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Feasibility of Driver Judgment as Basis for a Crash Avoidance Database

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A crash avoidance database structure that is based on driver judgments is proposed. The structure comprises four driving conflict states (low risk, conflict, near crash, and crash) that correspond with advisory warning, crash-imminent warning, and crash mitigation countermeasures. The feasibility of this database structure is investigated by answering two questions: (a) Can the driving states be reliably quantified? and (b) Can the quantified states be used to create a useful crash avoidance database? The feasibility discussion centers on a specific dynamic scenario that involved braking maneuvers by a following vehicle to avoid a rear-end crash with a stopped lead vehicle. The quantification of driver judgment data from a controlled test track study is discussed as a foundation to identify rough quantitative locations for the conflict and near-crash state transitions, and crash data from a driving simulator experiment are used to estimate the crash state boundary. A database of on-road, naturalistic driving data is compared with the controlled experiments to evaluate the results. The method is found to be feasible, and recommendations for further development are presented.

NHTSA has sponsored a number of crash avoidance research projects since the early 1990s under the Intelligent Transportation Systems Program and is currently engaged in developing a variety of crash countermeasures in support of the Intelligent Vehicle Initiative (1). This paper describes a database structure to support this research based on alert and aware driver judgments of the driving state. The power of this structure rests in its ability to portray driver expectations and performance, against which proposed crash countermeasures can be evaluated, insights can be developed for new countermeasures, data gaps can be easily identified, and guidance for experimental design in any media can be found so that all results fit together.

The feasibility of this database structure was investigated using existing databases on the driving problem of approaching a lead vehicle stopped in the lane ahead. While this scenario is only one of the 15 or so that dominate the national crash problem, it is, nevertheless, a common and important one. Assessing the feasibility of this scenario would justify further investigations for all the scenarios, to be done at a later date. The feasibility of the approach was assessed through two questions: (a) Can the driving states be reliably quantified? and (b) Can the quantified driving states be used to create a useful crash avoidance database?

CRASH AVOIDANCE DATABASE STRUCTURE

Figure 1 shows the database structure studied, which has four driving conflict states: low risk, conflict, near crash, and crash. These driving states allow us to focus analytic attention and develop suitable countermeasures for each, and each is needed as shown by the countermeasures in Figure 1. NHTSA long ago recognized the need to match time-to-crash with required intensity-of-evasive action (2). For countermeasures, the longest time-to-crash is in the "conflict" state, which matches the lowest intensity-of-evasive action and suggests intervention by situational awareness or advisory systems as indicated in the

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figure. As the time-to-crash decreases, the "near-crash" state is entered and the required intensity-of-evasive action increases. Further decrease in time-to-crash leads to imminent crash warning, and perhaps to partial automatic control. For a very short time-to-crash, an imminent crash may become an unavoidable crash as dictated by the driver's self-selected reactions, thus entering the "crash" driving state.

The arrows in Figure 1 represent the transitions between the various driving states. Each of these must be unambiguously and quantitatively defined for effective data analysis, which brings the immediate difficulty of establishing reliable quantitative boundaries. This is very important in order to perform the proper reduction of data collected during driving studies, to combine data files from different studies, and to establish consistency in assessing the safety impact of these systems among independent evaluations (3). At some point, it will be necessary to establish standardized quantifications for the driving state transitions, though this was determined to be beyond the scope of the present work. Instead, this study focused on using the existing databases to determine rough estimates for the quantified boundaries, thus showing a part of the feasibility.

The method used to estimate the driving state boundaries included the following steps:

1. Identify the precrash scenario of interest, in this case how drivers reacted to a lead vehicle stopped in the lane ahead.
2. Identify one or more human factors experiments where drivers judged the kinematics to place the boundaries of the driving state transitions.
3. Find a kinematic representation for these boundaries.

Given the quantified driving state transitions, Figure 2 illustrates the process for developing a comprehensive crash avoidance database. This process requires five sequential steps:

1. Collect the raw time history data.
2. Generate smoothed data and parse them into epochs using the driving state boundaries.
3. Identify significant epoch data.
4. Create discrete variable data.
5. Collect aggregated discrete data.

Step 2, the generation of smoothed and parsed data from raw data, is an art form that typically requires an iterative process to create a data time history ready for analysis. The third step includes evaluating the epochs to identify those ready for inclusion in the database (some may result due to sensor errors). The translation of the epochs into discrete variable format creates a data set that offers powerful opportunities for data mining, just as is presently done on national crash databases such as the National Automotive Sampling System (NASS) and the Fatality Analysis Reporting System (FARS). Thus, the last data type, discrete data for a variety of similar epochs, can be searched and analyzed to reach conclusions about a population of significant epochs for either an individual driver or a group of individuals. Further, if this data type is constructed to match the NASS and FARS data sets, then the data in those sets are further enhanced with more detailed knowledge of precrash events in addition to knowledge about successful crash avoidance maneuvers.

