one event.

Kinematic estimates of when three alternative responses ($-0.5g$, $-0.675g$, $-0.85g$) would need to begin to avoid collision are presented as vertical lines. The reaction-time distribution shown in Figure 7 is shown beginning at the start time of each of the alerts shown in Figure 5 (note that

alert A and C3 would begin at the same time, and so their response-time distributions are overlapping in Figure 8). If a 0.5g deceleration is anticipated as a driver response to alert C1, in the illustrated event, approximately 88% of the population would be expected to avoid collision. If a harder driver response is anticipated (e.g., -0.85g), more people would be expected to avoid the collision.

This evaluation process was developed into software to permit rapid evaluation of the effect of different CAS algorithms, sensitivity settings, and design alternatives. The process provides directional guidance for improving algorithms. For example, summarizing performance across all of the crash and near-crash events provides an initial comparison of algorithms. Tabulating results according to some variable of interest, such as initial speed or strength of lead-vehicle deceleration, indicates conditions where algorithms perform well and where they might break down. Looking at the range of results across variables such as the anticipated level of driver braking (e.g., 0.5g to 0.85g) or the range of algorithm sensitivity settings provides data about the responsiveness of alternatives to these types of variables. Finally, algorithm performance, or the state of specific variables within an algorithm, can be tracked frame by frame during individual events to isolate algorithm design problems.

Different reaction-time distributions can be used to provide additional insights. Potential differences between distributions based on volunteers in experimental settings and the range of drivers and scenarios found in actual driving should be considered. Distributions should be selected that provide the closest representation of the scenario and stimuli of interest. Distributions developed in research investigating similar stimuli to that being considered for the CAS provide greater validity. Selection of reaction-time distributions representing two extremes in the literature could also be used to bracket the range of CAS benefit estimates. As distributions are developed from actual crash events, these should be incorporated into the method.

For the algorithms tested in this effort, a number of algorithm design considerations were highlighted by the analysis. For example, performance of the algorithms varied with vehicle speeds. Simplistic assumptions of driver response, such as use of a single anticipated driver braking level, tended to create a narrow band of effectiveness. Algorithms designed for specific speed ranges tended to perform poorly or not at all for common events that fall outside these speed ranges (e.g., low-speed events). As will be discussed in the following section, the

frequency of alerts generated by the tested algorithms was found to be too high for implementation. Further explanation of results is avoided here in the interest of focusing on the method rather than the algorithms.

Frequency of Alerts

Any alert design must strike an acceptable balance between overly strict evaluation of inputs, that might fail to alert at an appropriate time, and overly cautious evaluation, that might generate too many false alarms. The fourth part of this evaluation method considers the number of alerts generated by each of the CAS algorithms during “normal” driving. Driving data, not from crash or near-crash situations, but from a sample of “normal” driving data was input into the algorithm models. Identical data were provided to each of the algorithms. The number of times alerts occurred per some standard time or distance was computed for each of the algorithms. A small set of trips from just a few drivers can provide sufficient information for comparing different alert algorithms to obtain an order-of-magnitude type estimation of whether the frequency of alerts during normal driving would be reasonable. In the present work, the FCW algorithms were tested with 24 mi (39 km) of data from three trips and three different drivers. Alerts generated solely by in-path lead vehicles, were found to occur almost once per mile for the most sensitive algorithms and approximately once per ten miles for the least sensitive algorithm. While these values differentiated the algorithms in terms of frequency of alert, all were considered high for an effective collision alert warning. For this reason, no further alert frequency testing was pursued. As greater test resolution is desired, a stratified sample of driving styles and traffic conditions from the naturalistic data set can be used to evaluate alert frequencies in greater detail.

The approach used in the present project only provided in-path vehicles to the alert modules. Experimenter review of video data was used to identify in-path vehicles, thereby simulating an ideal sensor suite. This approach was used to focus specifically on the CAS algorithm interpretation of lead-vehicle events. There are many alternative approaches or modifications that could be used. Target selection algorithms could also be tested either in coordination with alert algorithms or separately. The collected naturalistic data could be filtered to simulate different sensor types. For example, a sensor with narrow field of view could be simulated by filtering data outside this field of view before providing the data to the alert model

modules. Different thresholds for stopped object classification could also be implemented by modifying the naturalistic data before reporting it to the alert modules.

Conclusions and Future Work

The CAS evaluation approach described here provides a method for using naturalistic driving data from crashes and near-crashes to evaluate the performance of proposed collision-avoidance technologies. The method avoids the use of assumptions about driver reaction time and response behavior that might artificially indicate differences in performance of CASs that incorporate these same assumptions. Assumptions as to when a risk develops are also avoided by instead identifying when CAS algorithms identify the need for warning or control, and determining if the timing would be sufficient in actual events. The method also permits generalization of naturalistic data beyond the low numbers of events currently available.

There are several areas in which related future work would be beneficial. The evaluation described here indicates the percentage of the population who would be expected to avoid crashes and near-crashes. In addition to estimating crashes avoided, the method could estimate crash mitigation that might be achieved by the CASs. Addition of crashes and near-crashes to the test set is anticipated. The described method evaluates CAS performance at the microscopic level (i.e., the effect of design alternatives on specific crashes). The method could be developed to translate CAS performance on the tested crashes and near-crashes into an estimation of benefits on a larger scale. This work might, for example, develop a function for converting the number of crashes and near-crashes evaluated using this method into a prediction of the number of crashes that would be avoided on a national level. It is also appropriate to purposely explore the potential that certain scenarios (e.g., very severe) are not represented in the test set.

As described here, the method uses simple step functions for evaluation of alternative responses. As more is understood about response behavior in crashes, future work will incorporate this information into more sophisticated models of response alternatives. The benefit of vehicle control systems such as adaptive cruise, brake assistance systems, and lateral control systems will be explored. The influence of driver and traffic differences on algorithm design will be considered. Also, where this method proves a measure of alert frequency per mile in normal driving conditions, a method for evaluating this alert frequency in terms of annoyance could be developed. Driver annoyance levels at different false alarm rates could be measured

experimentally. Functions could then be developed to translate alert frequency estimates into estimates of CAS acceptance. Additionally, there is the potential that driver response or behavior could change positively or negatively due to the presence of CASs. Models of changes in behavior could be incorporated into estimates as capabilities progress in this area.

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Chapter 3. Assessment of Three Rear End Collision Avoidance Algorithms Using Naturalistic Driving Data

Abstract

Collision avoidance systems (CASs) are being developed and fielded to reduce the number and severity of rear-end crashes. Kinematic algorithms within the CAS evaluate sensor input and apply assumptions describing human-response timing and deceleration to determine when an alert should be presented. An analytical assessment was conducted of three rear-end collision avoidance algorithms. The three algorithms varied in assumptions regarding driver response, operational envelope, levels of alert, and accommodation of driving styles. Data from actual crashes and near-crashes collected during naturalistic driving were input into the algorithms to determine the percentage of the population who would be expected to avoid a crash under similar circumstances when alerted with each of three CAS algorithms. A sensitivity analysis was performed to consider the effect of alternative inputs into the assessment method. The algorithms were found to warn in sufficient time to permit 50–70% of the population to avoid collision in similar scenarios. However, the accuracy of this estimate was limited because as tested, all three of the algorithms were found to alert too frequently to be feasible. The response of the assessment method was most sensitive to differences in assumed response-time distributions and assumed driver braking levels. Altering response-time distributions from a slow distribution to a faster distribution changed the estimate of the percentage of who could avoid by 15 percentage points. In cases where driver response deceleration was assumed to be low (e.g., 0.5g or less), small changes have a greater effect on outcomes than in cases where deceleration is assumed to be higher (e.g., 0.85g). Low-speed crashes were not addressed by two of the algorithms. Recommendations for algorithm design and future work are provided.

Keywords

Collision avoidance, false alarm, rear-end crash

Introduction

Though fatality rates in other crash types are higher, the rear-end crash type is one of the two most common crash types (the other being angle crashes, which includes all crashes not categorized as rear-end, sideswipe, head on, or rear-to-rear crashes). The rear-end crash type represents the highest percentage of crashes resulting in injury or property damage. In 2005, 2,354 people were killed in rear-end crashes. There were over 500,000 rear-end crashes resulting in occupant injuries and 1.3 million more rear-end crashes that were limited to property damage (National Highway Traffic Safety Administration (NHTSA), 2007). Collision avoidance systems (CAS) or braking assistive systems are being fielded by manufacturers (DaimlerChrysler, 2006; Lexus, 2006) and evaluated by government agencies (NHTSA, 2007; Runge, 2005; National Transportation Safety Board, 2001) as a potential method to reduce the number and severity of rear-end crashes.

Guidance in the development of CAS systems typically comes from analyses of crash databases (Knipling, et al., 1993; Najm, Mironer, and Yap, 1997; Kiefer et al., 1999), experimental research done in simulators (Lechner and Malaterre, 1991, Broen and Chiang, 1996, Mazzae, et al., 2000), review of original accident reports (Eberhard, et al., 1994), crash investigation teams (Treat et al., 1977; Ferrandez et al., 1984 as reported in Malaterre, et al., 1988), or test-track and on-road studies (Mazzae et al., 1999; Kiefer et al., 1999; Lerner, 1993; Olson and Sivak, 1986). These methods have provided valuable guidance but also have limitations. Databases are limited to crashes that are reported to police or insurance companies, which under-represents the number of actual crashes, primarily because of the large number of low-severity crashes (Knipling et al., 1993; Najm et al., 1997; Dingus, 2006). Accident reports rely on witness interviews and/or re-creation of events, and complete details of an event cannot be retained. In comparison, though the data are more complete, experimental studies may not replicate the real-world environment, and participants may behave differently than they do in their own vehicles during a typical drive.

Estimates of CAS effectiveness generally are made based on the ability of system algorithm logic and parameters to address expected crash scenarios and subsequently by estimating the number of the crashes that will be avoided by implementation (Burgett et al., 1998; Knipling et al., 1992; Kiefer et al., 1999). The same assumptions about expected crash

scenarios in terms of vehicle-to-vehicle speeds and distances, and in terms of frequency of events, are relied on both in the design of CAS algorithms and in the estimation of benefits. Through field operation trials (FOTs) of prototype systems (University of Michigan Transportation Research Institute and General Motors Research and Development Center, 2005) and post processing of FOT data (Glasco and Cohen, 2001), it has been possible to explore many of the design considerations of CASs. Recently, time-series data have been collected that include real crashes (Dingus et al., 2006) and have sufficient video and parametric data to evaluate performance of CAS algorithms using real events.

The present study estimates the effectiveness of three rear-end CAS algorithms using actual crash and near-crash data collected by Dingus et al. (2006). The naturalistic data employed include measurements of vehicle states such as speed, acceleration, yaw, range to lead vehicles, speed of lead vehicles, and driver inputs. Also obtained were video of the forward and rear roadway, the driver's face, and an over-the-shoulder view of the steering wheel and driver's hands. Algorithms were selected from those available in public literature and to explore different algorithm design strategies. Details of the algorithms are provided in the Methods section. Using the three algorithms, estimates were derived of the percentage of the population that would have been able to respond and avoid impact by braking, with these estimates based on actual crashes and near-crashes. The sensitivity of these estimates to changes in assumptions was measured. An analytic approach was also used to estimate of the frequency with which the different algorithms might generate alerts during normal driving.

Method

Najm et al. (1995) describe a method for estimating countermeasure benefit by working backwards from initial conditions to determine when decelerations are required, and then to an estimate of the proportion of the driver population that would benefit. This method is extended here to incorporate models of proposed CASs and actual driving data from crashes and near-crashes. In the present work, crash, near-crash, and normal driving data are input into CAS algorithm models to determine when alerts would occur. Vehicle trajectories over time from crashes and near-crashes are then used to determine when deceleration was required. Based on this, an estimate of the percentage of the population who might be expected to avoid colliding is determined. Additionally, the frequency of alerts occurring in normal driving is estimated. A

sensitivity analysis is performed to investigate changes in outcomes based on different evaluation approaches. The five parts of this process are shown in Figure 9.

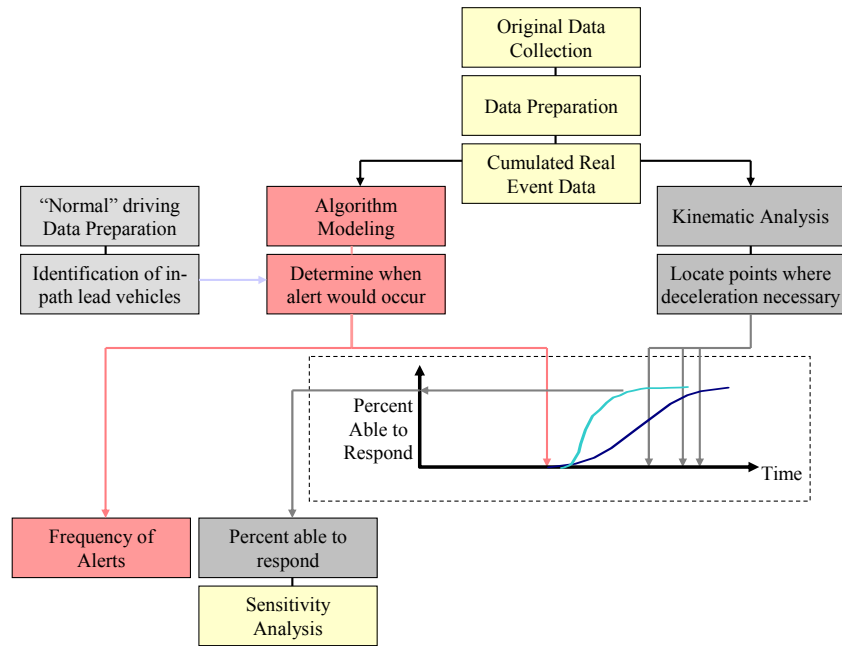


Figure 9. Schematic of method.

Original Data Collection

In the original 100-Car Naturalistic Driving Study (Dingus et al., 2006), instrumented vehicles were driven by participants for one year. Drivers were fully informed of the presence of video and other sensors, but were given no instructions other than to use their vehicle and drive normally. Seventy-eight of the vehicles were the participants' own vehicles, and the remaining vehicles were provided to the participants. During the year of driving, vehicles were driven both by the primary participant, for whom demographic data were known, and by other drivers, such as spouses or friends. Driving data from 109 primary participants and 132 additional individuals were collected. Six different vehicle models were used in the study (Table 1).

Table 1. Vehicle makes, models, and model years.

Make	Model	Model Year
Chevy	Cavalier	2002
Chevy	Malibu	2002
Ford	Explorer	1995-2000
Ford	Taurus	1996-2002
Toyota	Camry	1997-2001
Toyota	Corolla	1993-2002

Individuals under 30 years of age who reported driving 10,000 or more miles annually were enrolled and were provided a vehicle if their own vehicle was not one of the types listed above. Older drivers who reported driving 15,000 miles or more annually, and who drove one of the vehicle types above, were also enrolled.

Forward range, range rate, and target azimuth were recorded at 10 Hz for up to seven targets using radars. Vehicle yaw, longitudinal and lateral acceleration were recorded at 10 Hz. Variables collected from the standard vehicle network included speed, brake press, and gas-pedal position. These vehicle-network variables were collected at 3.3–10 Hz. Five video views were collected at approximately 7.5 Hz, including forward, rear, the driver’s face, and an over-the-shoulder view capturing the driver’s hands and reach to controls. The instrumentation was made unobtrusive by using small components and hiding components where possible.

Data-mining methods were used to locate crashes and near-crashes in the approximately 2,000,000 mi (3,200,000 km) and 43,000 hours of driving data. This data mining was designed to include many false triggers to avoid missing actual conflicts. Reductionists reviewed videos along with parametric data to determine whether a trigger identified a crash or near-crash. The operational definition of crash used in the original study was: “contact with an object...in which kinetic energy is measurably transferred or dissipated” (Dingus et al., 2006, p. 6). Near-crashes were situations in which a “rapid, evasive maneuver” (Dingus et al., 2006, p. 6) was required to avoid a crash. Lesser traffic conflicts were also analyzed but were not included in the present report.

