Report #23-UR-124

NSTSCE

National Surface Transportation Safety Center for Excellence

Understanding Crashes Involving Roadway Objects with SHRP 2 Naturalistic Driving Study Data

Eric Li • Haiyan Hao • Ronald B. Gibbons • Alejandra Medina

Submitted: March 8, 2023

Technology
Impairment
Mobility
Infrastructure

Housed at the Virginia Tech Transportation Institute
3500 Transportation Research Plaza • Blacksburg, Virginia 24061

ACKNOWLEDGMENTS

The authors of this report would like to acknowledge the support of the stakeholders of the National Surface Transportation Safety Center for Excellence (NSTSCE): Zac Doerzaph from the Virginia Tech Transportation Institute; John Capp from General Motors Corporation; Terri Hallquist from the Federal Motor Carrier Safety Administration; Mike Fontaine from the Virginia Department of Transportation and the Virginia Transportation Research Council; and Melissa Miles from State Farm Insurance.

The NSTSCE stakeholders have jointly funded this research for the purpose of developing and disseminating advanced transportation safety techniques and innovations.

EXECUTIVE SUMMARY

Crashes involving roadway and related objects can cause severe injuries and are a major concern for the traveling public, state transportation agencies, and the automotive industry. Many previous studies addressed such crashes in the context of roadway departures. Such studies tended to focus on how to prevent roadway departures, sometimes without fully addressing why and how such crashes occur. Traditional safety studies also rely on police-reported crash data, omitting potentially important information available through unreported crashes. The analyses based on traditional crash data are also limited to post-crash information, potentially missing some critical information about real-time driver behavior and reaction before and during crashes.

This project used the second Strategic Highway Research Program (SHRP 2) naturalistic driving study (NDS) data as an alternate data source to police-reported crash data to better understand such crashes. The objectives included determining crash causation, recommending strategies for crash prevention, and understanding the implications for highly automated vehicles (HAVs). Researchers addressed these objectives with a three-pronged approach: (1) a detailed engineering study of roadway object events to identify and quantify effects of a large number of relevant variables; (2) a machine-vision-oriented study to document the implications of roadway object events on machine vision performance; and (3) a detailed case study analysis of representative roadway object events to provide further qualitative results on how and why roadway object crashes occur and what potential actions can prevent such events effectively.

The study used a total of 1,639 safety-critical events (SCEs) for analysis, including 1,029 crashes and 610 near-crashes. Note that, although the focus of this project was roadway object crashes, researchers included crashes involving animals in the study. Animal-related crashes frequently involve vehicles traveling at high speeds and can cause roadway departures leading to secondary crashes involving roadside objects. The research team also requested 1,050 balanced baseline events for comparison purposes. In addition to the detailed event data reduced by the SHRP 2 data team and additional data elements collected based on the event videos, researchers also used Roadway Information Database (RID) roadway and traffic information for 1,538 events, including 694 SCEs and 844 baseline events.

FINDINGS

The results of the analysis showed the following:

- Significant increases in the crash odds ratios for driver behaviors, with pre-incident maneuvers such as turning or drifting on the roadway and secondary task performance having the most significant impact.

- Fewer significant factors in terms of the roadway and traffic, with only the free flow traffic (level of service A1) and local roads being significant; however, fewer of these categories of crashes were analyzed, and further research should be considered.

- In terms of the roadway environment, the time of day (nighttime versus daytime) had a significant impact on the occurrence of fixed object crashes, while roadway surface conditions and adverse weather increased the severity but not the occurrence of crashes.

- Drivers were able to make safe maneuvers in most cases, especially in cases involving on-road objects, such as animals and roadway debris. Among the evasive maneuver types, drivers were more likely to make safe maneuvers when the scenarios required braking, with drivers reacting incorrectly more frequently when steering left or when acceleration was considered safe.