PRIOR WORK IN CONFLICT IDENTIFICATION FOUNDED ON DRIVER JUDGMENT

In past studies, traffic and highway engineers did not make a clear distinction between a traffic conflict and a near-crash event in their application of traffic conflict techniques. A traffic conflict was defined as an event involving two or more road users in which one user performs some atypical or unusual action, such as a change in direction or speed, that places another user in jeopardy of a collision unless an evasive maneuver is taken. The quantification of conflicts or near-crashes was based on either the intensity of the evasive maneuver taken by the driver or some time-based measures (4). A popular time-based measure has been the time-to-collision (TTC) defined as "the time required for two vehicles to collide if they continue at their present speed and on the same path" (5). The TTC parameter assumes constant speed and does not account for vehicle deceleration/acceleration. The minimum TTC (TTC_{min}) reached during the approach of two vehicles on a collision course was also taken as an indicator for the severity of a near-crash event. A quantitative analysis of video-based traffic data concluded that TTC_{min} is an important variable in discriminating between low risk and safety-critical driving states, with a distinct detection threshold of 1.5 s (5). Most previous traffic conflict studies were limited to very few sites (high-conflict intersections), where driving conflict was judged by roadside observers. This is contrasted with the present work, where the levels of driving states were based on the drivers' opinions as expressed in their braking performance, albeit with the authors' interpretations.

The driving state construction approach in this paper was initially guided by prior work in the area of lane change crash avoidance. The objective of that work was to determine how a lane change advisory system affected lane change opportunity selection (6). The first step in the work located the boundary between conflict and nonconflict driving. To do this, four research team members drove an instrumented vehicle and observed in the side view and center mirrors other vehicles attempting to pass in the adjacent lane at relative speeds between 8 km/h (5 mph) and 64 km/h (40 mph). These subjects indicated the "last moment at which they would change lanes" by momentarily pressing a switch. Thus, a test track human factors experiment was used to capture driver preferences and these were used as a basis for a successful lane change advisory warning. Based on the results of that work, the authors hypothesized that a similar boundary exists for other crash problems, such as rear-end crash, which could be established through test track and driving simulator experiments.

STATE BOUNDARY ESTIMATION

The four driving states defined in Figure 1 are separated by three boundaries that indicate transitions between the low-risk driving state and the conflict state, between the conflict state and the nearcrash state, and between the near-crash state and the crash state. The boundary between the near-crash state and the crash state should ideally be determined from crash data. Unfortunately, national crash databases such as the NASS General Estimates System and Crashworthiness Data System do not currently contain any kinematic information to enable us to quantify the crash state boundary. Instead, this paper analyzes rear-end crash data from the Iowa Driving Simulator (IDS) to construct the crash state boundary and illustrate the feasibility of the approach. The other two boundaries, the conflict state and near-crash state boundaries, are best estimated based on test track studies. Such data can be obtained from various controlled driving experiments that show the judgments of drivers by when they first applied the brakes under suitable driving instructions. Thus, drivers indicated their sense of "conflict" through last-second comfortable brake presses, and they showed their sense of "near-crash" through last-second hard brake presses.

Even though the focus of this paper is on driver initial brake presses and subsequent braking maneuvers as a response to a lead vehicle stopped in the lane ahead, it is true, nevertheless, that a significant portion of drivers resort to steering maneuvers to resolve these conflicts, or enter into them. However, the steering response was not jointly analyzed with braking since this was deemed as an unnecessary complication in assessing the feasibility of this method.

Crash State Boundary Estimation

Figure 3 illustrates the distribution of data at the onset of braking for 10 subjects responding to a lead vehicle stopped in an IDS experiment (7). Points 1 to 5 refer to test subjects who crashed or steered off the road at the last second because they saw they were going to crash. Points 6 to 10 mark the subjects who successfully avoided a crash. The objective of this IDS study was to investigate how drivers react when purposefully distracted at the moment when a stationary vehicle is revealed in their travel lane ahead, with and without the assistance of rear-end collision warning systems. The IDS creates a highly realistic motion-based ground-vehicle simulator with a fully instrumented Saturn cab that produces the motion cues experienced during typical driving. Figure 3 displays the results of 10 subjects, aged 18 to 24 and evenly split by gender, who were tested in the baseline condition (without the assistance of a rear-end crash warning system). After a 5-min practice drive, the subjects drove on a rural two-lane highway until they came upon a freeway entrance and merged onto a multilane freeway. Several kilometers later, the subjects came across a truck in the lane ahead. The IDS scenario then coupled the subject vehicle with the truck at a 3.2-s headway. Once the vehicles were coupled, a digitized voice came over the vehicle's speakers and asked the driver to "press the button above the rearview mirror until the red light comes on." Three hundred milliseconds after the driver pressed the button above the rearview mirror, the truck swerved to the center lane and exposed a stopped passenger vehicle in the right lane. A shadowing vehicle was used to the left of the subject so that a safe, on-road lane change was not possible. As a result, half the subjects crashed in this experiment.