Data Preparation

The 100-Car vehicles were instrumented with the intention of piloting large-scale data collection methods, and recording a range of environmental, traffic, and driver-related measures. Starting with the events identified in the original data collection, 13 rear-end crashes and 70 rear-end near-crashes were selected for inclusion in the present research. These crashes represented all of the rear-end crashes that were collected with complete video records. Sixty near-crashes were selected randomly from approximately 400 rear-end near-crashes. Ten additional near-crashes were included that were cases where the subject vehicle departed the lane to avoid a rear-end collision. These 83 events represent a test set on which the algorithms were evaluated.

The data were reviewed using data-visualization software to determine completeness of the parametric data and to collect initial landmarks that would serve as start and end points in kinematic analysis. Custom software permitted review of the parametric data synchronized with the video data. To focus on alert algorithm design, rather than other system aspects such as sensor design or target selection algorithms, two simplifications were made. First, the lead vehicle was manually identified in the radar data. Second, if there were dropouts or missing data in the original data, the data were reconstructed using one or more alternative variables. Reconstructed variables were checked either through comparison to alternate vehicle data or by testing the reconstructed variables against equations of motion. The events were also reviewed frame by frame to record where the drivers were looking over time and when the lead-vehicle brake lights were on or off.

Model Algorithms

Three kinematics model-based algorithms were tested analytically. Each of the algorithms provided unique design characteristics. The first algorithm, described by Knipling et al. (1993), was used to perform initial estimation of rear-end CAS benefits. Of the three tested, it is the only one that did not have a low speed threshold (i.e., low-speed cut-off), thus it was operation at all speeds. An early algorithm developed by the Collision Avoidance Metrics Partnership (CAMP) is unique in that it is based on research investigating the last-moment timing of driver braking. In this CAMP Linear algorithm (Kiefer et al., 1999), a regression equation is used to interpret conditions ahead and estimate the point where driver braking is required based on driver braking measured in test track scenarios. The third algorithm, developed by NHTSA and refined by Brunson et al. (2002), is unique in two respects. It includes driver-selectable settings that guide the algorithm performance, and it uses a multi-stage alert. The CAMP Linear and NHTSA algorithms also included low-speed cut-offs. Each of the algorithms is described in additional detail in subsequent sections.

The Knipling et al. (1993) algorithm uses two equations, one for a lead-vehicle-stationary situation and another for a lead-vehicle-moving situation. The algorithm computes a range at which a warning is given (r_w) based on three variables: following-vehicle speed (v_{FV}), lead-vehicle speed (v_{LV}), and acceleration of the lead vehicle (a_{LV}). The algorithm parameters are an estimation of time delay for the driver and braking system (t_d), and anticipated deceleration level

of the following vehicle (a_{FV}) once the driver responds to the alert. A time delay of 2.05 s is used and an anticipated following-vehicle acceleration of $-0.6g$. These variables and parameters, input into Equation 1, provide the warning range in lead-vehicle-stationary scenarios.

$$r_w = t_d v_{FV} + \frac{v_{FV}^2}{2a_{FV}}. \quad [1]$$

In lead-vehicle-moving scenarios, Equation 2 is used.

$$r_w = \frac{v_{FV}^2}{2a_{FV}} + t_d v_{FV} - \frac{v_{LV}^2}{2a_{LV}}. \quad [2]$$

The equations are evaluated simultaneously. If the computed warning range (r_w) is less than the current range, the driver receives a warning. No limitations are indicated in Knippling et al. (1993) as to the speeds for which the algorithm was designed.

The second alert algorithm tested, which was developed by CAMP is somewhat primitive compared to more recent efforts by CAMP (Kiefer et al., 2003), but was selected for several reasons. First, rather than using a set estimation of how hard the following driver will brake once the alert is provided, the CAMP Linear algorithm (Kiefer et al., 1999) varies the estimate of how hard a driver will respond based on a linear regression estimation. The regression equation was developed by measuring the necessary average deceleration at the time drivers braked on a test track. Driver responses were measured for different initial conditions. The second reason for use of this algorithm is that the description found in the literature includes specification of details that would be expected in actual implementation. For example, speeds at which the algorithm is operational are defined as well as methods used to squelch cases that meet the computed criteria, but would be inappropriate for a warning in production.

The CAMP Linear algorithm logic begins with prediction of speed of the lead vehicle (v_{LVP}) and following vehicle (v_{FVP}) after a driver and braking-system response delay (t_d). The prediction for following-vehicle speed is

$$v_{FVP} = v_{FV} - (a_{FV})t_d \quad [3]$$

where v_{FV} and a_{FV} are speed and acceleration of the following vehicle, with negative values indicating deceleration. The predicted speed of the lead vehicle after the time delay is

$$v_{LVP} = v_{LV} - (a_{LV})t_d \quad [4]$$

The results of Equations 3 and 4 are input into Equation 5, which is an estimate of the average deceleration needed when attentive drivers braked at the last moment in similar conditions. This required-deceleration estimate sets both the last-moment timing of braking and the magnitude of deceleration that are needed.

$$\text{Decel Required} = -5.308 + 0.685 * a_{LV} + 2.570 * (v_{LV} > 0) - 0.086 * (v_{FVP} - v_{LVP}) \quad [5]$$

In Equation 5, a_{LV} is the current acceleration of the lead vehicle. The third term is set to 1 when the lead vehicle is moving and 0 when stationary. Three cases describing the state of the lead vehicle before and after the response delay are used to set up appropriate terms in equations of motion. Each case estimates when braking needs to begin, given the regression-based estimate of how hard the following-vehicle driver will decelerate. An additional distance is added to accommodate the range lost during response delay. If the sum of the range at which braking needs to begin and the range lost during delay is greater than the current range, then an alert is given. The time delay for the driver and system is set to 1.72 s. This algorithm is operational at following-vehicle speeds of greater than 10 mph (16 kph).

The third algorithm, which was developed by NHTSA and further refined by Brunson et al. (2002), incorporates three driver-selectable sensitivity settings (near, middle, and far) to accommodate different driving styles and also generates early, intermediate, and imminent warnings to the driver. The “near” sensitivity setting, which could be considered a more aggressive setting, uses an estimate of the maximum expected following-vehicle deceleration of 0.38g to trigger the “early” warning, 0.45g for the “intermediate” warning, and 0.55g for the “imminent” warning. The “far” sensitivity setting, which could be considered more conservative, uses an estimate of maximum expected following-vehicle deceleration of 0.27g to trigger the “early” warning, 0.35g for the “intermediate” warning, and 0.55g for the “imminent” warning.

The logic of the alert first determines the time required for the following vehicle to stop given the driver's selected warning sensitivity and the associated lookup table values, and the time required for the lead vehicle to stop based on its current speed and acceleration. These times are then used to predict the reduction in range occurring during a response-time delay and during deceleration. An estimate is computed using the acceleration level (a_{FVmax}) for each of the three alert levels. The alert level provided to the driver is the level of the highest alert that indicates an estimated remaining range which is less than a minimum allowable range. The minimum allowable range is computed as 2 m with an additional adjustment for speed of the following vehicle. A 1.6-s driver-plus-system delay estimate is used if the following vehicle driver is not braking at the time of the alert. This delay estimate is reduced to 0.5 s if the driver is already braking at the time of the alert. The algorithm is specified to be operational at speeds greater than 20.57 mph (33 kph), once the host vehicle has exceeded 25 mph (40 kph). In the present investigation, the algorithm is operational whenever following-vehicle speed is greater than 20.57 mph (33 kph). The algorithm description includes a tailgating mode, which was not modeled. Also, the algorithm literature specified that an alert would be presented if conditions were present for two out of three previous samples. In this modeling effort, the alert was issued on the second sample after an alert condition first occurred. The model of this algorithm permitted selection from the three sensitivity settings. In most of this report, output from the "near" sensitivity setting will be reported due to its lower frequency of false alarms compared to the "middle" and "far" settings, as well as when compared to the other two algorithms tested.

General Limitations to Modeling

To narrow the scope of the modeling effort, the following assumptions and limitations were applied to all of the algorithms:

- Time samples in the parametric data are assumed to be 0.1 s apart and kinematic analysis is limited to this resolution.
- No effort was made to model the duration of alerts or termination of alerts. With the exception of the NHTSA algorithm, if conditions for an alert were met for one time sample (0.1 s), this was considered an alert. For the NHTSA algorithm, which specified requirements, two samples were required for an alert.
- Alerts occurring prior to the event of interest were not included in this analysis.

- In some of the algorithm literature, methods are proposed for addressing noise in measurements and radar dropouts. In this effort, some corrections for radar dropouts or anomalies were included as described in the Data Preparation section. These corrected data were provided equally to the three algorithms.
- The lead-vehicle radar track was manually identified by a researcher using video and radar data.

Kinematic Analysis

A kinematic analysis was conducted to measure the severity of the events and determine the last point in time when braking was required to avoid collision. In the crashes, the driver's response was either too late, not sufficient to avoid, or not present. In near-crashes, the driver avoided, but responses could be more than the minimum necessary or earlier than the last possible moment. Therefore, rather than evaluating the events using measures of when or how severely the involved driver responded, kinematic analysis was used to quantify the events according to what response was necessary at what time.

In the kinematic analysis, using the point in time just prior to when the following driver responded, the two vehicles were placed in a coordinate system based on the range at that time. With the initial location of the following vehicle providing the zero point, the range (x_i), speed (v_i), and acceleration (a) of the vehicles were input into Equation 6

$$x_{i+1} = x_i + v_i t + \frac{1}{2} a t^2 \quad [6]$$

at each subsequent time sample to determine the position of the vehicles in the coordinate system. The acceleration of the lead vehicle (a_{LV}) was computed using Equation 7

$$a_{LV} = a_{LV} + \ddot{r} \quad [7]$$

where \ddot{r} is the time derivative of range taken from the radar, a_{FV} is the acceleration of the following vehicle taken from an accelerometer. During analysis of the events, it became apparent that once heavy braking by the following driver occurred, Equation 7 became inaccurate. This was noted by comparing estimated lead-vehicle acceleration from Equation 7 to additional data, such as whether or not the brake lights of the lead vehicle were on, or whether or not it would still be moving forward given the computed acceleration. To address this, the input

lead-vehicle acceleration used in Equation 6 was altered. The inaccurate acceleration data from the point where the following-vehicle driver responded forward was replaced with a continuation of the lead-vehicle acceleration observed before the following-vehicle driver responded. The lead-vehicle speed was still collected from the radar for input into Equation 6. The contribution of the acceleration term in Equation 6 is small compared to the velocity term, and error did not accumulate from one time sample to the next. In this way, any error between the estimation of lead-vehicle acceleration and actual acceleration had minimal effect on position estimation because lead-vehicle velocity was updated at each time sample.

Having located the position of the lead vehicle over time in the coordinate system, software routines were then applied to evaluate different alternative outcomes. The first alternative explored represented a situation in which the following-vehicle driver never responded. The following-vehicle speed and average acceleration level from just prior to driver response were projected forward in time to determine when collision would have occurred had the driver not responded. The next alternatives determined the last point in time when different decelerations by the following-vehicle driver would be sufficient to avoid colliding. Driver response deceleration levels of $0.4g$ to $0.85g$ have been used in previous algorithm-related work (Knipling et al. 1993; Brown et al. 2001). In this work, $0.5g$, $0.675g$, and $0.85g$ were used with the intention of testing a set of decelerations that includes drivers braking hard in actual events as well as what automated, or assistive braking systems would achieve. If the following-vehicle driver braked before one of these levels was necessary, following-vehicle speed and position from before the driver's response were predicted forward up to where the tested deceleration would begin. If the tested deceleration would need to occur before the driver braked, actual values were used up until the point where the tested deceleration began. Details of this process are provided in Chapter 2.

Two alternatives were explored in the model of test deceleration. In the first alternative, no allowance for brake onset time was included. It is assumed that at the time the driver responds, the deceleration goes immediately to the tested level. To avoid collision, the test braking level would need to be applied at or before the point indicated and the level would need to be sustained until closing speed goes to zero. In the second alternative, the application is still modeled as a step function, but a time delay is added to reach the tested deceleration level. Delays of 0.2 s, 0.3 s and 0.5 s were used for the deceleration levels of $0.50g$, $0.675g$ and $0.85g$

respectively. These delays represent approximations of the time required for drivers to reach these levels of deceleration (McLaughlin et al., 2005). The kinematic analysis conducted on each of the events determined when braking needed to occur and be maintained at each of the three levels to avoid colliding.

Algorithm Performance Metrics

As described in the beginning of the Methods section, the performance of the different algorithms was primarily measured as the percentage of the population that is predicted to avoid colliding in the tested collisions. To calculate this metric, the time-series event data were input into the algorithm models, and the time at which the alert would have occurred was identified. The kinematic analysis was then used to determine when deceleration was necessary to avoid collision. Next, cumulative response-time distributions were used to estimate the percentage of the population who would be expected to respond between the time of the alert and the time when deceleration needed to start. The frequency of false alarms that might be generated due to the algorithm design was also estimated. This was done by inputting driving data from three trips without crashes or near-crashes and determining the number of times an alert would have occurred.

Sensitivity Analysis

To address the uncertainty in some of the parameters in the evaluation methodology, alternatives were tested. The three deceleration levels described in the Kinematic Analysis section and the two approaches to applying the test deceleration (i.e., with a delay and without) permit exploration of the range of outcomes that might be expected according to different assumptions. Exploration of three deceleration levels provide an indication of how the results vary based on how hard the driver or driver-assistance system will respond to an alert. Similarly, changes in outcome according to two fairly primitive models of brake onset are considered. One approach does not account for brake onset at all (no delay) and one includes a delay (but still without ramp up to a deceleration). The actual result would be expected to fall between these two onset modeling approaches. Performance of the algorithms according to initial following-vehicle speed was also computed.

Similarly, human response times differ depending on factors such as the stimulus, number of response alternatives, and expectancy (Wickens, 1992). Two response-time

distributions were used in the evaluation. The two distributions together, one faster and one slower, serve to bracket the expected range of response times. Sivak et al. (1981) measured response time by capturing a vehicle in traffic between two experimental vehicles, then illuminating the brake lights of the lead vehicle and measuring the time until the observed vehicle brake lights came on. A distribution from their work, shown in Figure 10, provides the slower response-time distribution of the two used in the present analysis. Application of their distribution in the rear-end CAS situation includes some construct agreement, but there are also differences. In their testing, the lead vehicle did not decelerate and so the following vehicle did not need to decelerate. In fact, in approximately 50% of the trials, the following driver never applied brakes in response to the lead-vehicle brake lights. In the crashes and near-crashes considered here, hard braking was required. Their scenario also was purely a car-following situation. The events used here, and events to be addressed by rear-end CASs, also include situations with approaches to slower or stopped vehicles. The second response-time distribution (Johansson and Rumar, 1971) was selected to provide representation of a more rapid response. The Johansson and Rumar distribution (Figure 10) was developed by measuring the brake response time of drivers upon hearing a klaxon (loud horn). The participants were driving on their own after being informed of the study. The sound was presented approximately 5 km from where the participants received instructions.