- The sensitivity analysis of the three support vector machine (SVM) classifiers confirmed that driver behavior/errors, critical speed, struck object type, and reaction time were major factors affecting roadway object event occurrence and severity. The SVM models also indicated the potential for machine-learning algorithms to identify the risks of roadway object crashes.

- Machine vision reaction time for fixed object crashes was shorter than human reaction time in many cases, indicating that camera-based machine vision detection range was generally shorter than the range for humans. The exception was incidents with animals, where the machine vision reaction time was equal to or longer than that of the human. Note that this analysis is limited to the technology used for the SHRP 2 study, and advances in camera technology could influence this result.

RECOMMENDATIONS

The results based on the statistical, machine learning, and case study analyses point to the following recommendations to mitigate roadway object crash risks effectively:

- **Roadway improvements**. Several findings suggested the importance of improving roadways to mitigate roadway object crash risks. Transportation agencies should avoid sharp curves whenever possible to reduce roadway departures and provide delineation options for improved visibility of the roadway and the travel path.

- **Traffic control and signage**. The findings of this study demonstrated the risks caused by insufficient and/or improperly designed traffic control devices and methods for mitigating roadway object crashes. Based on the results, the researchers recommend the following:
    - Delineate raised channelizing islands at intersections.
    - Remove or relocate unnecessarily on-road or roadside structures.
    - Provide pavement markings at intersections to guide turning vehicles.
    - Provide sufficient, proper lighting when necessary.

- **Consider driver education and enforcement whenever possible**. Several findings showed the significant role of driver errors in the occurrence and severity of roadway object crashes.

- **Implement advanced vehicle technologies and features**. Vehicle vision-based advanced technologies offer the possibility of identifying and avoiding roadway object crash risks.

TABLE OF CONTENTS

LIST OF FIGURES

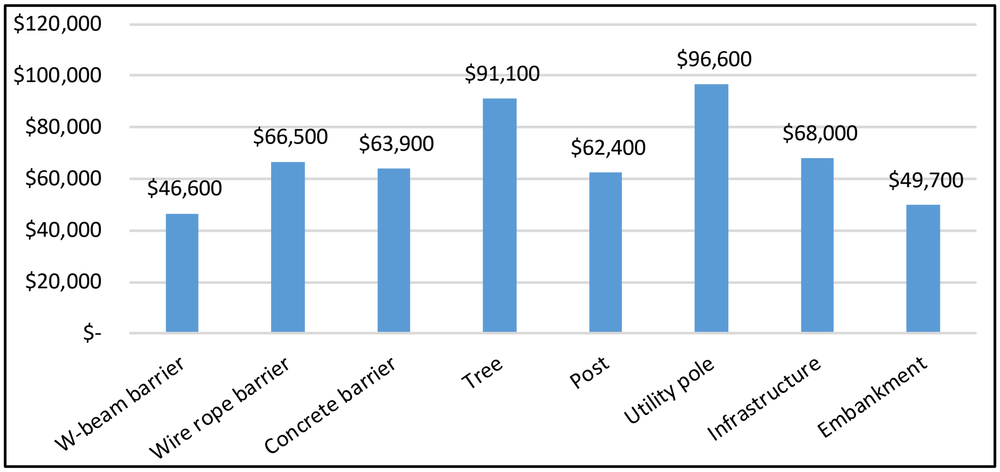
LIST OF TABLES

LIST OF ABBREVIATIONS AND SYMBOLS

AADT	annual average daily traffic
AASHTO	American Association of State Highway Transportation Officials
AIC	Akaike's information criterion
CCD	charge-coupled device
CMOS	complementary metal oxide semiconductor
DAS	data acquisition system
DOT	Department of Transportation
FARS	Fatality Analysis Reporting System
GIS	geographic information system
HAV	highly automated vehicle
IRI	International Roughness Index
LOS	level of service
MUTCD	Manual on Uniform Traffic Control Devices
NDS	naturalistic driving study
NSTSCE	National Surface Transportation Safety Center for Excellence
OR	odds ratio
PII	personally identifiable information
RBF	radial basis function
RDG	Roadside Design Guide
RID	Roadway Information Database
ROC	receiver operating characteristic
SC	Schwarz criterion
SCE	safety-critical events
SHRP 2	Second Strategic Highway Research Program
SVM	support vector machine
VMT	vehicle miles traveled