Nearly all of the drivers in Figure 3 selected 0.75 g as their hardest braking level, but they all clearly initiated braking at differing conditions. The figure shows that those who initially braked above the crash boundary were able to avoid the crash. Those who initially braked below the boundary crashed, or braked first then steered to avoid a likely crash. The boundary of the crash state was thus estimated using these initial braking data, as illustrated in the figure. This boundary is roughly represented by the following equation:

$$\text{Range} = \frac{\text{Range rate}^2}{2 \times 0.65\ \text{g}}$$

where $g = 9.8\ m/s^2$.

Based on a comparable test track study, about 55% of the test subjects did not self-select an average deceleration level greater than 0.65 g during emergency braking to avoid a stopped object ahead on a dry pavement when initially driving at 88 km/h (55 mph) (8). Thus, the above estimate for the crash boundary from IDS data is likely to be conservative, but may be close to a median response.

A better estimate of the crash state boundary will be obtained as more precrash kinematic data become available. As mentioned earlier, available crash databases still lack the necessary kinematic details to reconstruct crashes that occur on U.S. roadways to the degree necessary. Current national crash databases only provide a qualitative description of the conflict or near-crash events that arose immediately prior to collision. Future crash data collection using crash recorders on-board motor vehicles in the U.S. vehicle fleet or from extensive naturalistic driving studies would enhance the description of precrash scenarios by adding quantitative kinematic information to existing qualitative data.

Conflict and Near-Crash State Boundary Estimation

Figure 4 plots the boundaries of the conflict and near-crash driving states, which were derived from drivers' last-second braking judgments to a stopped lead vehicle ahead on a test track. The GM-Ford Crash Avoidance Metrics Partnership (CAMP) conducted this study to develop a fundamental understanding of drivers' last-second braking behavior so that drivers' perceptions could be properly identified and modeled for forward collision warning system crash alert timing purposes (9).

Test participants consisted of 108 subjects split evenly by gender and three different age groups. Data were gathered on a 1.6-km (1-mi) long, 2-lane wide (3.7 m or 12 ft each), straight, level, smooth asphalt road at a test track under daytime conditions on generally dry road and in dry weather. Subjects were asked to approach a parked vehicle at an instructed speed of 48, 72, or 97 km/h (30, 45, or 60 mph), and wait to brake at the last possible moment in order to avoid colliding with the parked vehicle under three different braking instructions:

1. "Comfortable braking" instruction: brake with normal braking intensity or pressure.
2. "Comfortable hard braking" instruction: brake with the hardest braking intensity or pressure that they felt to be comfortable.
3. "Hard braking" instruction: brake with hard braking intensity or pressure.

Drivers were discouraged from "second-guessing" and correcting their initial braking onset judgment by releasing brake pressure (or "double-pumping"), because the interest here is when drivers perceive the need to begin braking.

The authors' analysis assumed that braking onset was the correct indicator of when subjects judge the start of the conflict and near-crash states respectively in the "comfortable" and "hard" braking instructions. CAMP defined the braking onset as the point in time when the vehicle actually began to slow as a result of braking, and not the brake switch trigger point, since some subjects had a tendency to momentarily ride the brakes during their last-second braking decision. Rough estimates of the conflict and near-crash state boundaries were drawn in Figure 4 by using the average values of braking onset range in each of the three test speeds listed. These two lines were not extended beyond the range rate value of 36 km/h (22 mph) since CAMP did not evaluate driver judgments at very low or very high travel speeds.

Incorporating the conflict and near-crash state boundaries with the crash state boundary, Figure 4 provides a rough quantitative breakdown of driving performance into the four levels defined in Figure 1. This result demonstrates the feasibility of assigning quantitative bounds to various driving states based on actual driver judgments.

DATABASE DEVELOPMENT ANALYSIS

Next, the reliability of this database structure and its use to develop a crash avoidance database are discussed using driver performance data from an on-road naturalistic driving study and an IDS-controlled experiment.

Driver Performance in Low-Risk and Conflict Driving States

Figure 5 shows the distribution of data at the onset of braking by a following vehicle in response to a lead vehicle stopped in the traffic lane, as observed in a naturalistic driving data collection study (10). NHTSA's Vehicle Research Test Center conducted this study to observe the behavior of following vehicles as they reacted to an instrumented vehicle that is either moving very slowly or is stopped. A radar set and a video camera were mounted on the rear of the lead vehicle, pointing straight behind to record the response of the following vehicle. The instrumented vehicle was driven on country and suburban roads, stopping for stop signs, red lights, and midblock left turns. These roads mostly consisted of two lanes, thus minimizing the potential for following vehicles to pass rather than to stop behind the lead vehicle. The instrumentation suite captured the behavior of vehicles at a frequency of 30 Hz, as they approached the lead vehicle from 120 m (394 ft) up to the time when they came to a stop behind the lead vehicle. The onset of braking by the following vehicle was inferred when its deceleration exceeded 0.04 g (0.39 m/s^2). In all cases shown in Figure 5, the lead vehicle was already stopped by the time the following vehicle saw it and began to brake.