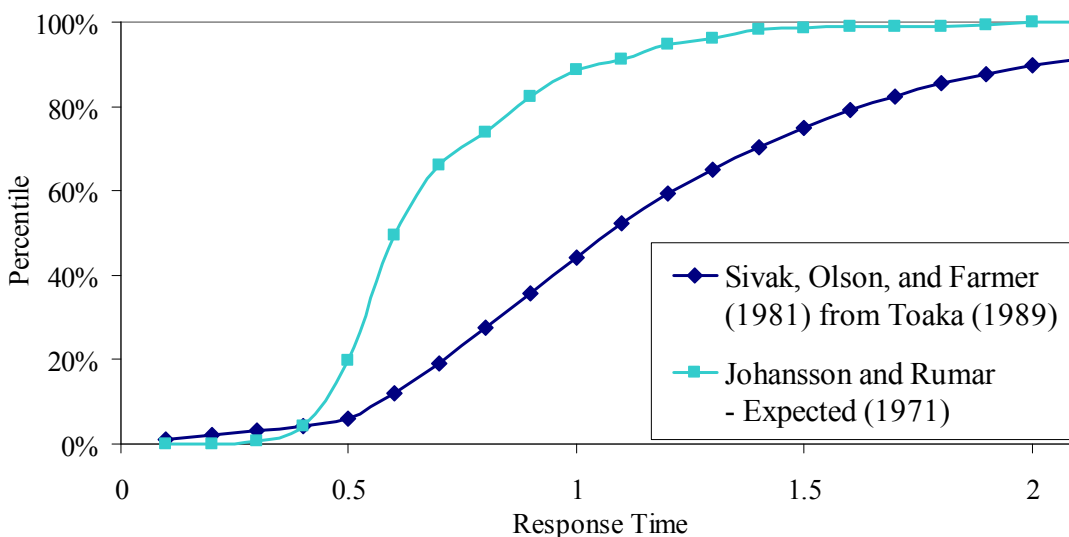


Figure 10. Driver braking response-time distribution alternatives.

Input Data

The evaluation method used in this research purposefully attempts to exclude the response of the involved driver; however, the timing of the start of the driver's response does dictate the time span covered in a prediction of outcomes used in the analysis. The events included in the test set are also likely to be influenced by driver demographics. Sixty drivers only had one event included, five drivers had two events, and one driver had three events. There were 34 events in which a female was driving and 49 events in which a male was driving. The age of the driver was identified if available. Drivers in ten of the events were not primary study participants, and so their ages are unknown. A summary of the events and the age of the drivers are shown in Table 2.

Table 2. Summary of events and driver ages.

Age	Number of Events
18-19	11
20-29	27
30-39	7
40-49	15
50-59	11
60-69	2
Unknown	10
Total	83

The data used in evaluating the CAS algorithms represent 13 rear-end crashes and 80 rear-end near-crashes. The approximate conditions found in the events are reported according to the conditions present 2 s prior to impact. Following-vehicle speeds ranged from 1 mph (2 kph) to 62 mph (99 kph), with a mean speed of 29 mph (47 kph). The highest closing speed (range rate) was -30 mph (-49 kph). In one event, at the time the data were recorded, the vehicles were separating at 2 mph (4 kph). Mean closing speed was -9 mph (-14 kph). The range to the lead vehicle varied from 4 ft to 212 ft (1.1 m to 36.9 m), with a mean range of 39 ft (11.8 m). Lead-vehicle acceleration in the events varied from -0.52g to 0.29g with a mean acceleration of -0.19g. These and further details describing the conditions in the events are summarized in Table 3. In this summary information, time-to-collision values of greater than 20 s are omitted.

Table 3. Summary of event measures 2 s before impact.

Measure	Min	Median	Mean	Max
Range (ft) / (m)	4 / 1.1	36 / 10.9	39 / 11.8	121 / 36.9
Following-vehicle speed (mph) / (kph)	1 / 2	31 / 50	29 / 47	62 / 99
Following-vehicle acceleration (g)	-0.41	-0.03	-0.05	0.31
Lead-vehicle speed (mph) / (kph)	0	19 / 31	19 / 31	54 / 88
Lead-vehicle acceleration (g)	-0.52	-0.22	-0.19	0.29
Range rate (mph) / (kph)	-30 / -49	-9 / -14	-9 / -14	2 / 4
Headway (s)	0.3	-0.9	1	3.3
Time-to-collision (s)	0.6	-2.7	3.2	11.5
Time-to-collision w/ lead-vehicle acceleration (s)	0.3	1.8	1.9	4.9
Rate of angular expansion (rad/s) : assumed 6 ft (1.8 m) wide lead vehicle	-0.02	0.06	0.1	0.75

In addition to providing warning of potential collisions, an effective CAS must also have an acceptable level of false alarms. False alarms can arise due to sensor design, target selection logic, or algorithm designs. The objective of this study was to evaluate kinematic algorithm design. To focus on this area, video of the events was reviewed and the data were reduced to include only in-path lead vehicles and eliminate radar data representing roadside objects, overhead structures, or vehicles in adjacent lanes. Three trip files were used from three different drivers, covering approximately 24 total miles (39 km) of driving over one hour. The number of in-path vehicles per trip file ranged from 17 to 56. Maximum speeds for the three trips ranged from 44 to 65 mph (70 to 105 kph).

Results

Across the events and parameter alternatives (i.e., two reaction-time distributions, three levels of deceleration and two brake onset methods), the Knipling et al. and CAMP Linear algorithms were found to provide warning sufficient for approximately 70% of the population to respond and successfully avoid (Figure 11). The NHTSA algorithm, set to the “near,” or least conservative setting, provided warning in sufficient time for approximately 50% of the population to avoid.

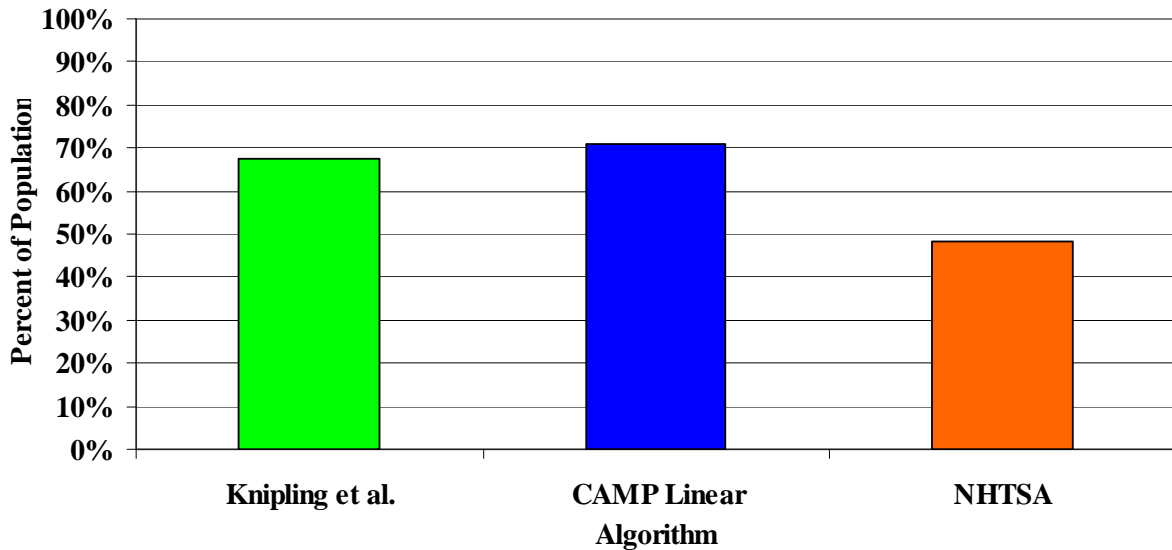


Figure 11. Percentage of the population who could avoid.

In Figure 12, the frequency of alerts is translated into an estimate of the number of alerts drivers would experience per mile driven.

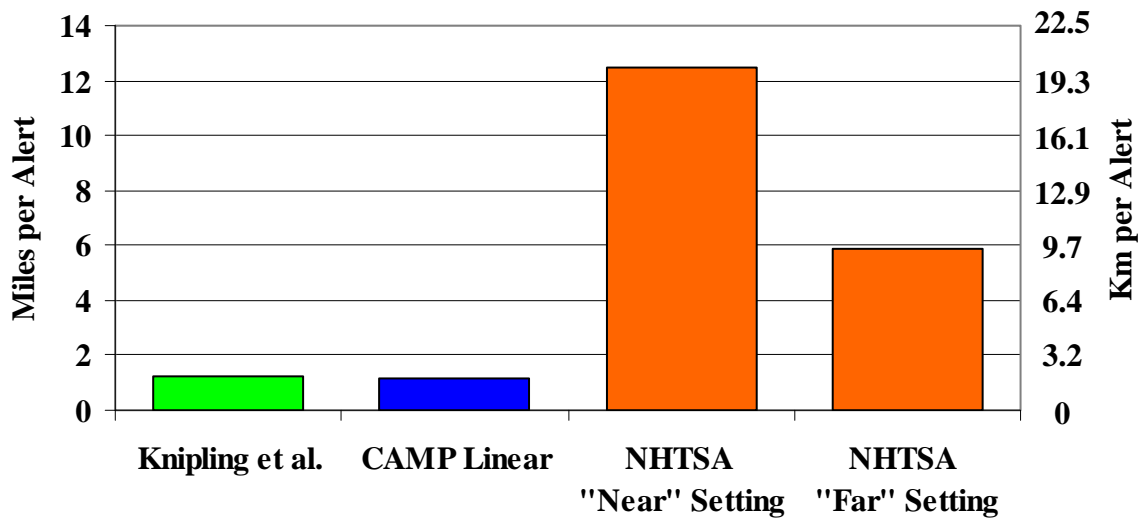


Figure 12. Estimated distance between alerts.

The Knipling et al. algorithm and the CAMP Linear algorithm generated alerts approximately twelve times more frequently than the NHTSA algorithm set to a “near” setting (i.e., low sensitivity setting) and six times more frequently than the NHTSA algorithm set to the “far” setting. The remainder of the results describes variations in algorithm performance in different scenarios and the responsiveness of the evaluation metrics to variation in parameters.

When using the faster response-time distribution of Johansson and Rumar, the estimate of the percentage of the population able to avoid was approximately 15 percentage points higher than estimates using the Sivak et al. distribution. Across all of the alternatives tested, the estimate of the percentage able to respond if the distribution of Johansson and Rumar is more appropriate is 70%, while with Sivak et al. it is 55%. The outcome of the model differs by approximately 10 percentage points when results for the 0.5g following-vehicle response deceleration are compared to the 0.85g deceleration. The difference from 0.5g to 0.675g is 8 percentage points. The difference between 0.675g and 0.85g is approximately an additional 2% of the population able to avoid if 0.85g is the better estimate of driver response capabilities. The result of the delay of braking to account for brake onset is a reduction in the estimate of the percentage of the population able to avoid. When the onset of the tested level of driver deceleration is applied without delay for braking onset, the estimate of the percentage of the population able to avoid is 66%. Application of a delay to account for time consumed during the onset of deceleration reduces the percentage able to avoid by 8 percentage points.

To investigate the performance of the algorithms in different speed ranges, the events were divided into 10-mph (16 kph) speed groups, and the estimated percentages of the population that might be expected to avoid collision were averaged across the events within each speed group. In Figure 13, the results of this analysis are shown using the data in which the delay is included to reach a 0.5g deceleration level.

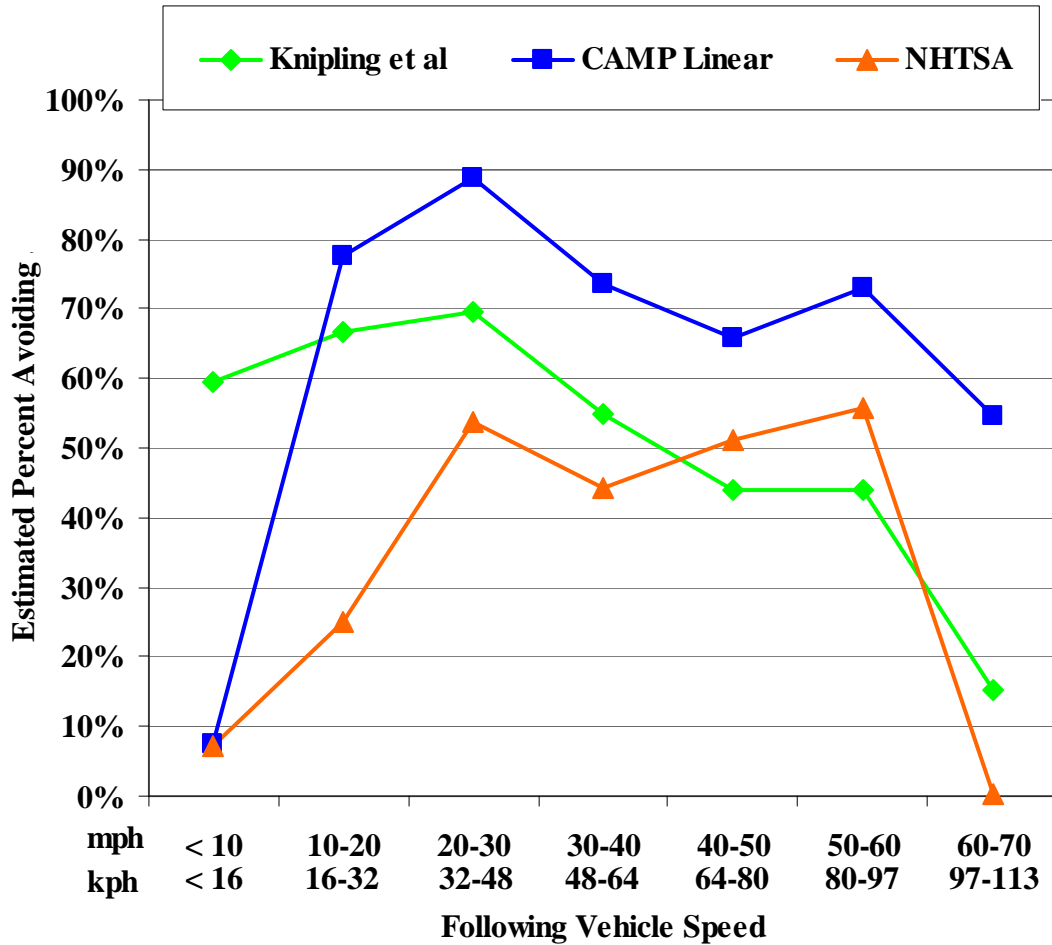


Figure 13. Percentage avoiding collision by speed assuming a 0.5g deceleration occurring with the brake onset 0.2 s delay.

Differences between the algorithms are evident in the low speed ranges. The CAMP Linear algorithm is disabled below 10 mph (16 kph) and the NHTSA algorithm is disabled below 20 mph (32 kph). The benefit that is shown for these two algorithms below their thresholds is due to events where the alerts occurred when the following-vehicle speed was above the threshold and decreasing. The driver's response, which is when the speed data were collected for this analysis, did not occur until speed was below the threshold. In the middle speed ranges, the CAMP Linear and Knipling et al. algorithms both exhibit decreasing effectiveness as speed increases. The NHTSA equation is closer to flat or increasing. In the 60–70 mph (97–113 kph) speed range, performance of the algorithms is lower than in the middle speed ranges. The same analysis of CAS performance across speeds is portrayed in Figure 9 with a 0.85g assumed response deceleration rather than the 0.5g assumption shown in Figure 13. The benefit gained by a higher response deceleration generally increases as the speed of the event increases. For

example, in the 60–70 mph (97–113 kph) speed range, if this 0.85g level of deceleration could be achieved, each of the algorithms show increased benefit to an additional 20% of the population.