CHAPTER 1. INTRODUCTION

Crashes involving roadway and related objects occur when a vehicle leaves the road and collides with a roadside object or strikes an object on the roadway. Such crashes can cause severe injuries and are a major concern for the traveling public, state transportation agencies, and the automotive industry. According to the National Highway Traffic Safety Administration, approximately one third (30.9% or 9,939) of fatal crashes and 15.6% (or 268,000) of injury crashes in 2015 were roadway object crashes.[1,2,3] Roadway object crashes also cause significant monetary losses each year due to property damage and hospital expenses (Figure 1).[4]



Source: (4)

Figure 1. Graph. Mean cost for roadway object crashes.

Roadway object crashes are an important topic for safety analyses, but many previous studies addressed such crashes in the context of roadway departures. Roadway departure studies generally focus on how to prevent roadway departures, sometimes without fully addressing why and how roadway object crashes occur. Roadway departure studies also tend to focus on rural roadways and curved roadway sections, underrepresenting the fixed-object crash risks on straight and/or urban roadways. Although a large proportion of roadway object crashes do involve roadside objects, many roadway object crashes involve objects on roadways, such as traffic control devices, sign structures, and debris. Debris on roadways, for example, contributed to over 200,000 police-reported crashes, resulting in nearly 39,000 injuries and 500 deaths between 2011 and 2014.[5]

Traditional safety studies rely on police-reported crash data. Studies based on traditional crash data are generally limited to post-crash information, which leaves out critical information about driver behavior and actions before and during the crashes. Studies have also shown that approximately 60% of property damage-only crashes and 20% of injuries were not reported.[6] While such minor crashes may not cause significant injuries or property damage, they could still provide more balanced insights on how roadway object crashes occur.

The second Strategic Highway Research Program (SHRP 2) was a large-scale naturalistic driving study (NDS) intended to develop a data source to better understand driver behavior and traffic safety issues. The SHRP 2 NDS data set has several advantages compared to traditional crash data:

- The NDS data acquisition systems (DASs) had the ability to capture a significant number of crashes and near-crash events, which may allow more balanced and complete information on roadway object crashes and events.
- The video cameras and vehicle kinematic sensors in the DASs recorded detailed information about the driver and the vehicle throughout each event truthfully and continuously. The data was used to determine other factors such as the roadway environment, resulting in a rich data set that fully depicted each roadway object event.
- The SHRP 2 data set contains many sampled baseline epochs with information about normal driving conditions. These epochs provide an opportunity for researchers to understand complex crash risk factors via controlled statistical comparisons.

SCOPE AND APPROACH

Recognizing the significance of the safety concern and the potential of the SHPR 2 NDS data, a group of stakeholders representing federal/state transportation agencies, vehicle manufacturers, and the insurance industry funded this National Surface Transportation Safety Center for Excellence (NSTSCE) research to identify cost-effective strategies to curb roadway object crashes nationwide. The project used SHRP 2 NDS data as an alternate data source to police-reported crash data to better understand such crashes.

The specific objectives of this project were to:

- Analyze roadway object crashes and near-crashes in the SHRP 2 NDS database to understand exactly how and why roadway object crashes took place.
- Recommend strategies relevant to traffic control and roadway design to prevent roadway object crashes.
- Understand and document the implications of roadway object crashes relevant to the emerging vehicle vision technologies used by highly automated vehicles (HAVs).

Note: the term “crashes/events involving roadway and related objects” refers to those crashes involving fixed objects (on road or roadside), animals, and roadway debris. For simplicity, the authors also referred to such crashes as “roadway object crashes/events” throughout the report.