The raw data collected by the instrumented vehicle (first column in Figure 2) encompassed many events that included true and false targets. The raw data were postprocessed to reduce and filter sensor noise and target dropouts, resulting in a number of braking episodes (second column in Figure 2). The numeric data file as well as a video file were then used to characterize each braking episode. The review of video files revealed that some following vehicles initiated braking and later changed lanes to pass the stopped lead vehicle. In some instances, the following vehicle braked to make a turn or enter a parking space. When these epochs were eliminated as insignificant to our braking study, the search for significant epochs next went to the end condition (fully stopped behind the instrumented vehicle) and worked back through continuous deceleration to the initial condition (first brake press). This method resulted in 140 braking episodes of interest (significant epochs as indicated by the third column in Figure 2), which are captured in Figure 5.

In naturalistic and normal driving, most drivers initiate their braking action in response to a stopped lead car in the low-risk driving state. This is to be expected because, unlike the CAMP drivers, they are not operating under the last-second braking instruction. As seen in Figure 5, 56% of the cases initiated braking at closing speeds below 12 m/s or 43 km/h (27 mph). This high percentage at low speeds was expected since data collection was mostly done in the vicinity of intersections. Further, the trend of the naturalistic data for closing speeds less than 12 m/s agrees nicely with a simple extension of the CAMP transition for the low-risk/conflict boundary, thus also confirming that result. A total of 33 cases were recorded at closing speeds between 12 and 15 m/s, the same interval as the slowest of the CAMP initial test speeds, as indicated by the vertical dashed lines in the figure. Of these cases, 12% initiated braking in the conflict driving state, which is slightly conservative compared to CAMP, but generally confirmatory. Similarly, 10% of the 29 cases observed at closing speeds greater than 15 m/s started braking in the conflict driving state.

Figure 6 plots the data time history ("trajectory") of a selected number of cases that had brake initiation at closing range rates between 12 and 15 m/s. Any trajectory that does not cross the low-risk/conflict state boundary would be discarded as a low-risk epoch, but none of these are shown here. It is observed that most kinematic trajectories transitioned from the low-risk state to the conflict state, and asymptotically approached a simple extension of the near-crash boundary, without any apparent crossing of that boundary. Thus Figures 5 and 6 show naturalistic data that conform to our rough quantifications of the conflict and near-crash state boundaries based on CAMP braking.

Driver Performance in Near-Crash and Crash Driving States

Figure 7 shows the use of the crash boundary definition to extract pieces of the trajectories called crash state epochs. It shows the data time histories of the range and range rate in the crash state for Test Subjects 1 to 8 (as numbered in Figure 3), excluding Subjects 9 and 10 since they did not cross the crash state boundary. Test Subjects 6 to 8 who did not crash began to brake or brake and steer in the nearcrash state, crossed into the crash state, and then moved back into the near-crash state. Figure 7 illustrates the need to capture the different types of response (epoch scenarios) that drivers might undertake to resolve traffic conflicts. In particular, this method has found three different crash epoch scenarios: (a) drivers who were braking at the onset of the epoch, (b) drivers who braked after entering the epoch and only braked to the crash, and (c) drivers who braked after they entered the epoch, but chose to steer off the road at the last second before the crash. The conversion of these significant epochs into discrete data (fourth column in Figure 2) should account for each different response type that was initiated.

DATABASE APPLICATIONS

A crash avoidance database needs to provide the knowledge base required for the development of effective crash countermeasure systems. Three types of countermeasure systems are being pursued, which include advisory (situational awareness), imminent crash warning, and crash anticipatory systems. The successful development of such systems rests on two primary tasks:

1. Design of sensors, algorithms (decision making), driver-vehicle interface, and automatic controls; and
2. Estimation of safety benefits.

A warning algorithm must achieve a balance between nuisance alerts and late alerts to create acceptable system effectiveness and safety benefits. Though little research has been done to date on nuisance alarms, it is expected that drivers will perceive an alarm as a nuisance if it is issued too early with respect to a suitable epoch. Typically, drivers ignore the output of a system that produces a high rate of nuisance alerts. Thus, an imminent crash warning that appears in the low-risk kinematic state is likely to be denied by the driver's sense of danger at that time and seen as a nuisance; this is the "too early" warning error. Similarly, imminent crash warnings that are issued too late for the driver to avoid the crash will be ineffective; this is the "too late" warning error.