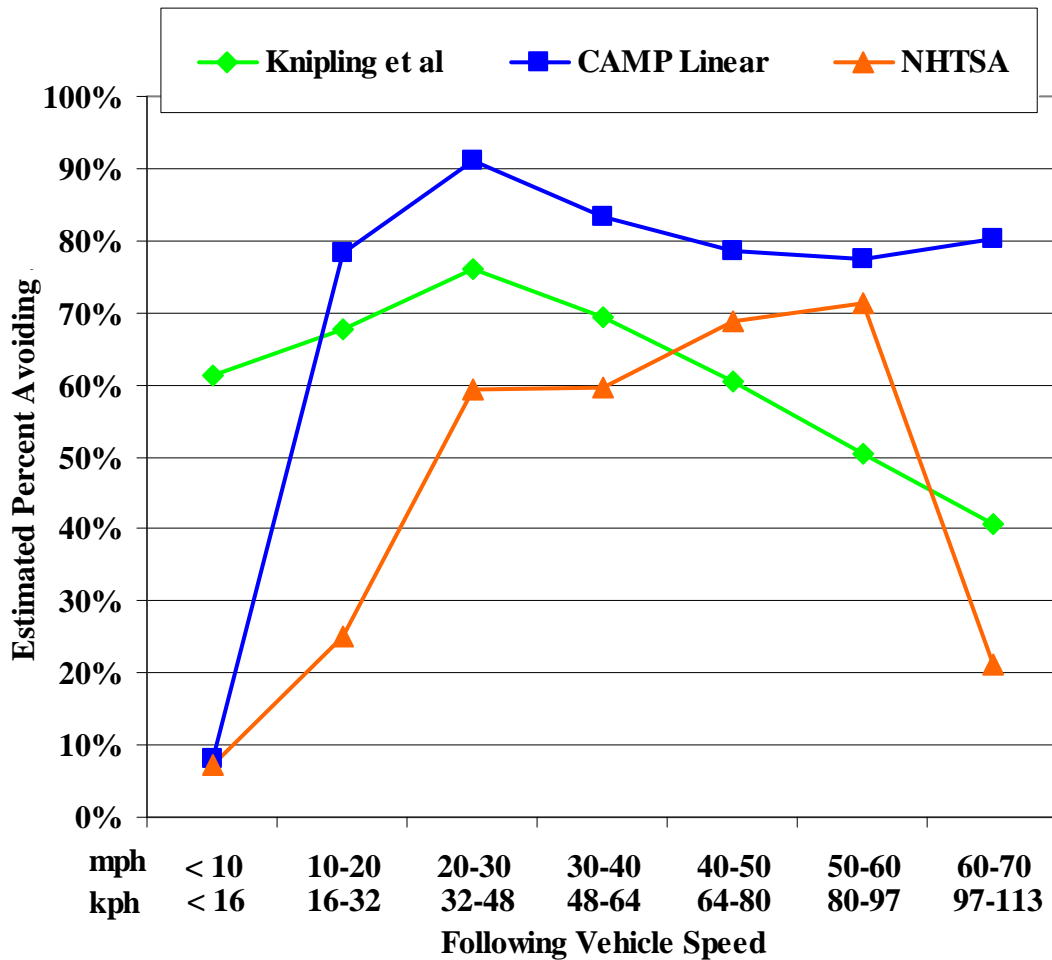


Figure 14. Percentage avoiding collision by speed assuming a 0.85g deceleration occurring with the brake onset 0.5 s delay.

When the combinations of the two response times are tabulated with the three investigated levels of deceleration, combinations of the parameters can be explored (Figure 15). As seen in the overall results, the CAMP Linear generally had the highest estimated benefit, followed by Knipling et al. and then NHTSA. The Johansson and Rumar distribution indicate higher estimated benefits for each algorithm when compared to estimates made using the Sivak et al. distribution. Also, the larger improvements of 0.675g over 0.5g as compared to 0.85g over 0.675g were found. Within the Johansson distribution estimates, the separation in outcomes for the algorithms is larger for the 0.5g parameter setting than for the 0.85g setting.

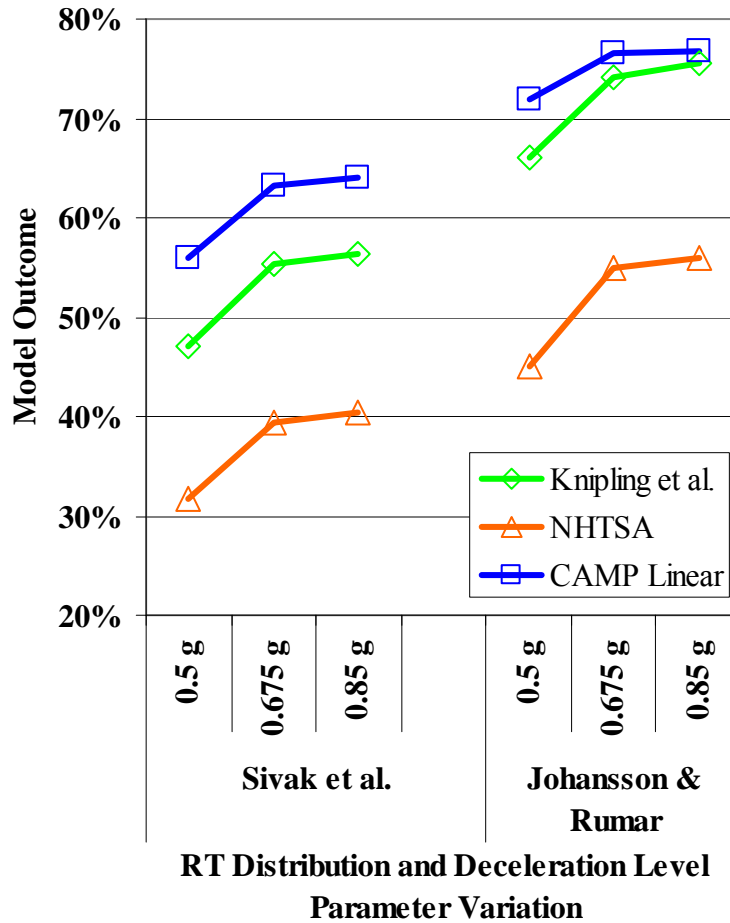


Figure 15. Percentage avoiding collision by RT distribution and deceleration level.

Conclusions

Some consideration of the estimated alert frequencies is needed before making further conclusions. It is difficult to determine what frequency of collision avoidance warnings would be both acceptable and beneficial to drivers. In addition to frequency, acceptance or annoyance will also be tied to the interface design and the desired response. In a test of 30 CAS sounds (Kiefer et al., 1999), participants on average indicated the sounds would be annoying if they occurred once a day when no response was needed. Another source of information comes from a field operational test (University of Michigan Transportation Research Institute and General Motors Research and Development Center, 2005) in which drivers received alerts from a prototype forward collision warning system at rates of between 15 and 71 mi (24–114 km) between alerts, depending primarily on algorithm and driving style. Drivers tended to have negative impressions of these systems, and as potential improvements, most commonly

recommended reducing the frequency of alerts or providing a method for turning the system off. Based on this, the three algorithms tested would not be acceptable or effective. Due to the high alert frequencies for the algorithms tested, evaluation of algorithm benefits in absolute terms will be limited here.

The algorithms performed differently at different speeds. At the lowest speeds, only the Knippling et al. algorithm was operational, and so achieved benefit there. Effectiveness reduced as speed increased with the Knippling et al. and CAMP Linear algorithms, particularly when lower driver response decelerations are assumed. Differences found between the two reaction-time distributions tested indicate that with the generally faster responses found in the Johansson and Rumar distribution, within the available time between alert and the need to brake, a higher percentage of the population is expected to be able to respond. Larger differences were found between 0.5g and 0.675g. This is due to the timing of when the different levels of deceleration are required, which in turn is due to the deceleration. The time separation between when 0.675g and 0.85g are needed is shorter than the separation between when 0.5g and 0.675g are needed, indicating that the model is more sensitive to errors in assumptions if the decelerations drivers achieve in actual events are closer to, or lower than, the lower decelerations tested here.

Discussion

This research provides the first test of CAS algorithms using data collected from crashes and near-crashes as they developed in natural driving. To provide an evaluation of algorithm performance in truly hazardous conditions, the method makes use of the overlap between proposed CAS sensing systems and instrumentation systems used to collect driving data in the natural environment. Kinematic analysis of the events provided a boundary against which the timing was measured. Adjusting parameters and exploring combinations of different parameter settings permitted investigation of changes in algorithm performance according to different assumptions. Additionally, where differences were observed in output, it was possible to work backwards from the results to determine what elements of the algorithms and events created the observed differences.

The CAMP Linear algorithm generally provided the greatest available time between alert and the need to brake, which translates to a higher percentage of the population able to respond. Though the alert with the Knippling et al. algorithm was later than with the CAMP Linear

algorithm, it was active in low-speed situations where the CAMP Linear algorithm was not. Two characteristics of the NHTSA algorithm created overall lower values in this evaluation. The NHTSA algorithm used a reduced reaction time for cases where the driver was already braking at the time of the event. This causes alerts to be later. The method of evaluation used here does not include an adjustment for this. The NHTSA algorithm also is not active at speeds below 20 mph (32 kph). Of the 83 events in the test set, approximately one-quarter of them occurred when the following-vehicle speed was below 20 mph (32 kph).

The downward notch in the NHTSA algorithm performance in the 30–40 mph (48–64 kph) speed range is primarily due to the reaction time adjustment in situations where the host-vehicle driver is braking. The NHTSA algorithm assumes a faster reaction time in this situation, and so delays alert. The actual benefit in these situations would likely be higher. Performance of all three algorithms dropped in the 60–70 mph (97–113 kph) speed range. In this speed range, there were only two events in the data set. In both cases, the drivers were braking early in the event. In one, the following-vehicle driver had just entered the lane behind a slower-moving lead vehicle and was already decelerating to match speeds when the lead vehicle braked. In the second event the following-vehicle driver started braking lightly early, but of an insufficient amount to address the situation. This braking delayed the presentation of the NHTSA alert in both events past the point where 0.5g deceleration was required to avoid. For the Knipling et al. and CAMP Linear algorithms, the severity of the scenario restricted their potential avoidance benefit, particularly if the response deceleration was 0.5g.

The braking level and response-time distribution parameters had the largest impact on the estimate of percentage of the population who would avoid collision. The sensitivity of the output is highest at the low end of the braking level parameter. Additionally, it appears that the unassisted driver infrequently maintains a deceleration of 0.5g or higher (see Chapter 4). Based on this, it may be appropriate in future evaluations of CASs to test at a lower anticipated deceleration level than 0.5g. In terms of system design, relative to entirely driver controlled braking, large benefits would be achieved by systems that support the driver in establishing and maintaining decelerations of 0.675g or higher. Rather than anticipating an increase in performance over what is recorded here, it may be necessary to rely on this type of assistive braking as part of a rear-end CAS simply to reduce the frequency of alerts to some acceptable level.

The algorithms tested here make use of response-time parameters more similar to the Sivak et al. (1981) data, which had a mean reaction-time value of roughly 1.4 s. Driver response-time values used in the three algorithms were 1.5 s for all three of the algorithms. In the Johansson and Rumar (1971) data, the median was roughly 0.7 s. The percentage of drivers able to avoid increased by 15 percentage points when the driver-input timing was altered in this way. Based on this, the response-time parameter used in the algorithms could potentially be shortened to achieve lower false-alarm rates. Further investigation of the effects of this is advised, however. If drivers were to begin to rely on a system that assumed a faster response time than typical, Brown et al. (2001) indicate higher impact collisions would arise in events that develop at longer headways.

Performance of the algorithms varied with speed. Benefits of the NHTSA and CAMP Linear algorithms are absent in low-speed events. Based on crash databases, approximately 25% of all crashes occur on roads with speed limits of 30 mph (48 kph) and below (National Highway Traffic Safety Administration, 2007a). Dingus et al. (2006) have estimated that unreported accidents may be five times the number of reported accidents. It is reasonable to expect that more low-speed accidents go unreported and so are not included in the databases. All of the algorithms provided the highest benefit at speeds between 20 and 30 mph (32 and 48 kph). The NHTSA algorithm results in the 50–60 mph (80–97 kph) speed range were close to the results in the 20–30 mph (32–48 kph) range. The CAMP Linear algorithm maintained a closer-to-constant benefit as speed increased when compared to the generally decreasing benefit obtained by the Knipling et al. algorithm.

For the purposes of discussion, it is helpful to select from the possible combinations of the evaluation parameters. A separate analysis of the driver responses in the events (see Chapter 4) indicated that the average driver deceleration would likely be closest to the 0.5g level, but may be below this level. Until further evidence is available, the 0.5g deceleration estimate, with a delay for brake onset, will be used to approximate a human responding without assistive support such as active braking. The Johansson response-time distribution will be used as a fast response-time estimate and the Sivak distribution results will be used as a slower response-time estimate. Finally, with the NHTSA algorithm as the closest to realistic for implementation, the results indicate that when presented with this alert in rear-end events like those tested here, on average 30–50% of the population would be able to brake to avoid collision.

A second combination of parameters can be used to approximate a maximum achievable benefit. This combination might be used to estimate benefit, for example, of a system that pressurizes the brake system in preparation for driver response, provides an effective alert to the driver, and upon being triggered by the driver's brake press, assists the driver in reaching and maintaining a braking level approaching the limit of the vehicle's capabilities. This combination would represent an ideal for a driver in the loop system achieving ideal interactions of system components and the driver. For this approximation, the 0.85g average-braking assumption will be used in combination with the shorter response-time distribution. Based on this combination of assumptions, approximately 60% of the population would avoid collision by braking.

Some interaction was found between the response-time distributions and the braking levels. In the three generally early warning algorithms that were tested, with the shorter response times of the Johansson estimate, differentiation of the algorithms is reduced by the time a higher braking level is required. The Knipling et al. algorithm has its best overall results when the algorithms are evaluated with the shorter response-time distribution and the high deceleration assumption. In most scenarios, the Knipling alert occurs shortly after the CAMP Linear alert. In low speed events, where the kinematic deceleration boundaries come close together, and where the alert conditions arise closer to the need to brake, the combination of a short response-time distribution and a hard-deceleration assumption create advantage to the Knipling algorithm while the inactive algorithms see no benefit.

There are a number of areas in which additional investigation would be useful. As algorithm development progresses, the next effort will be to develop more rigorous testing of algorithms for false alarms. This will include increasing the quantity of normal, non-event driving used in the testing and establishing methods for testing for algorithm differences across a range of driving styles, traffic conditions, and in particularly troublesome scenarios for algorithms. A method for translating the frequencies of false alarms into a measure of acceptance or annoyance is also warranted. Experimental approaches could be used to establish relationships between alert frequencies and alert acceptance. These relationships could then be used to evaluate alert frequency results.

The assumption of a reduced reaction time for drivers who are already braking used in the NHTSA algorithm is a reasonable assumption. Accuracy of the present results would be

improved either by estimation of outcomes with and without this feature of the algorithm active, or by application of some foot-on-brake response-time distribution within the evaluation method.

Based on this work and others, the challenge of achieving false-alarm rates that are acceptable deserves considerable attention. The present work and other ongoing work are beginning to provide potential guidance in this area. Chapter 4 of this dissertation reports shorter response times in rear-end crash situations than were previously expected. Reduction in the anticipated driver response time within algorithms could reduce the number of false alarms. Various researchers have defined limits of where steering may be effective for collision avoidance (Talmadge et al., 2000; Smith et al., 2003; Kiefer et al., 2003). These limits could be incorporated into the algorithm evaluation in a manner similar to the location of deceleration points. Where steering to avoid is possible, additional benefit may be obtained either through increased available response time or reduction in false alarms.

Publicly available algorithms, such as those tested here, tend to be somewhat behind state-of-the-art approaches. It is likely that the use of kinematic criteria alone within algorithms will not sufficiently control undesired presentation of alerts while providing needed warnings. Current research initiatives (Resendes, R. 2007) and manufacturer descriptions of production and concept systems (Lexus, 2007) reveal efforts to incorporate additional algorithm inputs. Though not directly evaluated here, review of the events appears to indicate that intelligent interpretation of the current driving scenario could assist in reducing false alarms as well as providing driver support at low speeds. For example, a common low-speed rear-end event occurs at intersections and yield areas. Thinking the lead vehicle has departed, the driver of the following vehicle begins rolling forward while looking left. If the lead vehicle stops during this time, the following driver is often unaware. Simple sensing of this scenario could recognize the acceleration from stop of the following vehicle coincident with a lead vehicle decelerating back to a stop. More sophisticated inputs such as a right hand yaw of the following vehicle, azimuth of the lead vehicle, map data or machine vision monitoring of the driver's gaze or forward roadway could be used to further verify the scenario. Other scenarios that may be identified include flying passes and lead vehicles departing the roadway. These types of approaches may be incorporated into the tested algorithms or others, and tested in a similar manner.

The measurement of benefit in the present analysis is based on the percentage of the population expected to avoid collisions. In addition to this measure, it would be useful to

quantify the benefits obtained from reductions in collision severity. Cases resulting in collisions could translate impact speeds into injury estimates using injury scales (Knipling et al., 1993; Nance et al., 2006; Gabauer and Gabler, 2006). Results could also be translated into estimates of property damage, inconvenience, or effect on traffic.

