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# A method for evaluating collision avoidance systems using naturalistic driving data

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**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

## 1. 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

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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; Glassco and Cohen, 2001). 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., 1999, 2003). Accident reconstructions (Tumbas et al., 1977; Ferrandez et al., 1984 as reported in Malaterre et al., 1988) or simulator studies (McGehee et al., 2000a,b) 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.

## 2. 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 Fig. 1.

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

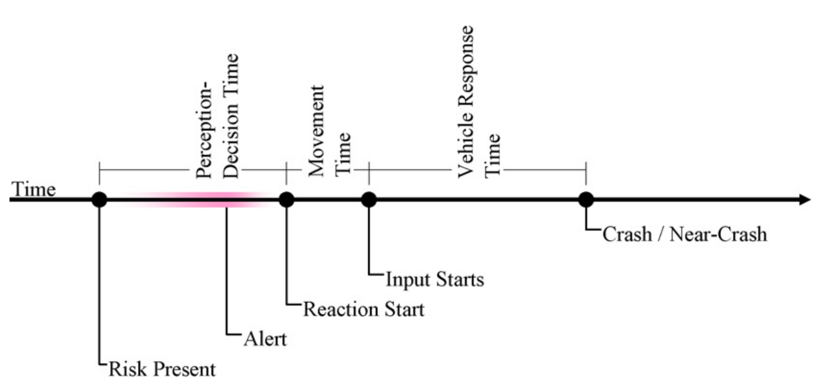


Fig. 1. Sequence of events during a crash or near-crash.

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.

## 3. 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 Fig. 2.

The first part (labeled with a 1 in Fig. 2) 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 Fig. 2) 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 Fig. 2) 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. Fig. 3 illustrates the overall approach to implementing this evaluation method with naturalistic data, including organization of the software and the analysis approach.

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.

## 4. 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.

Seventy-three 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

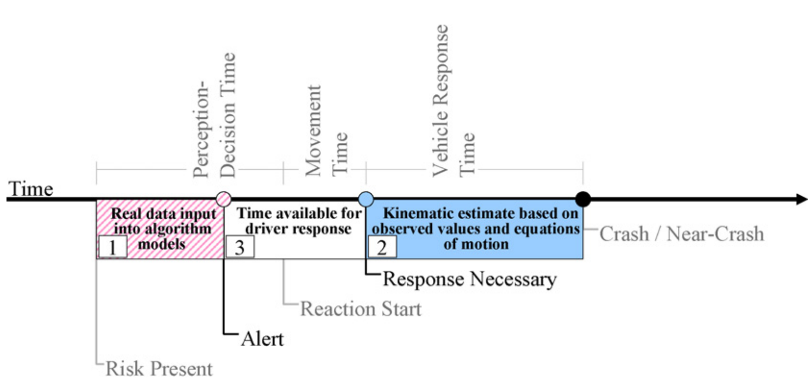


Fig. 2. Evaluation method parts 1, 2 and 3.