Figure 8 illustrates an example of the use of a crash avoidance database to evaluate the acceptability of warning algorithms. The timing of the crash warning algorithms shown in Figure 8 was based on TTC values of 3 and 5 s. A simulator study tested these algorithms by presenting 24 subjects at varying speeds with a stopped lead vehicle and an in-dash graded light display with the amber (advisory) and red (imminent warning) colors lit at the TTC values of 5 and 3 s, respectively (11). The low effectiveness of the results showed that drivers did not base their braking on a pure TTC rule. The plots in Figure 8 lend further insight to this conclusion. When approaching a stationary vehicle before braking, drivers follow a vertical line on Figure 8 down toward the range rate axis. Figure 8 shows that drivers approaching a stopped lead vehicle at 15 m/s normally initiate comfortable (amber light) and hard (red light) braking below the lines of 5- and 3-s TTC. Therefore, drivers could consider these alerts as "too early" for the situation. Conversely, drivers normally brake above the lines of 5- and 3-s TTC when approaching a stationary vehicle at 25 m/s. In this situation, TTC-based alerts could be perceived as "too late."

CONCLUSIONS AND RECOMMENDATIONS

This paper describes an approach to crash avoidance database development built upon driver judgments taken from controlled experiments (test tracks and simulators). The power of this approach rests in its ability to portray driver expectations and performance. This performance can then be used to evaluate proposed crash countermeasures, develop insights for new countermeasures, easily identify performance data gaps, and guide experimental design in any media so that results from disparate media and databases will fit together. This study proposed a database structure intended to fit driver judgment data into low-risk, conflict, near-crash, and crash driving states and investigated the feasibility of using these four driving states for database development.

The feasibility issue was reduced to two questions: (a) Can the driving state transitions be reliably quantified, and (b) Can the driving state transitions be used to create a useful crash avoidance database? The feasibility discussions were addressed for a specific, common dynamic scenario that involved a vehicle braking to avoid a rear-end crash with another vehicle stopped in the lane ahead.

For the first feasibility question, subjective "last moment braking" data from a test track study were utilized to identify rough quantitative locations for conflict and near-crash state transitions, and simulator data were used to roughly locate the crash state transition. The usefulness and reliability of these transitions were analyzed by comparing on-road, naturalistic driving data to the controlled experiments. Prior work with signal controls was also investigated to examine and confirm correspondence with the present results. The authors are confident that multiple data types indicate that the state boundaries are roughly in the locations that have been identified.

For the second feasibility question, the process of using the driving state transitions to create a useful crash avoidance database was discussed. A process was presented to develop such a database starting with the raw time history data collected from different sources, parsing the data into significant driving state epochs using the state boundaries, and finally generating aggregated files with discrete data for analysis purposes. The utility of the resulting database is to provide the knowledge foundation to develop safety-effective crash countermeasure systems that assist drivers via advisory (situational awareness), crash imminent warning, automatic vehicle control, and crash injury mitigation functions. The authors are confident that this data structure can fit together disparate data sources for a useful crash avoidance purpose. Further, the range/range-rate diagram provides a powerful graphical tool to show the combination of kinematic data with driver expectations in the case of rear-end conflicts.

Research questions that arise from this work center on whether or not the quantified boundaries of the driving states strongly depend on the following:

- Dynamic scenario encountered in the driving environment (e.g., lead vehicle stopped versus decelerating in potential rear-end crashes);
- Driver response (e.g., brake versus steer) that subjects were asked to perform as an indicator to the conflict or near-crash state;
- Context of the driving environment (e.g., slippery versus dry road, good versus reduced visibility, or light versus heavy traffic); or
- Age and gender of drivers.

It is recommended that the methods presented in this paper be extended to other dynamic scenarios that potentially lead to other high-priority crash types such as rear-end lead moving, lane change, and run-off-road crashes. In fact, there is every reason to believe that this approach would work well for any crash scenario because drivers in every case will experience the same series of events: they will begin to sense conflict, they will have comfortable avoidance and severe avoidance maneuver limits, and there will be a limit where avoidance maneuvers are simply started too late to avoid a crash. A crash avoidance database could then be created using automated data processing, which needs to be developed to convert massive raw data into searchable data files as much as possible. We believe that the key to this is the automated identification and encoding of significant epochs from a time history of driving data in a multimedia form (numeric, video, and audio).