The degree to which the events used in this analysis replicate the distribution of events in the general rear-end crash population should be evaluated. Unlike conventional crash reporting, naturalistic driving captures all collisions regardless of severity. However, limited sample sizes and lack of sample representativeness in relation to the full crash population may reduce the validity of the data. One approach to correct for such differences would be to apply a weighting method to adjust the estimates according to a larger crash population. Earlier CAS-benefit estimation approaches provide guidance in this area (Knipling et al., 1993; Tijerina et al., 1993; Chovan et al., 1994; Eberhard et al., 1995; Tijerina et al., 1995; Koopmann and Najm, 2001; Tijerina et al., 1994; Najm et al., 1995).

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Chapter 4. Rear-End Crashes, Near-Crashes, and Driver Braking Responses

Abstract

As with other system failures, automobile crashes occur as a result of and within a sequence of events. Designing potential safety interventions for crashes requires understanding the duration of the event, when different interventions are feasible, and the capabilities of drivers. Thirteen rear-end crashes and 70 near-crashes were analyzed to determine how much time drivers had to respond, how much time was required to avoid collision through deceleration, and how hard drivers decelerated. Required decelerations generally lasted less than 2 s. At the time of driver response, the time remaining to avoid collision using a 0.5g average deceleration ranged from -1.1 s (i.e., too late) to 2.1 s. In 10 of 13 crashes, no driver deceleration was present. Mean deceleration for the 70 near-crashes was 0.37g and the maximum was 0.72g. A set of three rear-end crashes and 27 rear-end near-crashes was used to investigate driver response time. These events were selected by locating crashes and near-crashes in which, without previous awareness, the driver returned his or her gaze to forward when braking was needed. Using all but the least-severe 10% of these rear-end collision-related events, the mean driver response was 0.7 s to begin braking and 1.1 s to reach maximum deceleration. Implications for collision countermeasures are considered, response-time results are compared to previous distributions, and future work is discussed.

Keywords

Rear-end crash, reaction time, driver deceleration, vehicle braking

Introduction

In 2005, 43,443 people were killed in the United States either while driving or riding in a motor vehicle, or by being struck by a motor vehicle. The number of people injured in 2005 was 2.7 million (National Highway Traffic Safety Administration, 2007b). These fatalities and injuries occur in angled, rear-end, and head-on crashes with other vehicles, crashes into trees, poles, ditches, or guard rails, and when vehicles strike pedestrians and bicyclists (National Highway Traffic Safety Administration, 2007a). A critical driving situation can arise due to a number of factors, but once present, the primary avoidance response is to brake (Manser and Even, 2002; Malaterre, et al., 1988; Lechner and Malaterre, 1991).

Our understanding of decelerations used by drivers in critical situations, as well as driver response times, is largely based on data collected in experimental settings. Driver braking responses have been collected on test tracks (McGehee et al., 2000; Smith et al., 2003; Kiefer et al. 1999), in simulators (McGehee et al., 2000; Mazzae et al., 1999; Barret et al., 1968; Broen and Chang, 1996; Lechner and Matteredre, 1991), and on the road (Lerner, 1993; Olson and Sivak, 1986). The experimental scenarios used in these studies incorporate assumptions about how events develop in real driving. Additionally, though often very realistic, the measures are collected in controlled situations with varying degrees of external validity. What occurs in the real world has been a persistent question.

This paper analyzes driver response time and driver-controlled deceleration found in rear-end crashes and near-crashes that occurred during a large naturalistic driving study employing instrumented vehicles used by drivers in their everyday driving. Crashes and near-crashes are quantified using kinematic measures. These measures provide a description of the situations in which drivers find themselves, the severity of the situations, and the time available to potentially intervene with braking. The responses of the involved drivers are also quantified in terms of timing and deceleration strength. These measures provide additional understanding of the rear-end crash problem and will be useful in developing effective roadway, vehicle, or behavior based countermeasures.

Methods

The work described in this paper uses data from rear-end crashes and near-crashes collected in the 100-Car Naturalistic Driving Study (Dingus et al., 2006). In the 100-Car study, 78 participant-owned vehicles and 22 leased vehicles were instrumented and driven for one year by the study participants. Participants were informed of the instrumentation and instructed to drive as they normally would. The manufacturer, model, and model year of the six vehicle types used in the study are shown in Table 4.

Table 4. Vehicle makes, models, and model years.

Make	Model	Model Year
Chevy	Cavalier	2002
Chevy	Malibu	2002
Ford	Explorer	1995-2000
Ford	Taurus	1996-2002
Toyota	Camry	1997-2001
Toyota	Corolla	1993-2002

The distribution of miles of driving collected for the primary participants in the study is shown in Table 5.

Table 5. Distribution of miles driven in study.

Miles Driven During Study	Number of Drivers	Percentage of Drivers
0-9000	29	26.6%
9001-12000	22	20.2%
12001-15000	26	23.9%
15001-18000	11	10.1%
18001-21000	8	7.3%
21000+	13	11.9%

Study participants lived and worked in the Northern Virginia/Metro Washington DC area. A description of the ages of participants involved in the events analyzed in the present work is provided later in this section.

The vehicles were instrumented to record subject-vehicle accelerations, yaw rate, speed, lane position, brake and gas pedal use, turn signal use, ambient light, and vehicle location. Forward- and rear-looking radar measured range to targets and speed of targets relative to the subject vehicle. The sample rate of vehicle data depended on the specific sensor. Radar data and

accelerometer data were collected at 10 Hz. Brake and accelerator pedal data were collected at 3.3 Hz to 10 Hz. Video views, collected at 7.5 Hz, included the driver's face, forward roadway, rear roadway, the driver's hands and instrument panel, and to the right rearward of the vehicle (Figure 16). Instrumentation was made unobtrusive through the use of miniature cameras and compact or hidden components.

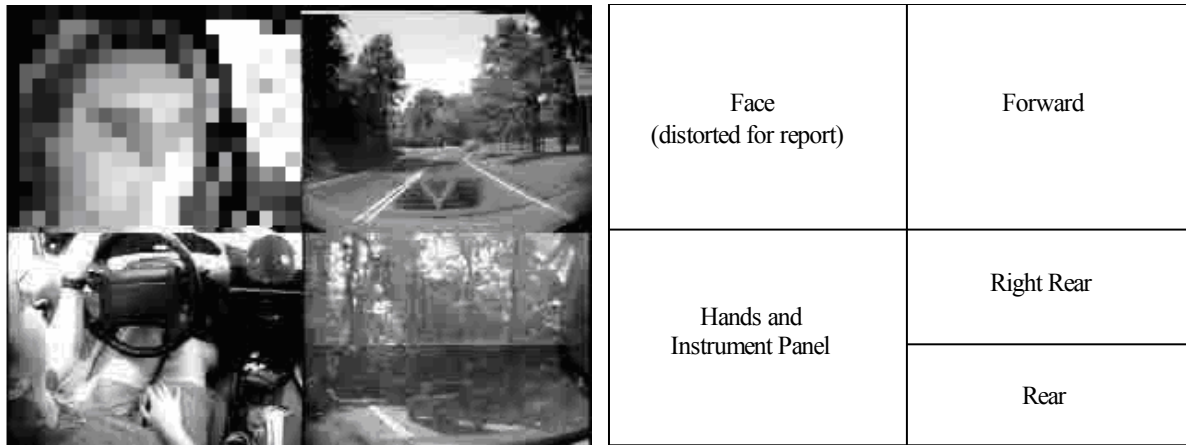


Figure 16. Video format showing five views: driver's face, forward, driver's hands and instrument panel, right rear, and rear.

The project accumulated approximately 2,000,000 mi (3,200,000 km) (~43,000 hrs) of driving data. Through data mining, analysis and interaction with participants, crashes and near-crashes of various types were identified in the driving and video data. The operational definition of crash used was: "contact with an object...in which kinetic energy is measurably transferred or dissipated" (Dingus et al., 2006, p. 6). Situations in which a "rapid, evasive maneuver" (Dingus et al., 2006, p. 6) was required to avoid a crash were considered near-crashes.

All of the events included in the present analysis involved the participant either striking, or decelerating and/or steering to avoid striking a vehicle that was traveling ahead and in the same direction as the participant. Events were selected for inclusion in this analysis in two ways. First, for the purpose of quantifying rear-end scenarios, 83 rear-end events were investigated—13 rear-end crashes and 70 rear-end near-crashes. All of these events were quantified using kinematics focusing on longitudinal measures (e.g., speed, longitudinal deceleration, range to a lead vehicle). This first set of data will be referred to as the Scenario Data. A second set of events was used to investigate driver response times. Based on criteria which will be described in subsequent sections, 18 events from the Scenario Data and 12 additional events were used in

an investigation of driver response times. This second data set will be referred to as the Response Time Data. These events were selected specifically because they involved a driver returning his or her gaze to the forward view at a time when collision was imminent.

For the 83 events in the Scenario Data, 56 different participants each had one event. Six participants had two events, and five participants had three events. There were 34 events in which a female was driving and 49 in which a male was driving. The age of the driver in each of the events was identified if available. Drivers in 10 of the events were not primary study participants; so, their ages are unknown. In the Response Time Data, one driver contributed four events, two of the drivers contributed two events, and the remaining 22 drivers contributed one event each. The driver was female in 16 of the events and male in 14 of the events. The number of events per age group is shown in Table 6 for both sets of data.

Table 6. Summary of events and driver ages.

Age	Number of Events	
	Scenario Data	Response Time Data
18-19	11	8
20-29	27	9
30-39	7	1
40-49	15	4
50-59	11	6
60-69	2	1
Unknown	10	1
Total	83	30

Vehicle model for each event was also identified and are summarized in Table 7.

Table 7. Summary of events and vehicle models.

Model	Number of Events	
	Scenario Data	Response Time Data
Cavalier	18	11
Malibu	21	6
Explorer	8	1
Taurus	9	3
Camry	13	7
Corolla	14	2
Total	83	30

Video was used to identify where a driver was looking over the course of the event. Manual syncing of the video with the parametric data was necessary to measure the time between when a driver looked forward and when the input response was evident in the accelerometer data. The video for each event was synchronized with the vehicle data by locating a hard deceleration (usually the deceleration event of interest) in the parametric data and adjusting the video until timing of frames from the video reflecting this deceleration coincided with timing of the deceleration in the parametric data. The most common video-based indication of the deceleration was the presence of vehicle pitch observed in the forward or rearward video views. Though the response characteristics of vehicle suspensions vary, the rapid transition to high decelerations in these events generally created a clear vehicle response in the parametric data and associated cues in the video. The synchronization was confirmed using multiple cues within the video scene. For example, when the deceleration returned to zero rapidly at the end of an event, this also was reflected by a pitch change in the forward or rearward video views.

Frame-by-frame glance analysis was conducted for all of the events to record where the drivers were looking over time. Analysis software was used to step through each frame of the video. Where the driver was looking was numerically coded according to general locations (e.g., left window) or objects (e.g., electronic device). The results of this glance analysis were stored as time-series data with the parametric vehicle data. The last glance away from forward prior to driver response was analyzed in additional detail to determine specifically at what the driver was looking and whether or not the glance appeared to be part of a driving maneuver. This more detailed review determined if a glance to the left window was for a reason such as to check traffic in an adjacent lane or to track some non-driving relevant object (e.g., a pedestrian or a house).

Although brake and gas pedal measures are included in the original data, due to the varying sample rate of these variables, the present investigation uses the accelerometer data as the primary source for measuring response time. As a result, driver response in this analysis is measured at the point where vehicle response indicative of driver braking was first evident. This measurement was made for the events in the following manner. Graphs of variables such as acceleration, gas pedal position, and subject-vehicle brake state were visually inspected along with video to locate the start of vehicle response indicative of a driver's avoidance braking input. This process included reviewing the video to consider factors such as when the driver was

looking ahead, what events were occurring ahead, and particularly, what changes were occurring in the visual scene, including the view of the driver and where the timing of these changes was shortly followed by a sharp change, or “knee,” in acceleration. Figure 17 illustrates one deceleration event. In this event, the first point in which a deceleration response indicative of braking was recorded is indicated with an arrow.

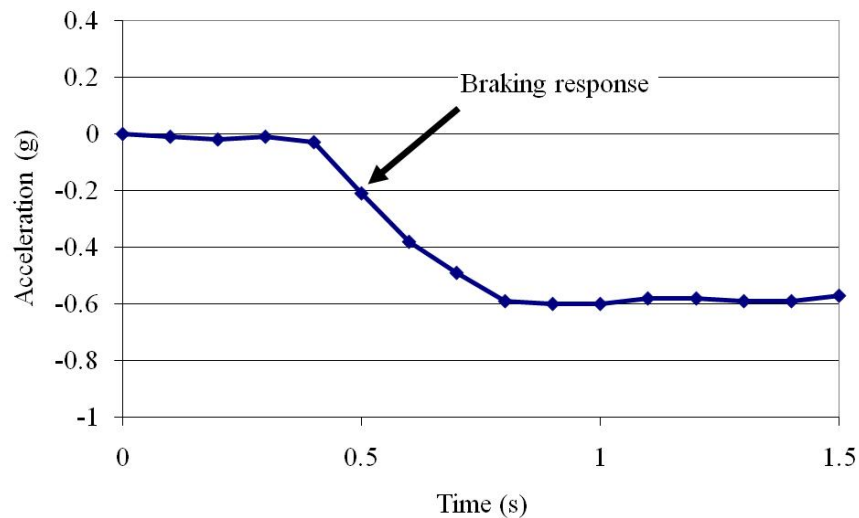


Figure 17. Example 1 – Driver response identification.

In some events, the transition to braking was less distinct. An example of this type of event is shown in Figure 18. In Example 2, the initial reduction in acceleration observed (from time 0.4 s to 0.5 s) is likely due to release of the accelerator pedal. To avoid potential difficulty in distinguishing gas pedal release from normal variation in acceleration, all measurements of response time here use the first point indicating deceleration greater than would be achieved through reduction in throttle. For these vehicles, this threshold was estimated to be a deceleration of 0.07g.

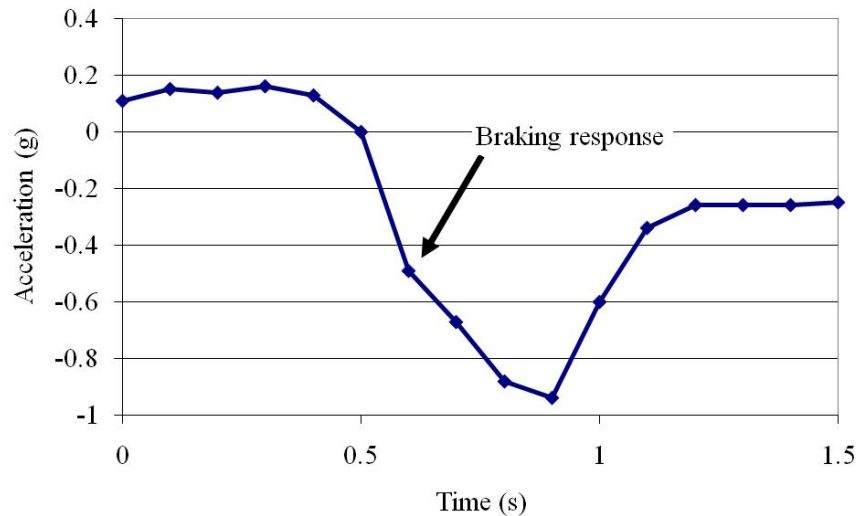


Figure 18. Example 2 – Driver response identification.

Having identified the start of deceleration, the end was identified as the point in time where deceleration returned to zero. A mean deceleration was computed between the start and end of the deceleration. The maximum deceleration found between the start and end point of the deceleration was also recorded.

These measures of deceleration quantified what the drivers did. Kinematic analysis was used to provide a measure of what was necessary for crash avoidance. This analysis provides a quantification of the events that is independent of the timing of the involved driver’s response. The outputs of this analysis are measures of how much time was required by the situation to decelerate sufficiently, assuming decelerations of different strengths than the driver executed during the event.