To accomplish the objectives, the research team conducted a variety of analyses:

- SHRP 2 NDS event data analysis, which was a comprehensive statistical analysis focusing on event detail data in conjunction with roadway and traffic information. The purpose of this analysis was to identify significant risk factors contributing to roadway object crashes and identify potential engineering solutions to mitigate such risk factors.

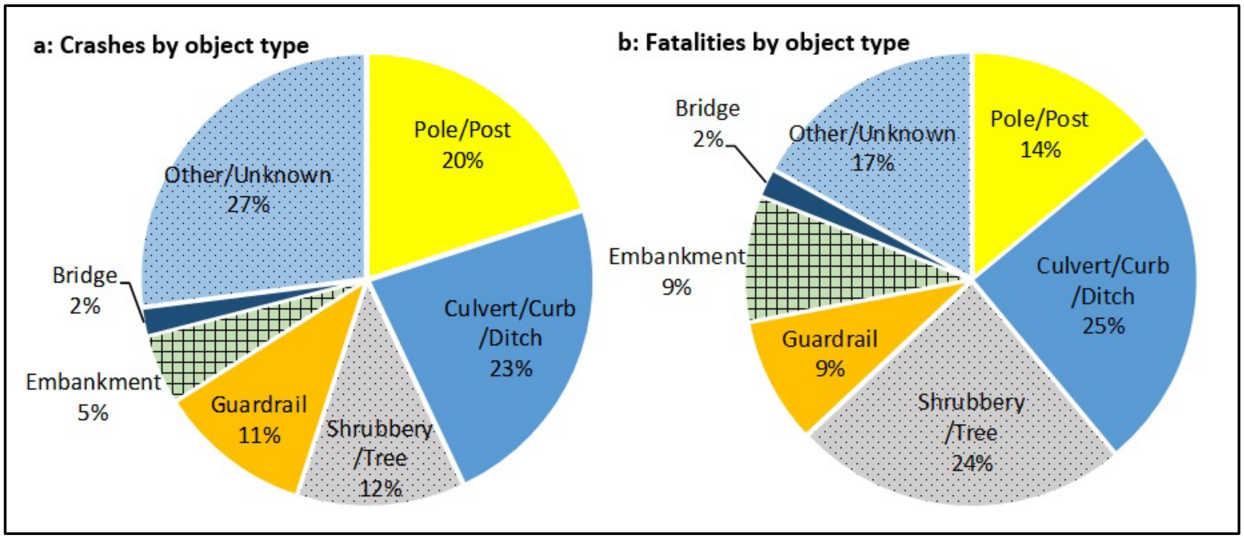
- Event video analysis and case studies, which involved a qualitative analysis of the event video data focusing on several sample cases representative of typical roadway object crash causation scenarios in the SHRP 2 NDS database. These case studies provided more tangible information on how the roadway object crashes occurred and what actions could be most effective in preventing them.

- Event data collection and analysis for vehicle vision implications. The project team collected and analyzed a number of data elements, primarily based on the analyzed event videos, that can be particularly relevant to and indicative of the development of vehicle vision-based countermeasures.

CHAPTER 2. BACKGROUND AND LITERATURE REVIEW

ROADWAY OBJECT CRASH CHARACTERISTICS AND CONTRIBUTING FACTORS

Roadway object crashes can involve a large range of objects located in, or on the side of, roadways. Based on 2015 Fatality Analysis Reporting System (FARS) data, poles/posts, trees, and guardrails were among the most common objects involved in roadway object crashes, and trees and poles/posts were responsible for more than 40% of fatalities when combined, as shown in Figure 2.[3] It is noteworthy that the other/unknown category is the largest in the sample. As FARS is based on police reporting, this indicates that the post-event crash cause in many cases is difficult to discern and highlights the significance of the naturalistic approach to crash analysis.