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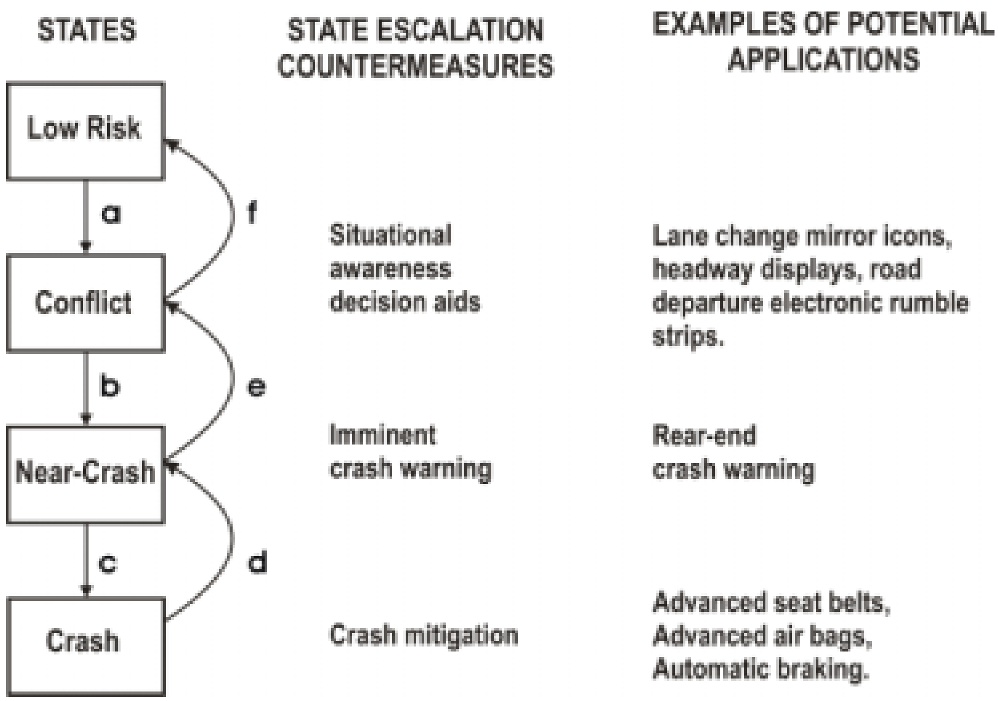

FIGURE 1 Driving states and corresponding crash countermeasures.

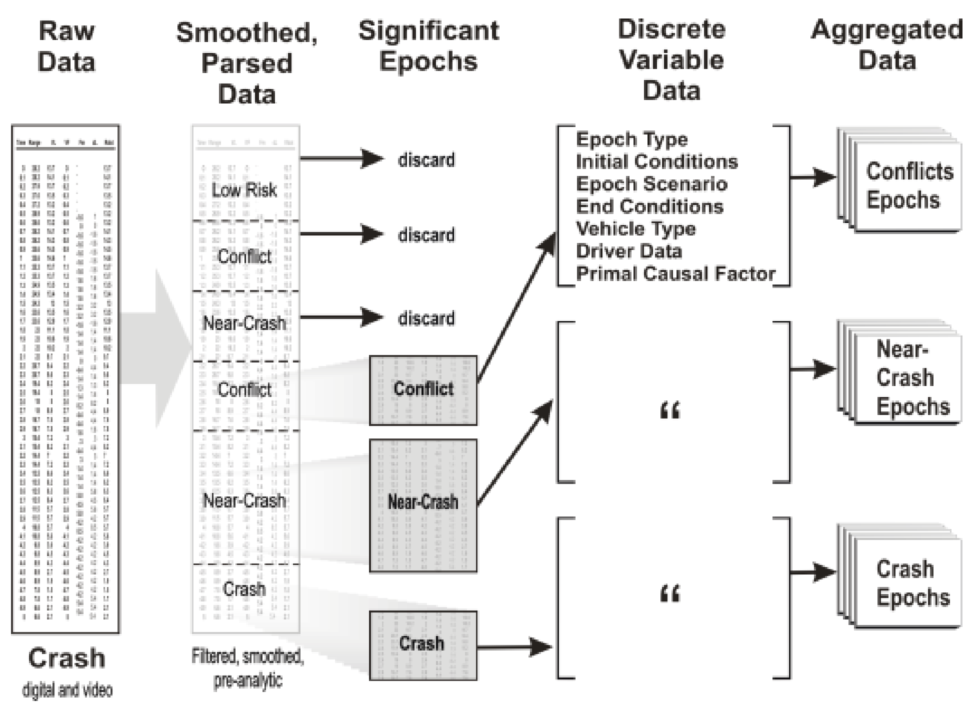

FIGURE 2 Process for the development of crash avoidance database.