Software routines were developed that used the speed and acceleration values of the lead vehicle as they were observed in each time sample to determine a position of the lead vehicle over time. The performance of the subject vehicle was then varied to test alternative deceleration levels and the necessary timing of different subject vehicle decelerations to avoid the collision.

Four deceleration alternatives were explored. The first alternative was the no-response alternative. The subject-vehicle speed and average acceleration level from a point just before the involved driver’s response were used to project forward in time. This approximated the outcome had the driver never responded to the forward event and provides a prediction of subject-vehicle speed at each time interval, as well as subject-vehicle position relative to the lead vehicle.

The next three alternatives identified the points in time where the subject vehicle would need to begin braking to avoid colliding with the lead vehicle based on different assumed response decelerations. Decelerations of 0.5g, 0.675g, and 0.85g were evaluated with the intention of testing decelerations within the feasible range for unassisted drivers in extreme situations (e.g., 0.5g deceleration) as well as decelerations that might be expected of driver support systems or automated braking (i.e., 0.85g deceleration). At each point in time, based on the actual range, speed, and acceleration values, the predicted values, and the deceleration level being tested, the spatial relationship of the two vehicles was computed. An iterative software routine computed predictions for the subject vehicle, and used the actual values for the lead vehicle, to find the point in time where each of the three levels of deceleration needed to start to just avoid the collision. In successive iterations testing deceleration levels that would need to begin prior to when the subject-vehicle driver braked, the measured subject-vehicle speeds and accelerations were taken from the parametric data up until the time where the tested level of deceleration would begin. In iterations testing subject vehicle deceleration onset occurring after the involved driver braked, the forward prediction method of computing the no-response alternative was used until the point in time where the tested deceleration onset was to begin. The start of subject-vehicle deceleration was modeled as a step function. Additional details of this method are provided in Chapter 2.

Using the times at which different levels of braking were required, the amounts of time available to reach these levels were computed for the times of the driver's response. In some of the crashes, no driver deceleration response was observed prior to impact. For this reason, these events were not included in this analysis.

To measure response time, it is necessary to know when a stimulus is presented. In naturalistic data, events often develop gradually and it is difficult to determine when the need to respond was present and discernable to the driver. In the interest of locating events in which the need to brake was clear and presented at a distinct point in time, the Scenario Data (83 events) were analyzed further. The purpose of this analysis was to locate events in which the driver looked forward at a time when to most drivers, the need to brake was likely compelling. The following approach was used to identify appropriate events.

Average decelerations during the crashes and near-crashes in the Scenario Data indicated that the drivers executed a 0.5g average deceleration or higher in only 20% of the events. Based

on this finding, conditions requiring a 0.5g average deceleration were considered severe. If the time available to reach 0.5g was short at the time the driver looked forward, the driver would be expected to be motivated to respond quickly. To define “short,” the distribution of time available at response in the crashes and near-crashes was inspected and the events with time available above the 90th percentile (1.3 s available) were eliminated. This elimination of the events with longer than the 90th percentile time available was somewhat arbitrary, but is believed to isolate the more-severe of these already severe events while retaining some events for analysis. Events in which the driver looked forward under these conditions would likely elicit rapid response. In addition to these, measures of the more critical 75th percentile (1.0 s available) and 50th percentile (0.4 s available) are also collected.

The Scenario Data were then reviewed to locate events in which the driver was not braking, looked away from forward, then returned his or her gaze to forward within 1.3 s or a shorter time available to reach 0.5g deceleration. Further data reduction was then necessary to eliminate cases where it appeared the driver was aware of the need to respond, although he or she was not looking forward. For example, it is common for drivers to notice a slow or decelerating lead vehicle and glance to mirrors or elsewhere to determine if changing lanes is possible. Events that included these types of glances were eliminated from the analysis. Cases in which it appeared the driver was unaware of the need to brake were retained. In general, these cases tend to represent non-driving related distraction including drivers watching people or objects along the roadside but not potential threats (e.g., on the far side of medians), interacting with interior vehicle components, operating handheld electronic devices, looking at paperwork, food, or situations in which the driver closed his or her eyes for 0.2 s or longer. Two types of events were retained, but should be considered for elimination in future analyses. A driver looking toward a passenger seat was probably not aware of an impending need to brake at the time he or she looked away from forward but may have been forewarned of a need to brake by a passenger before looking forward again. Because it is difficult to know if the passenger provided any indication, or even if a passenger was in the car (since passengers were intentionally not captured by the video views), events involving glances toward the passenger seat were retained (unless they appeared to be part of a lane change maneuver). Events in which the lead-vehicle brake lights were on at the time the driver looked away were also retained. In these cases, though the lead-vehicle brake lights were on, the subsequent glance, for example to an interior component

or object was interpreted to mean that the brake lights were not a sufficient stimulus to indicate braking was required. It is reasonable that the brake lights might have made the driver more ready to respond upon looking up. This will be addressed further in the Discussion and Conclusions.

When reduced according to the requirements described above, 18 of the Scenario Data events were retained in the Response Time Data. Due to the low number of events, additional rear-end near-crashes were identified in the 100-Car data which met the same requirements—an unaware driver, who was not already braking, returning his or her gaze to forward when 1.3 s or less was available to reach 0.5g deceleration. Twelve additional events meeting these criteria were located. These 18 events from the Scenario data and 12 additional events were combined together into the 30 events that made up the Response Time Data.

Measures of driver decelerations, time available to respond, time needed for deceleration, and driver response time were collected in the events. The results were tested for goodness-of-fit to normal and lognormal distributions using SAS 9 statistical software. The Anderson-Darling test statistic was used to evaluate fit. In cases where a lognormal distribution appeared to have the best fit, the scale parameter (ζ) and shape parameter (σ) are reported. Gender and age differences in response time were explored using a Wilcoxon Rank Sum test. The Wilcoxon Rank Sum test was used due to lack of fit of the data with a normal distribution.

Results

First, considering the Scenario Data, of the 13 crashes analyzed, only three included a deceleration response by the driver. In two of these, it appeared the vehicle had reached some maximum, and the driver would not have achieved a stronger deceleration. The maximum deceleration in these two events was 0.87g and 0.80g. It should be noted that these maximum decelerations were not sustained. In these two crashes, the mean deceleration from driver response until collision was 0.66g. Average decelerations of these two crashes are different from the near-crashes in that the period of averaging terminates in collision rather than including a deceleration offset back to zero, as is the case in the near-crashes. The average of the mean decelerations employed by the drivers in the 70 near-crashes and the average of the maximum deceleration employed in the 70 near-crashes and two crashes with maximums, are shown in Table 8.

Table 8. Summary values describing deceleration responses for the events.

Measure	Deceleration Measures (g)				Number of Events
	Minimum	Mean	Maximum	Standard Deviation	
Average Deceleration	-0.75	-0.37	-0.12	0.14	70
Maximum Deceleration	-1.07	-0.72	-0.34	0.18	72

Figure 19 provides a cumulative distribution of the mean and maximum decelerations achieved for the near-crashes. Tests for goodness-of-fit indicated a lognormal distribution provided the best fit with both mean ($p > 0.25$, $\zeta = -0.73$, $\sigma = 0.26$) and maximum deceleration values ($p=0.19$, $\zeta = -0.83$, $\sigma = 0.08$). The mean deceleration for the near-crashes was less than $0.4g$. Maximum deceleration recorded in the events was, on average, almost twice the mean deceleration recorded.

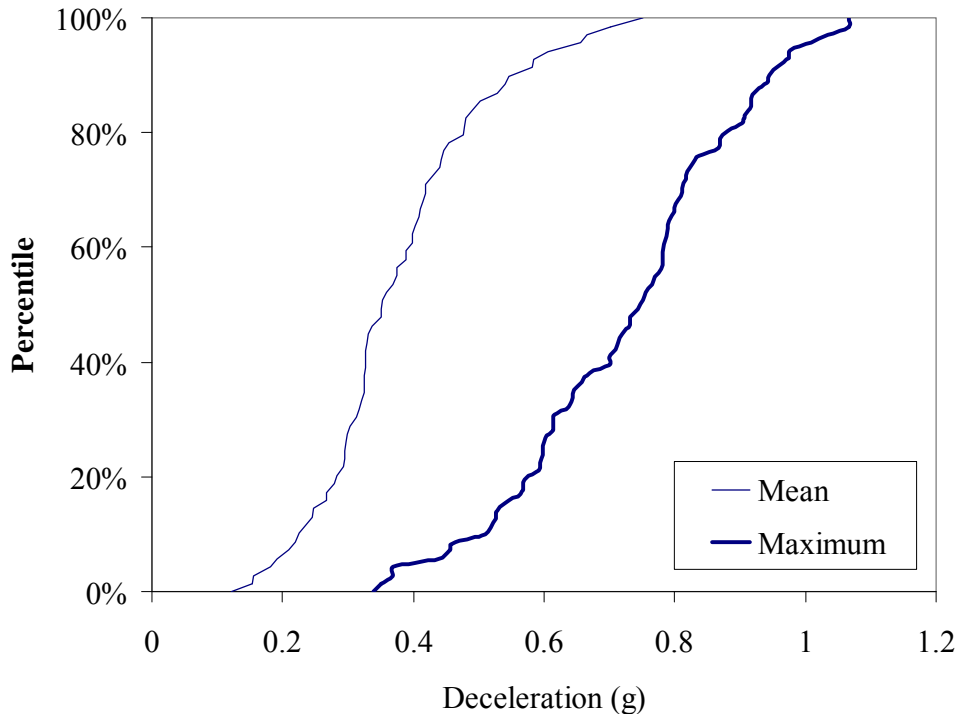


Figure 19. Mean and maximum decelerations obtained in near-crashes.

The deceleration time necessary to avoid collision was measured assuming average decelerations of $0.5g$, $0.675g$, and $0.85g$. All of the events in the Scenario Data could have been managed successfully with a $0.85g$ average deceleration that started 1.7 s prior to what otherwise would end in collision. A $0.5g$ average deceleration, starting 2.0 s before impact, would be

required to manage all of the events. Less-severe events would have required less advanced notice. Approximately 90% of the events would be avoided by a 0.5g average deceleration starting 1.7 s before impact. Average minimum, maximum, and mean times before impact when the three levels of braking were necessary are shown in Table 9. Figure 20 provides a cumulative distribution of the times for the 83 events in the Scenario Data.

Table 9. Times required to just avoid predicted impacts for three levels of deceleration.

Test Deceleration	Time Required (s)				Standard Deviation	Number of Events
	Min	Mean	Median	Max		
0.5 g	0.1	1.0	1.1	2	0.5	83
0.675 g	0.1	0.8	0.8	1.7	0.4	83
0.85 g	0.1	0.6	0.6	1.7	0.3	83

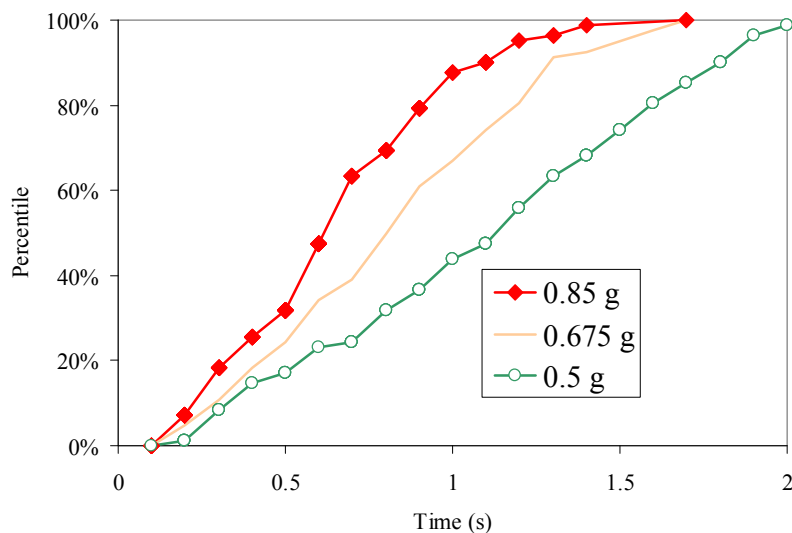


Figure 20. Distributions of the time prior to predicted impact when braking at the indicated level is necessary to avoid collision—70 near-crashes and 13 crashes.

Fit with the normal distribution was better than with a lognormal distribution. P-values for the fit of the 0.5g, 0.675g, and 0.85g braking level distributions with a normal distribution were $p > 0.15$, $p = 0.12$, and $p < 0.1$, respectively.

While the above analysis quantified the time required by the event, the next analysis quantifies how much time remained at the time the drivers began responding. In this analysis, the number of crashes is reduced to three, because for 10 of the crashes there was no observed

driver response. Summary values for the 73 remaining events (three crashes plus 70 near-crashes) are provided in Table 10, and distributions are provided in Figure 21.

Table 10. Summary values of time available to initiate deceleration at the time of driver response.

Test Deceleration	Time Available (s)					Standard Deviation	Number of Events
	Min	Mean	Median	Max			
0.5 g	-1.1	0.5	0.5	2.1		0.7	73
0.675 g	-0.7	0.8	0.8	2.5		0.7	73
0.85 g	-0.4	1.0	0.9	2.7		0.7	73

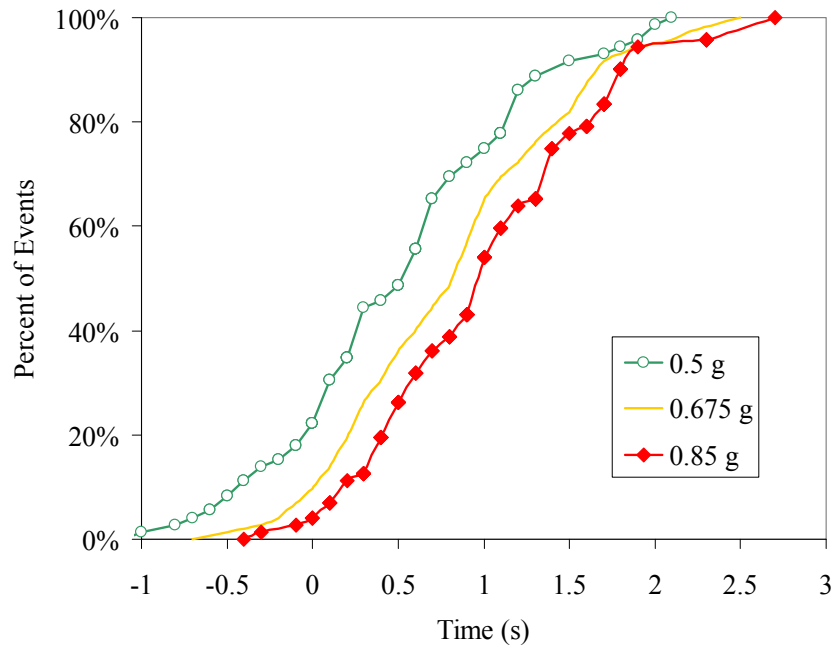


Figure 21. Distributions of time available to initiate deceleration at the time of driver response.

In Table 10 and Figure 21, negative time values indicate cases where the driver’s response occurred too late to avoid colliding using the tested deceleration (e.g., -0.5 s indicates the driver’s response occurred 0.5 s after the indicated braking level was needed). At the time of the driver’s response, for approximately 22% of events, a 0.5g or higher average braking was insufficient to avoid collision. For approximately 10%, it was too late to avoid impact with a 0.675g or lower average deceleration. At the time of driver response, all but about 5% of the events were avoidable with a 0.85g deceleration. Fit with a lognormal distribution was best for

all three braking levels (0.5g, $p>0.5$, $\zeta = 1.57$, $\sigma = 0.15$; 0.675g, $p>0.5$, $\zeta = 1.26$, $\sigma = 0.19$; 0.85g, $p>0.25$, $\zeta = 1.21$, $\sigma = 0.20$).