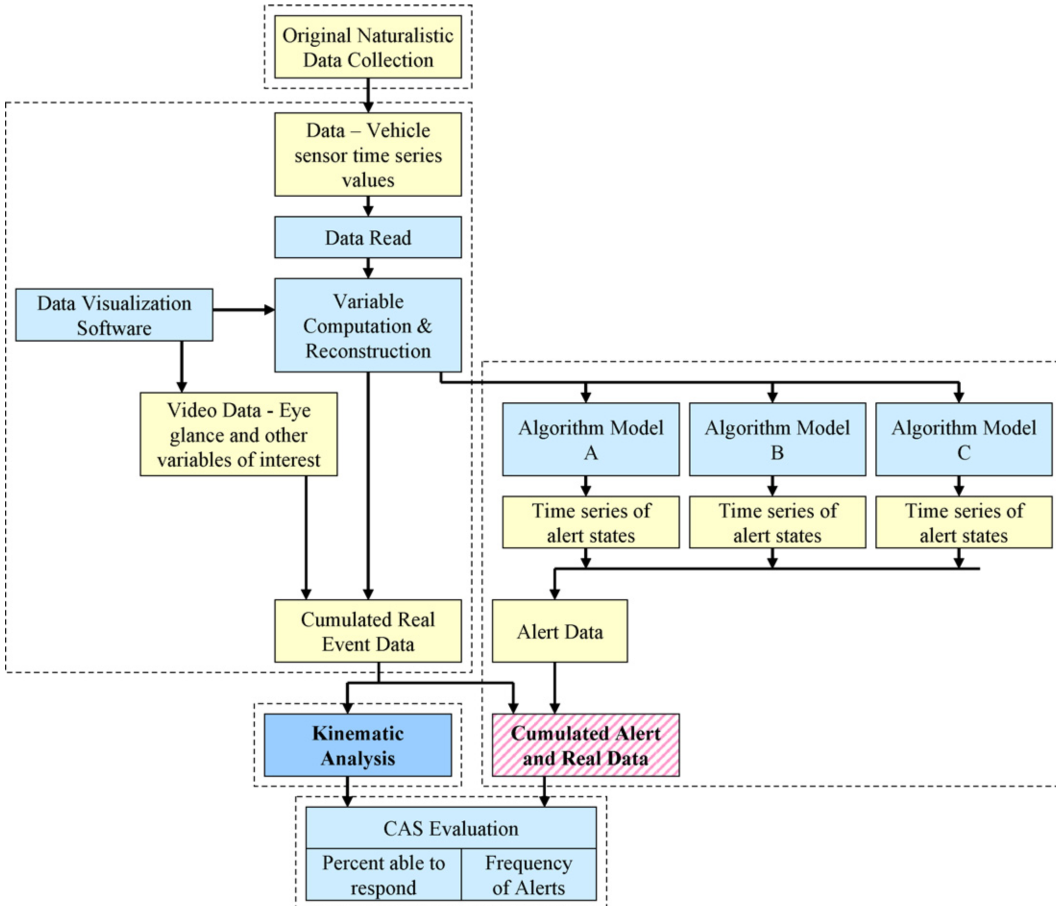


Fig. 3. Overview of the evaluation method.

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.

## 5. 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. Fig. 4 illustrates time-series data from one event and the output of the algorithm models for the event.

The bottom plot in Fig. 4 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 Fig. 4. 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.

## 6. 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 maneu-

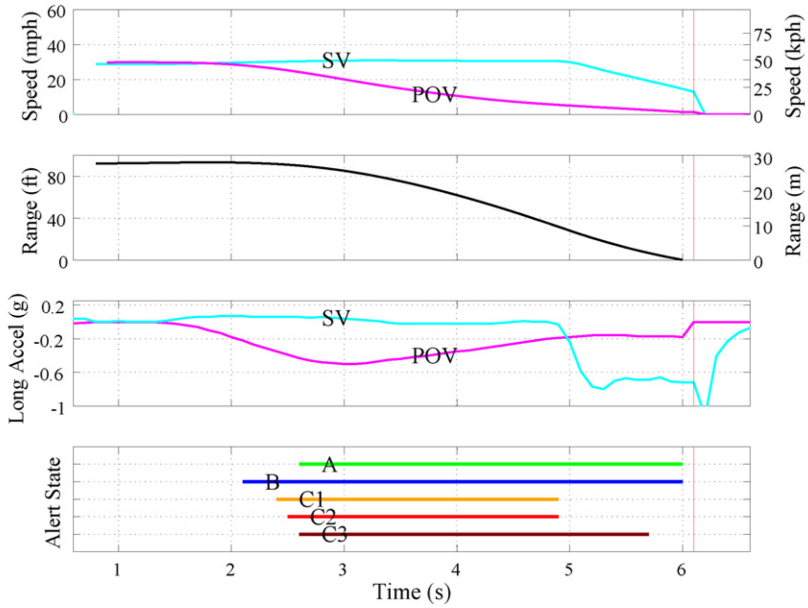


Fig. 4. Illustration of values of various event related variables and algorithm model output.

ver 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 Fig. 5.

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. Fig. 5 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