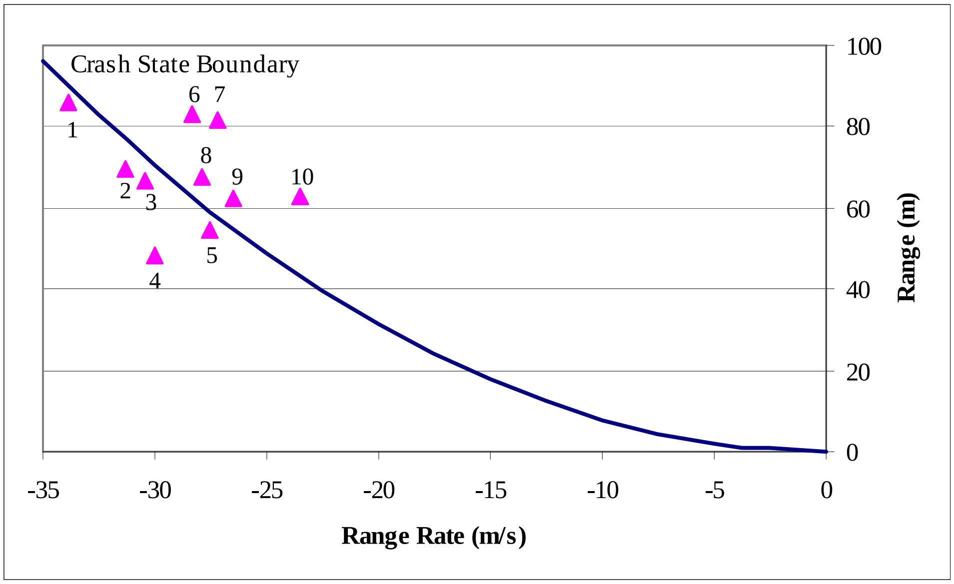

FIGURE 3 Estimation of crash state boundary based on driving simulator data.

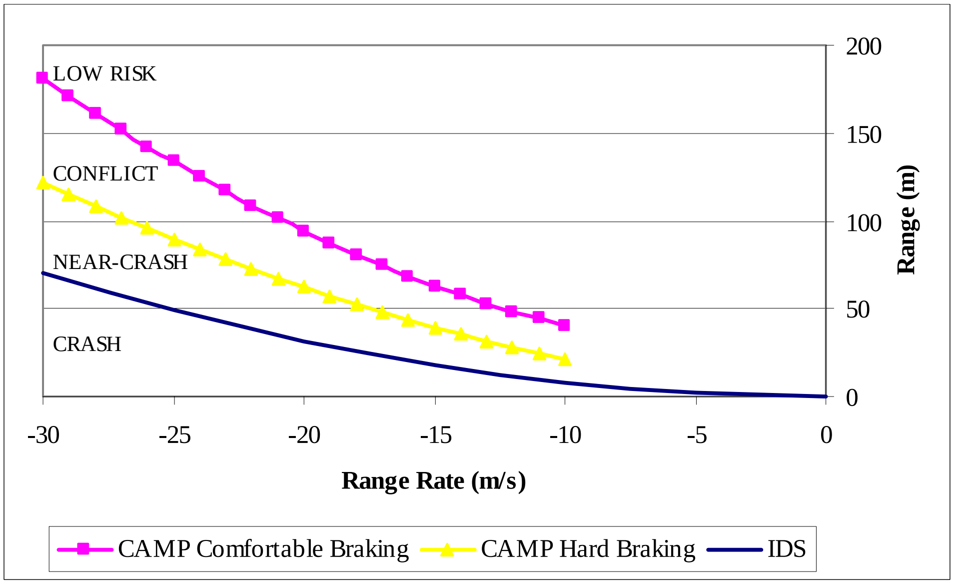

FIGURE 4 Estimation of near-crash state and conflict state boundaries based on test track date.

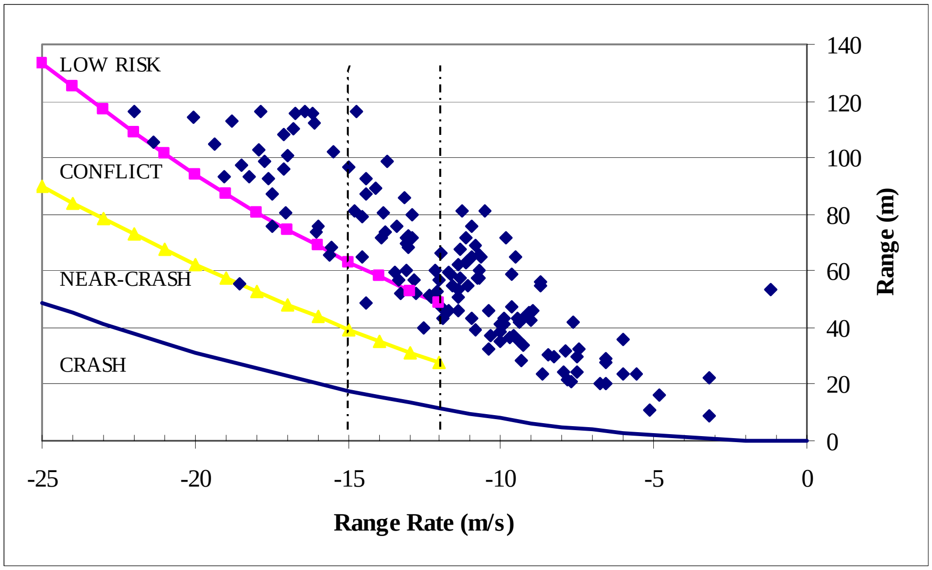

FIGURE 5 Distribution of data at onset of braking observed in naturalistic driving.