For use in quantifying response time in rear-end events, the Response Time events were collected as described in the Methods section. These 30 events were cases in which the driver looked forward when the conditions were compelling to respond. Response times in these events ranged from 0.4 s to 1.4 s, with a mean of 0.7 s. Recall that for inclusion in the Response Time data, the time available to reach 0.5g deceleration had to be at the 90th percentile or shorter based on the forward conditions at the time drivers responded in the Scenario Data. The 90th percentile captures events in which 1.3 s or less were available to establish a 0.5g deceleration to avoid colliding. The objective of that cut-off was to focus on events in which it appeared that the driver returned his or her gaze to forward at a time when the need to respond was likely both salient and immediate for most drivers. In addition to this 90th percentile cut-off for inclusion, the 75th percentile and the 50th percentile were also quantified. There were 20 events that met the 75th percentile limit of 1.0 s or less to reach 0.5g, and 10 events that met the 50th percentile limit of 0.4 s or less. Summary measures for the events in these three groups of data are shown in Table 11, and cumulative distributions of these response times are shown in Figure 22.

Table 11. Response time summary values for the three groups of data

Percentile	Time available to reach 0.5 g (s)	Response Time (s)					Standard Deviation	Number of Events
		Minimum	Mean	Median	Maximum			
90th	1.3	0.4	0.7	0.7	1.4	0.2	30	
75th	1	0.4	0.7	0.7	0.9	0.2	20	
50th	0.4	0.5	0.7	0.6	0.9	0.1	9	

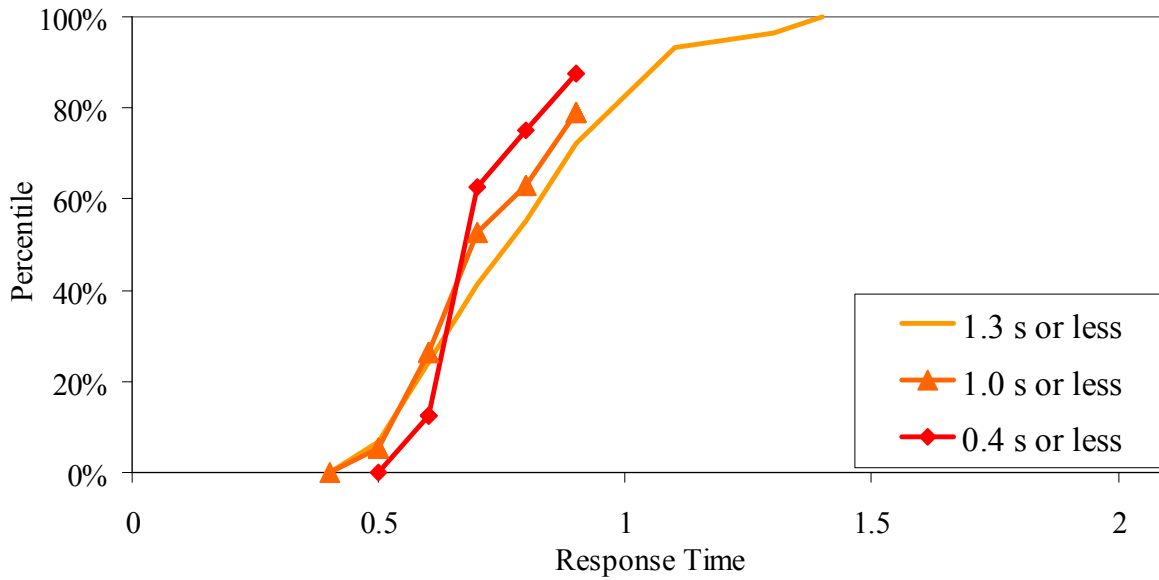


Figure 22. Distributions of times from forward glance to deceleration response for three groups of data.

The 90th percentile events were found to have significant lack of fit with both normal and lognormal ($p < 0.04$). The more immediate response time samples were not tested due to low sample size.

Gender differences were found to be marginally statistically significant, with $p=0.05$. The mean male response time ($n=14$) was 0.6 s and the female response time ($n=16$) was 0.8 s. In reviewing the distribution of males and females across the range of braking immediacy found in the 30 events, it was noted that the females were overrepresented in the scenarios with longer available times to brake. Based on this difference, an additional test was conducted on the 75th percentile events, in which 1.0 s was available. In this test, males and females were more equally distributed in terms of available time to respond. There was no difference found between the genders in this test ($p=0.18$). The mean time for the males ($n=13$) was 0.6 s and for females ($n=9$) was 0.7 s. Age groups were tested by assigning responses from individuals 29 years or younger ($n=18$) to a young age group, and those of drivers 44 years or older ($n=11$) to an older age group. Means of 0.7 s for the young group and 0.8 s for the older group were not statistically different ($p=0.7$).

Driver controlled deceleration in one of the crashes included in the Response-Time Data did not appear to reach a maximum, and so it is not included in the investigation of time to reach

a maximum deceleration. In the remaining 29 events (two crashes and 27 near-crashes), the time required to reach maximum deceleration ranged from 0.6 s to 2.1 s. The time available to reach 0.5g deceleration is used again here to quantify the urgency of the event. Several summary measures are provided in Table 12 for the three groups of data and a cumulative distribution of the time to reach maximum deceleration is shown in Figure 23.

Table 12. Time to reach maximum deceleration for the three groups of data

Percentile	Time available to reach 0.5 g (s)	Time to Maximum Deceleration (s)				Standard Deviation	Number of Events
		Minimum	Mean	Median	Maximum		
90th	1.3	0.6	1.1	1.1	2.1	0.4	29
75th	1	0.6	1.0	1.0	1.7	0.3	19
50th	0.4	0.7	1.2	1.1	1.7	0.4	9

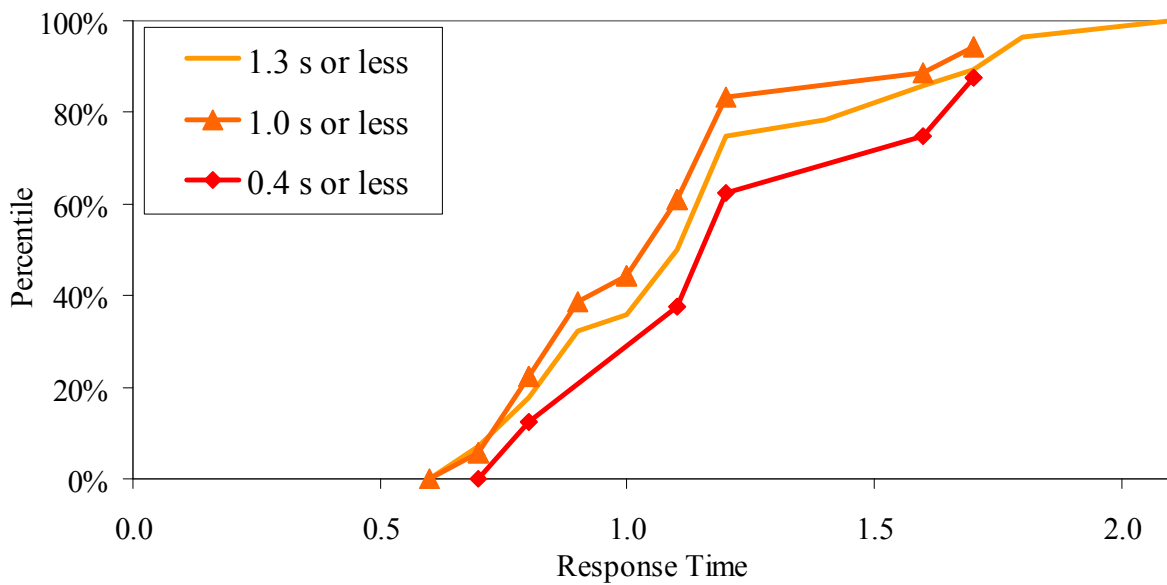


Figure 23. Time from start of response to maximum deceleration for the three groups of data.

Goodness-of-fit of the 90th percentile events was better with a lognormal distribution ($p > 0.12$) than with a normal distribution ($p = 0.014$). No differences were found between the gender groups ($p=0.18$) or the age groups ($p=0.4$) using the Wilcoxon Rank Sum test.

Discussion

Driver decelerations were measured for the real-world rear-end collision situations in which they occurred. Decelerations were characterized in terms of the maximum deceleration

achieved during the events and the average deceleration over time. These measures describe the decelerations drivers used. To understand what decelerations the situations demanded, the events were kinematically analyzed to determine when different levels of deceleration were necessary to avoid collision, and how long the decelerations would need to be maintained. A relationship was developed between the timing of when drivers began responding and when three different levels of deceleration were required. Drivers were found to generally brake earlier than required by even the lowest deceleration level tested (i.e., 0.5g). This is likely in part because drivers tend to avoid approaching as close as the kinematic analysis considers and in part because the observed decelerations were lower, on average, than the deceleration levels tested. Of course, safe driving is characterized by avoidance of collisions by comfortable margins rather than minimally successful margins.

Of the two deceleration measures, mean and maximum, the mean deceleration has generally greater utility. It is the mean deceleration that defines the distance and time needed to decelerate. Decelerations found in the present work are comparable to other research. In the 70 near-crashes, the mean deceleration was 0.35g. This falls between 0.27g recorded in lead-vehicle-moving scenarios and 0.37g found in lead-vehicle-stationary scenarios (Smith et al., 2003). Kiefer et al., (1999) observed “last second” braking on a test track in various lead-vehicle-stationary and lead-vehicle-decelerating scenarios. As would be expected, the mean deceleration of 0.35g found in the present study is higher than the “normal” braking instruction results found by Kiefer et al. Participant “normal” average braking deceleration on the test track tended to fall between 0.21g and 0.32g except for the two most extreme scenarios, in which it reached 0.41g. When participants in that work were instructed to use “hard” braking, the average decelerations were generally stronger than the average recorded here except where the lead vehicle was decelerating at its lowest level (0.15g) or in lead-vehicle-stationary situations with the slowest subject-vehicle approach speed (30 mph / 48 kph). An order effect could be suspected of leading to higher overall braking in the repeated test-track trials when compared to the single surprise events studied here. However, this explanation of differences seems to be negated by the small order effects (less than 0.02g) observed by Kiefer et al. More likely explanations relate to the scenarios tested, control within the experiment, and the instructions to the participant. The lead-vehicle-deceleration scenarios involved average decelerations of 0.28g and 0.39g. Using the present work for comparison, these represent strong average braking

compared to what generally arise in everyday driving. A participant responding to this scenario would be expected to execute a strong deceleration in response. The controlled nature of the test track allows drivers to execute hard decelerations which create a mean closer to the extreme. In the more varied situations recorded in naturalistic data, the spread of responses is going to be wider, reducing the mean of the decelerations. Test-track participants are also pursuing a hard braking level based on the instructions. In real-world events, due to, for example, surrounding traffic and graver consequences, extreme inputs are rare and likely more uncomfortable.

Similar to the average deceleration results, the 0.75g maximum deceleration falls near the low end of those recorded by Kiefer et al. in trials with hard-braking instructions. Under their comfortable-but-hard-braking instructions, with a lead vehicle executing a 0.15g deceleration, participant decelerations were the same (0.75g) as those found in the present work. In their tests in which the lead vehicle was braking harder, or the participant was instructed to use stronger braking, their maximum decelerations were closer to 0.90g. Test-track results in a surprise intersection incursion scenario recorded maximums of 0.65g, while the same scenario in a simulator recorded an average of the maximums of 0.80g (Mazzae, et al., 1999).

Appropriate selection of results from the present and previous findings depends on the application. First, it is important to note that the average deceleration executed by drivers in the events was approximately 0.30g less than the maximum deceleration achieved. Similar or larger differences between average deceleration and maximum deceleration were found by Kiefer et al. In estimating stopping distance, the average deceleration should be used. If it is desirable to design a system that recognizes when kinematic conditions have surpassed the comfort threshold or normal conditions for a driver, the average deceleration distributions or the braking needed distributions from the present work could be used to establish an upper limit. The “hard” braking tests of Kiefer et al. provide similar outcomes. For example, an approximately 0.5g average actual deceleration recorded in the most severe test track scenarios agrees with the 85th percentile average deceleration observed in the present work. This type of threshold might be used to determine when situations require unattainable braking levels for most drivers. When considering what effective average braking levels could be expected of drivers, the middle or lower ranges of the distributions found here provide better guidance.

The 13 rear-end crashes and 70 rear-end near-crashes generally could be addressed by a 0.5g average deceleration starting 2 s or less before impact. For approximately a quarter of the

events, deceleration 0.675g or higher could be initiated as late as 0.5 s before impact, and the collision would be avoided. It should also be noted that these kinematic measures describe the last instant possible to avoid physically contacting a lead vehicle. Additionally, the tested 0.5g average deceleration may be somewhat higher than can be expected of drivers when estimated using the decelerations observed in the near-crashes. In the near-crashes, the average deceleration was 0.37g. In two crashes, however, drivers were able to establish an average deceleration of 0.66g.

When examined in terms of what is necessary to avoid colliding at the instant a driver's response occurred, approximately 5% of the events could no longer be avoided even with a 0.85g average deceleration. Approximately one quarter could no longer be avoided if the average response deceleration was 0.5g. For 70% of the events, though uncomfortable, a 0.5g deceleration or higher established and maintained 0.1 s after the driver's deceleration began would avoid collision. If a 0.85g deceleration could be established and maintained within 0.1 s of the driver's response, over 90% of these events would end without collision.

A frequently cited claim regarding rear-end crash causation and prevention is that a 0.5–1.0 s earlier response would eliminate approximately 50% of rear-end crashes (National Transportation Safety Board, 2001 citing Ankrum, 1992; Lund and O'Neill, 1994 citing Enke, 1979; Sivak and Flannagan 1993, citing Enke, 1979). For comparison, if only the 13 crashes in this data set are considered, the 10 cases where no response was present must be addressed. A 0.5-s earlier response in the three response present crashes, or for the ten no-response crashes, a response starting 0.5 s prior to what otherwise would be collision, would lead to avoidance in eight of 13 of the crashes (62%). This estimate includes assumptions of braking at 0.5g for 0.3 s or less to avoid. The remaining five of the crashes would require a response between 0.5 s and 1.0 s or earlier response to avoid. For these five crashes, the estimate uses assumptions of either a 0.5g deceleration for 0.5 s to 0.7 s, or the average deceleration achieved in the event, starting 0.3 s to 0.7 s earlier. Inclusion of the near-crashes adds cases that may be borderline depending on the level of deceleration achieved. However, based on this analysis, with a 0.5 s or earlier response, a 70% avoidance claim may be reasonable. This estimate includes a 15% reduction from the values shown in Figure 21 to accommodate average response decelerations closer to 0.35g. The estimate also includes a number of assumptions and uncertainties that should be considered. The reduction estimate is based solely on the kinematics of the rear-end crashes and

near-crashes included in the present analysis. Whether or not the crashes and near-crashes in this investigation reflect the complete rear-end crash problem should be considered further. How an earlier driver response is achieved is undefined and could influence the outcome. Losses would arise if, for example, a successful avoidance of striking a lead vehicle is replaced by being hit from behind by another vehicle or if unintended behavioral or performance consequences arise.

When measured against the point where average decelerations of 0.5g, 0.675g, and 0.85g were required, drivers started braking earlier, and initially harder. Seventy-five percent of the driver responses in these events occurred before even the 0.5g average deceleration was needed. This makes sense, for two reasons. First, given the levels of decelerations found in the sample, drivers do not often reach even a 0.5g average deceleration. In these crashes and near-crashes, this level of average deceleration was exceeded in only approximately 20% of the events. Maintaining a 0.5g average deceleration is an extreme for drivers. The second reason response occurs before 0.5g is needed is that drivers will tend to manage the situation earlier than the minimum timing required. Similar results were found by Kiefer et al. (1999) in which the most extreme required deceleration at the time of driver braking on average did not exceed 0.45g. Responses at the minimums in terms of time available also provide little comfort in terms of how much space is left between vehicles at the end of the deceleration. The required timing based on kinematics is computed at a desk using objective and reliable data. It is likely that the driver, faced with potentially uncertain perception of exactly what is necessary and little time to evaluate, relies on an initially strong response followed by a more controlled input.