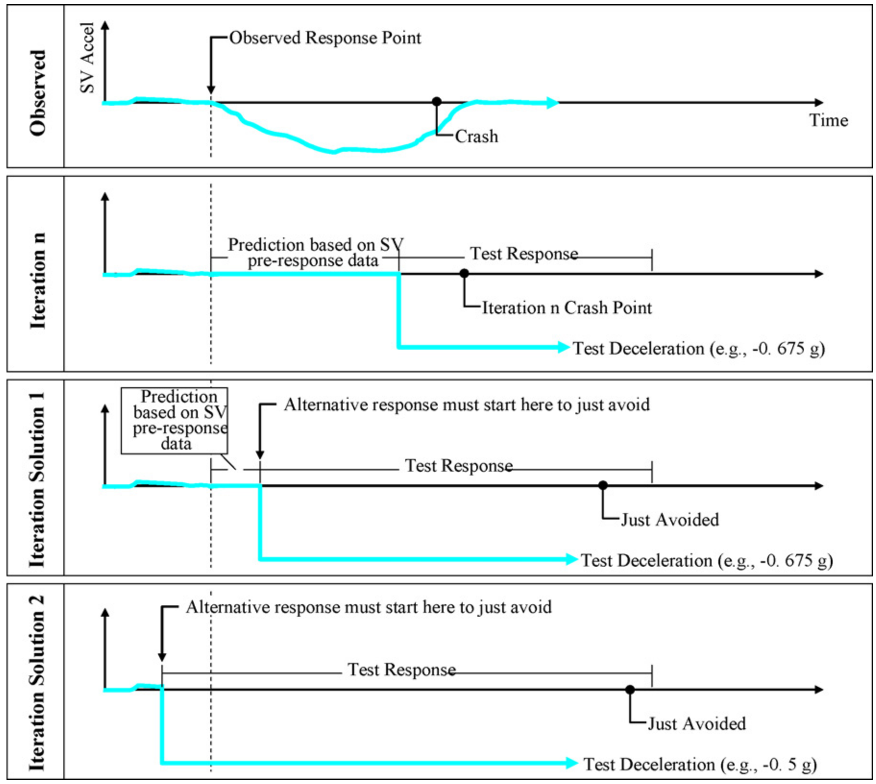


Fig. 5. Iterations to determine when a given response needed to begin to just avoid collision.

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.

## 7. 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. Fig. 6 illustrates how a cumulative reaction-time distribution was used to estimate the percentage of the population able to respond within the time available.

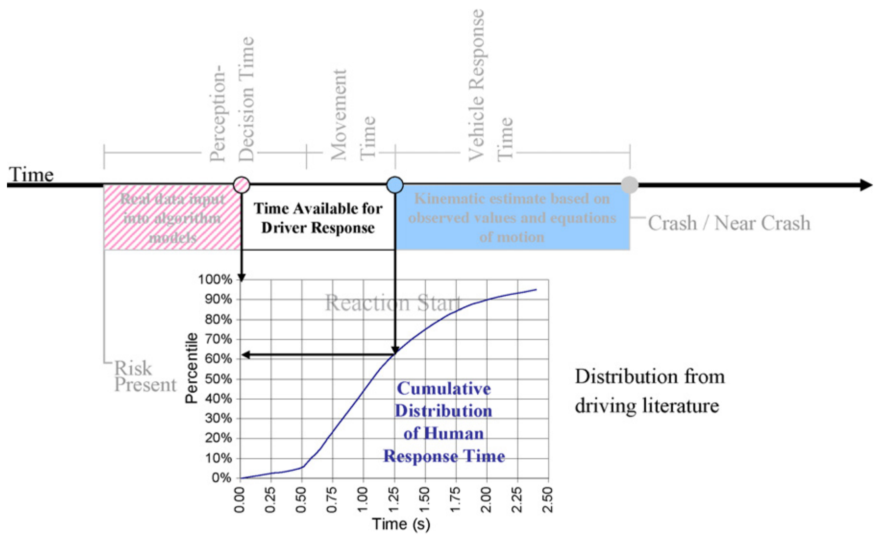


Fig. 6. Use of response–time distributions in evaluation.

In Fig. 6, 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 Fig. 7, 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 Fig. 4).

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 Fig. 6 is shown beginning at the start time of each of the alerts shown in Fig. 4 (note that alert A and C3 would begin at the same time, and so their response time distributions are overlapping in Fig. 7). 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

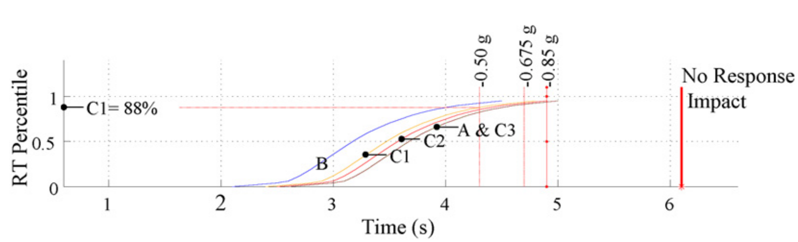


Fig. 7. Illustration of output from kinematic modeling, timing of alerts, and evaluation of available driver response time for one event.

is avoided here in the interest of focusing on the method rather than the algorithms.

## 8. 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.

## 9. 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 number 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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