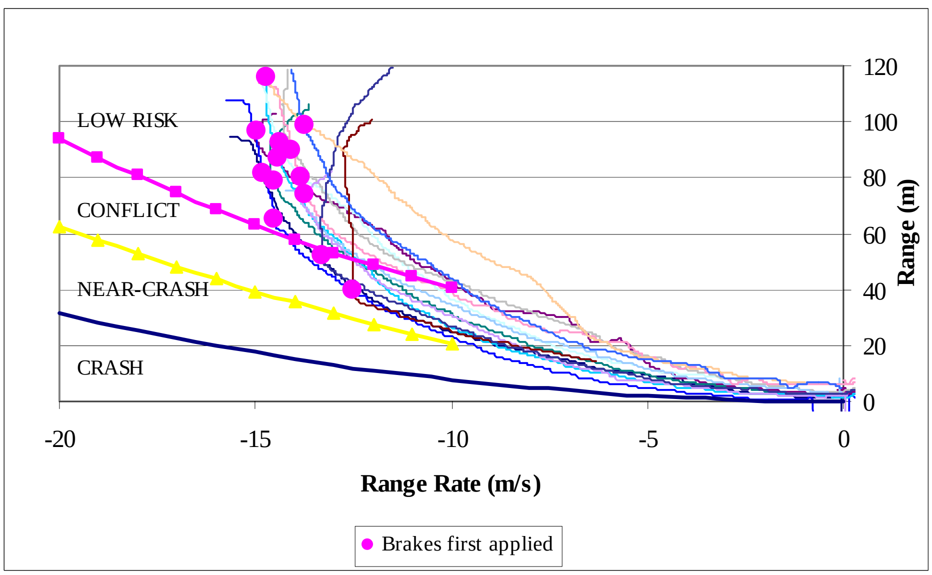

FIGURE 6 Selected time histories of braking events observed in naturalistic driving.

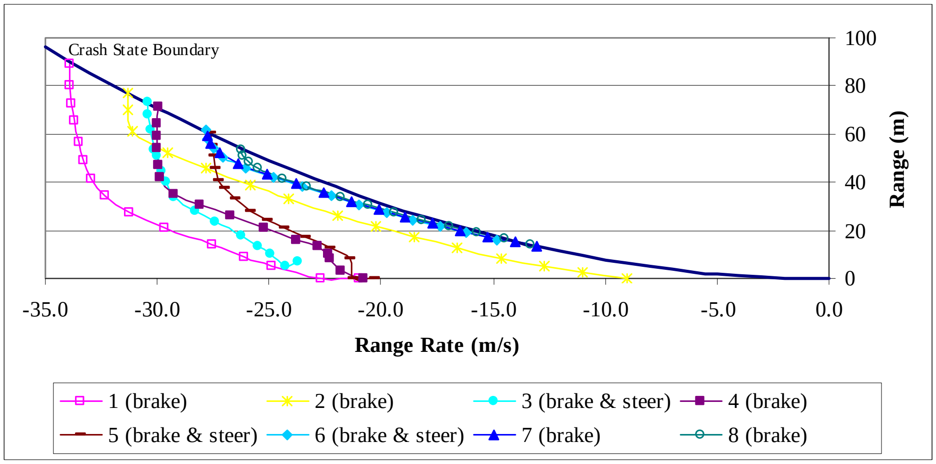

FIGURE 7 Driver actions in the crash state as observed in time histories from driving simulator data.

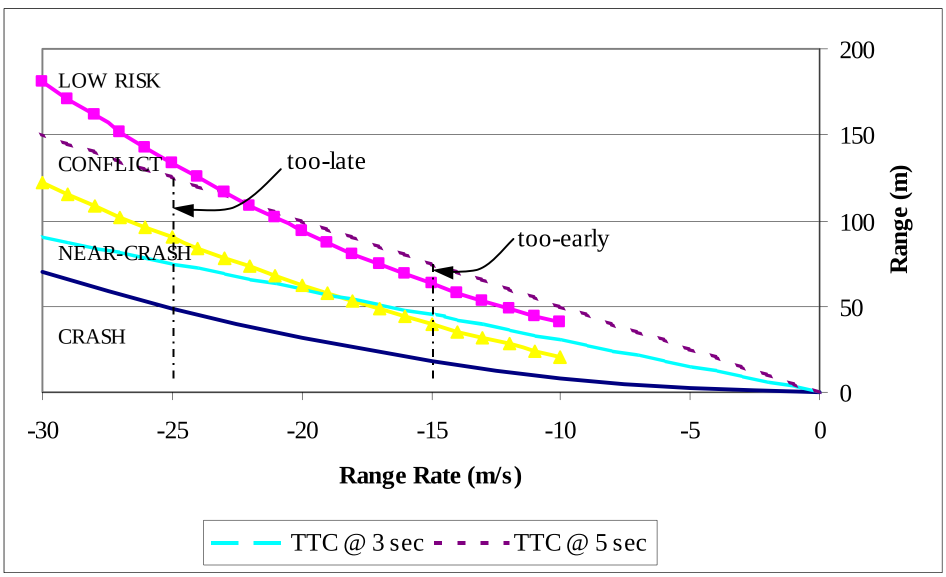

FIGURE 8 Evaluation of a warning algorithm based on time-to-collision.