The response times found here appear to be fast compared to other studies. This is particularly true given the selection of events in which the driver appears to be unsuspecting of a developing need to brake. Also, response is defined here as the point where the vehicle begins responding to the driver's input. McGehee et al. (1999, 2000); Barret, et al. (1968); Lerner (1993); Broen and Chang (1996); and Lechner and Matteredre (1991) found mean or median times from presentation of an event to brake press ranging from 1 s to 2.3 s. Times between presentation of an event and release of the accelerator ranged from 0.69 s to 1.28 s. The median response time found here was 0.7 s. Several factors may explain these differences.

The stimuli in the studies listed above are different than the stimuli in the present analysis. The stimuli in the previous studies, which included intersection incursions, pedestrians, barrels, and foam blocks, cannot be anticipated, are infrequent, and may permit decision making

prior to response. In the present analysis, using events collected from rear-end crash and near-crash situations, even though they were looking away, the drivers had been monitoring the conditions ahead and were probably maintaining some level of readiness based on the following or closing situation in which the events developed. Additionally, the driver response in the lead-vehicle braking situation is well practiced, and may provide fewer options than in other scenarios, both leading to shorter response times. Finally, as was mentioned, in some cases, the brake lights of the lead vehicle had been on at the time the driver looked away.

Cumulative response-time distributions developed from two additional sources (Sivak et al., 1981; Johansson and Rumar, 1971) are compared in Figure 24 to the distribution found in the present work.

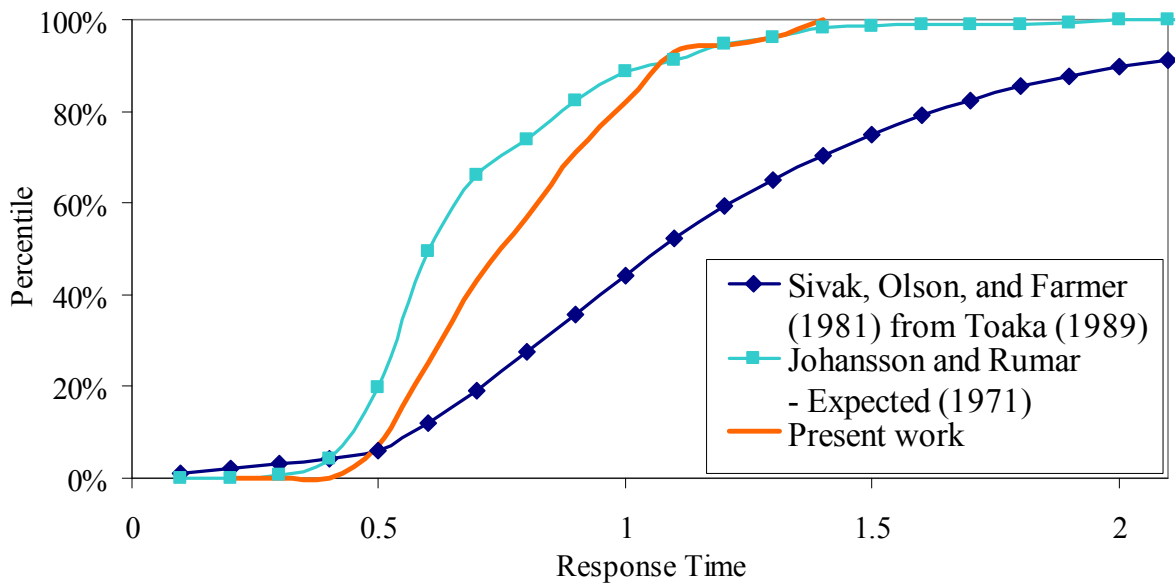


Figure 24. Response-time distribution comparison.

Sivak et al. (1981) measured driver responses during following, which is somewhat similar to the initial conditions of the present work. The measurements were taken on the road without the driver being aware of the study. The stimulus in that study was different in that it involved illumination of lead-vehicle brake lights without deceleration. In fact, in that work, in approximately half of the trials, the following-vehicle driver never applied the brakes. In the present work, at the time the stimulus was presented (i.e., the subject-vehicle driver looked forward), braking was necessary and needed fairly immediately. The generally faster response time found in the present work compared to Sivak et al. may be due to these differences.

In Johansson and Rumar (1971), the participants were driving their own vehicle, along their own route, without an experimenter, and were instructed to respond by braking at the sound of a roadside klaxon (loud horn). The stimulus was presented approximately 5 km from the location where the participant instructions were given. The response times of those drivers were somewhat faster than the times recorded in the present study, but more similar than those recorded by Sivak et al. The driver's readiness in the present study might be heightened, for example, by a general awareness of short time headways or by lead-vehicle actions leading up to the measured event.

There also may be differences between the experimental setting and the natural driving environment. Previous studies involved experimental situations, on a test track, in simulators, or on the road. It could be that the drivers in real conditions are somehow ready to respond in a way that surpasses their readiness in experimental testing. Or, it may be that events occurring in real driving, with real consequences, illicit more rapid responses than experimentally measured responses. Response times in the present study may also be due to shorter time on task (e.g., short trips), familiarity with the vehicle, or by the absence of experimental factors. For example, it may be that researcher efforts to ensure the participant is unsuspecting tend to reduce the participant's readiness below that of a driver in real conditions.

For additional comparison, Sohn and Stepleman (1998) provide a meta-analysis of total brake time from studies involving both emergency and normal braking situations. The response-time distributions recorded in the present work appear to indicate that a driver following a lead vehicle, when presented with an imminent need to brake, may be able to respond fairly quickly compared to what has been found in other situations or studies.

There are several potential limitations in the present work. The driver demographics included in the events are somewhat biased toward younger male drivers and high-mileage drivers. It will be beneficial to expand on the analysis as additional data of this type accumulate. In the measurement of response time, there is some indication that driver response times increase in the events with longer, though limited, time available. Based on this, the Response Time Data in which 1.3 s was available to reach 0.5g may include some responses that are controlled rather than reflexive. The shorter-time-available data appear to eliminate these cases, but leave low numbers in the distribution. Finally, the scenarios investigated here were fairly restricted. Much

more information is necessary about how these measures would differ, for example, if the scenario, stimuli, expectancy, or driver attention were different.

Conclusions

The measurements of driver capabilities collected in this study will be of value in the design and evaluation of vehicle-based collision countermeasure strategies. The relatively fast response-time distribution collected here as compared to response-time distributions incorporated into rear-end warning systems (e.g., Knippling et al., 1993 and Kiefer et al., 1999), can be explored as a possible method for reducing the false-alert rate of rear-end collision algorithms. Quantification of the time required for drivers to reach maximum deceleration can be compared to the onset time achieved by braking-assistance systems. Some combination of the driver as a supervisor, triggering the start and monitoring a braking response that is prepared and optimized by a forward-looking vehicle-based system, may provide a strategy that is realistic, optimized, and beneficial to safety.

Future work is needed in several areas. The mean decelerations collected in this study include near-crashes. In these types of events, the driver's braking follows a hard and fairly fast onset, but then once the situation is managed, the driver can reduce braking. The average deceleration computed here for near-crashes includes that offset until deceleration returns to zero. Though short, that offset reduces the mean. For this reason, values in the present work may describe values between what is normal or comfortable, and what drivers would maintain if there was no other choice. In 10 of the 13 crashes investigated here, the driver never responded. These no-response cases present a challenge to braking assistance systems that would be waiting for driver response to actuate, but provide considerable opportunity for improving outcomes through some type of automated control where collision appears imminent. In the two of the crashes in which driver response was present, the drivers reached a maximum deceleration, but were unable to maintain it. Additional analysis of the onset, offset, and decelerations achieved in near-crashes and crashes is necessary both for distinguishing normal from critical, and for improving estimates of the value of collision warning or braking assistance systems.

Exploration of driver response times in actual driving in other scenarios will be beneficial. The response times recorded here arise in a following situation and involve a braking response. Consideration of other scenarios, or potentially how response time may vary

according to the time available, will also be valuable. Deceleration was quantified in the present investigation. Expected next steps include measurement of steering as a response and steering and braking combined.

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Chapter 5. Overall Conclusions and Future Work

The objective of this effort was to incorporate data collected in naturalistic driving studies into the design and testing of collision avoidance systems (CASs). These data are appropriate for application in CAS design and testing for several reasons. CAS algorithms operate on streams of data collected through sensors in real-time. Naturalistic driving data, such as those collected in the 100-Car study, include many of these same streams of data collected with similar sensors. The stored data can be delivered to CAS models directly, or changed to explore different design alternatives or scenarios. The streaming, or time-series nature of the data, provides a clear description of the entire event. Measurement of the timing of different parts of these infrequent and short-duration events can be used to determine where time may be available for intervention, and based on that, what approaches might be successful. The data also include for the first time, driver performance within real crash situations. Measurement of the driver can be used to identify realistic boundaries in terms of what can be expected of the driver controlling the more easily tested vehicle. In all of these areas, the data provide new and extremely comprehensive information. Instant-by-instant video, combined with parametric data from an array of sensors, can be used to evaluate previous assumptions and identify new opportunities.

The method used permits evaluation of CAS alternatives while minimizing reliance of point estimates of reaction times. Use of response-time distributions in the place of the response time of the involved driver provides a generalized estimate of how the larger population would be expected to fare with the provided alert in the tested event.

The ability to estimate the percentage of the population able to avoid collision with the algorithms was limited due to the high frequency of alerts that would be expected of the algorithms. Though more complete testing of alert frequencies is advisable as algorithms improve, the rough estimates developed here indicated the tested algorithms would generate alerts too frequently for implementation. The NHTSA algorithm on the “near” setting, which generated approximately one alert per 12 miles, was the best in terms of frequencies of alerts. The Knippling et al. algorithm and the CAMP Linear algorithms were closer to one alert per mile. These findings indicate first, that additional work focusing on reduction in false alarms will be valuable. Second, it illustrates large differences in frequencies of alerts between different

algorithm approaches. The differences between the NHTSA algorithm and the other two algorithms that would lead to differences in frequencies of alerts are the higher speed cutoff of the NHTSA algorithm and the adjustment to a 0.5-s driver response time if the driver is already braking.

A number of measures were collected that assist in understanding the general crash problem and are also of relevance to crash countermeasure development. For the 83 rear-end crashes and near-crashes included in the CAS test set, the maximum separation between vehicles at the time of driver response was 121 ft (36.9 m). The mean range was approximately 40 ft (12.2 m). Though there are several reasons that a sensor would need to provide longer preview than these ranges, in general the distances at which driver response occurred in these events were roughly one-third the 300 ft to 400 ft (91.4 to 121.9 m) sensor requirement ranges found in various CAS functional requirements (Zador et al., 2000; Kiefer et al., 1999). With further analysis, these results may reveal an area where sensor or system requirements could be relaxed.

The speeds at which these events occurred also have implications in design. The difference in speeds at which the algorithms were operational had a large effect on their overall performance. Algorithms that were not operational at lower speeds did not provide benefit there. The composition of the event test set will influence the outcomes here. Approximately 25% of the events in the test set occurred when following-vehicle speeds were below 20 mph (32 kph), and the mean following-vehicle speed was 29 mph (47 kph). Though further work is necessary to determine how well the test set reflects the distribution of events in the larger crash population, the test set and results highlight an area that warrants additional attention.

Response times in these rear-end collision-related events were faster than the 1.0 s to 2.3 s found for various scenarios in previous work (McGehee et al., 1999, 2000; Barret, et al., 1968; Lerner, 1993; Broen and Chang, 1996; Lechner and Matteredre, 1991; Sivak et al., 1981; Sivak et al., 1982). The median response time in the selected rear-end events was 0.7 s (*SD* 0.2 s). This value is closer to the 0.7-s median response time collected by Johansson and Rumar (1971). In their experiment, drivers responded to an auditory alert while driving their own vehicle. In the present analysis, though the drivers were involved in some task drawing attention away from the forward view, they may have been maintaining a heightened level of expectancy, potentially combined with a simple response (braking alone). Other explanations should also be explored. The selection of events for this analysis assumed that drivers would not divert to a

secondary task if they were aware that braking was going to be necessary. It may be that drivers were anticipating needing to brake even though they looked away. Upon returning their attention to the forward view, they may have only been surprised by how much braking was required. Subsequent investigation could explore the relationship of visual stimuli, such as the rate of angular expansion or time-to-collision values, and the driver's response time. Investigation of the potential changes in response time as a function of time available within a scenario is also advised. For example, where extreme maneuvers are required, response time may increase, or drivers may simply not respond. In a test of vehicle handling, Koppa and Hayes (1976) observed participants essentially giving up in maneuvers that appeared impossible.

For CAS design, the faster response-time results have two implications. First, the 0.7-s median response is faster than what appears to be anticipated in the rear-end CASs tested here. The three algorithms tested used a driver response-time parameter of approximately 1.6 s. If a shorter response time can be anticipated, it would shorten the span of time required for accommodating driver response, and so reduce the number of false alerts generated. Second, driver response may be viable as an avoidance strategy later in crash sequence than would previously have been anticipated. CAS applications that target fully automated pre-crash vehicle control may need to operate in a shorter pre-crash temporal window, or anticipate simultaneous driver inputs, to ensure advantages over human capabilities.

Levels of deceleration used by the drivers align with previous work that indicates drivers may have difficulty utilizing the maximum capabilities of their vehicles (Koppa and Hayes, 1976; Prynne and Martin, 1995). For two of the crashes, the maximum deceleration was followed by some lower deceleration prior to impact. The maximum decelerations in these two crashes were 0.87g and 0.80g. The average deceleration prior to impact, for both of these crashes, was 0.66g. One occurred on wet pavement and one on dry. For the third crash in which a driver response was present, the deceleration was still increasing at the time of impact. Additionally, though the mean time to begin deceleration was 0.7 s, times to reach maximum braking ranged from 0.6 s to 2.1 s, with a median of 1.1 s. These results indicate that fielding systems which assist the driver in reaching a higher level of deceleration more quickly, and in sustaining the deceleration, may provide benefit in terms of rear-end crash avoidance or a reduction in crash severity.

A number of areas exist where further analysis is appropriate. An obvious question related to CAS design is how to avoid negative behavioral adaptation in drivers. Driver distraction has been identified as the most common cause in rear-end collisions for some time. The recent increase in cellular phones and other handheld electronic devices may be increasing the prevalence of driver distraction. In developing countermeasures, the challenge is to support the driver without creating incentive or additional opportunities to become engrossed in secondary tasks. Creative approaches to testing, systems approaches to evaluating potential negative effects, and longitudinal studies are necessary to evaluate the potential benefit of these types of technological safety interventions.

Improvements to the present approach include determining how well the event test set describes the larger crash population. For large-scale estimation of benefits, weightings could be developed to translate results to predict benefits on a national scale. An approach to examining collision mitigation, and the translation of results to injury scales would also be useful. For focused design guidance, groupings of crash types could be created that would support system developers as they work on particular components of CAS systems. The approach can be applied to additional crash types. Inclusion of steering envelopes would provide broader application of the assessment method, and would also provide steering-related quantification of events analogous to the longitudinal kinematic quantification collected in the present analysis.

Naturalistic data were found to present a unique set of challenges compared to experimental studies. The real world in which the events occurred includes a wide range of conditions and behaviors that are potentially influential and difficult to anticipate. The research required careful review of the events, particularly using video, to avoid misinterpretation of the parametric data. For example, in measuring driver response time, several analyses were required to establish a suitable data set. While these types of methods are established during experimental design in controlled studies, at least for now, the naturalistic data seem to always include surprises.

More advanced approaches to addressing false alarms is necessary both for CAS algorithms and for the CAS assessment methods described here. The method of inputting naturalistic non-crash data into algorithms provides a low-cost method for estimating the frequency of alerts. Future developments in this area can make use of controlled samples from naturalistic driving data to explore the effect of differences in driving styles, traffic conditions,

and sensor alternatives. CAS performance can be tested in particularly challenging scenarios, such as lead-vehicle-turning situations or flying passes. More sophisticated methods of evaluating targets can be explored. Machine vision could be used both for identifying threats and interpreting the driving scenario. Similarly, navigation systems could support CAS algorithms by parsing the driving environment into more interpretable or predictable scenarios.

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