Source: adapted from (3).

Figure 2. Pie charts. Roadway object crashes and fatalities by object type.

A range of factors relevant to the driver, roadway, environment, and vehicle can contribute to roadway object crashes. Previous studies identified the following contributing factors:

- **Human factors**. Drowsiness, alcohol involvement, speeding, improper steering, inattention, distraction, and improper braking were found to have contributed to roadway object crashes.[2,7,8,9] In addition, one study showed that travel speeds and seatbelt usage were factors significantly correlated to roadway object crashes for older drivers.[10]

- **Roadway-related factors**. Roadways characterized by lower functional classifications, asphalt pavement (as compared to concrete pavement), unpaved shoulders, and no median barriers tended to have more roadway object crashes.[11] Undivided rural roadways with curved alignment and high posted speed limits were particularly prone to roadway departures that could lead to crashes involving fixed objects.[5] Intersections and narrower clear zones could also increase the probability of severe crashes involving fixed objects.[12]

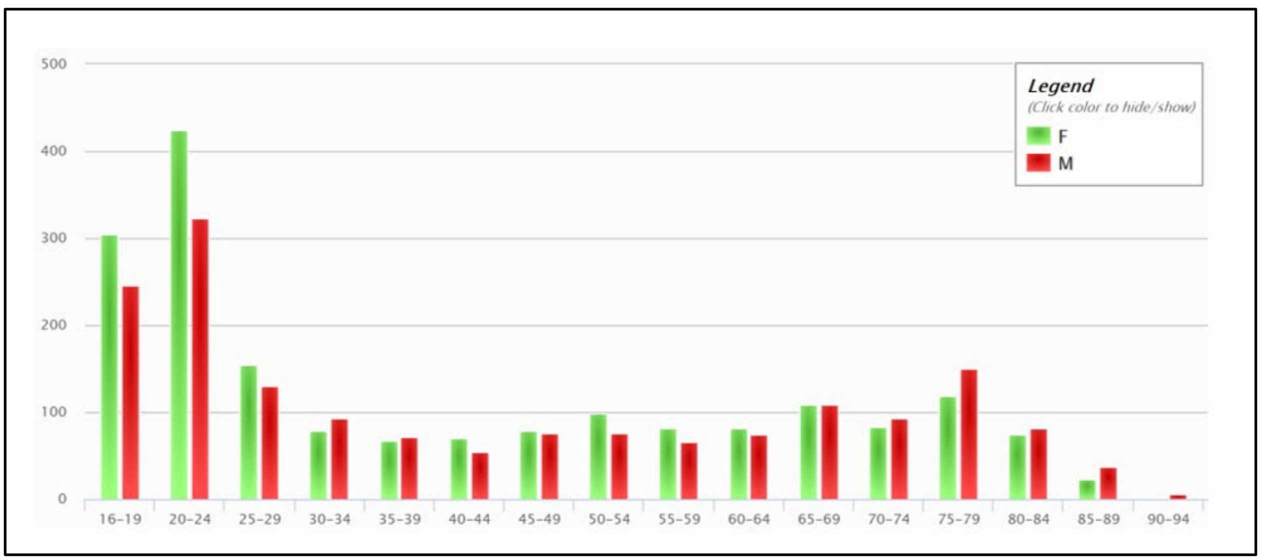
- **Environmental factors**. Studies showed that roadway lighting was significantly correlated with decreases in crash severity, while foggy weather was correlated with increased crash severity in roadway object crashes.(10) Note that another study, however, showed little association between crash severity and weather and lighting conditions.(8)

- **Vehicle-related factors**. Studies showed that vehicle type (e.g., heavy trucks versus passenger cars) and vehicle function failures (e.g., ineffective brakes and blown tires) were frequently associated with more severe injury outcomes, while the activation of air bags and the use of seatbelts reduced crash severity during roadway object crashes.(8,10,13)

SHRP 2 NDS DATA

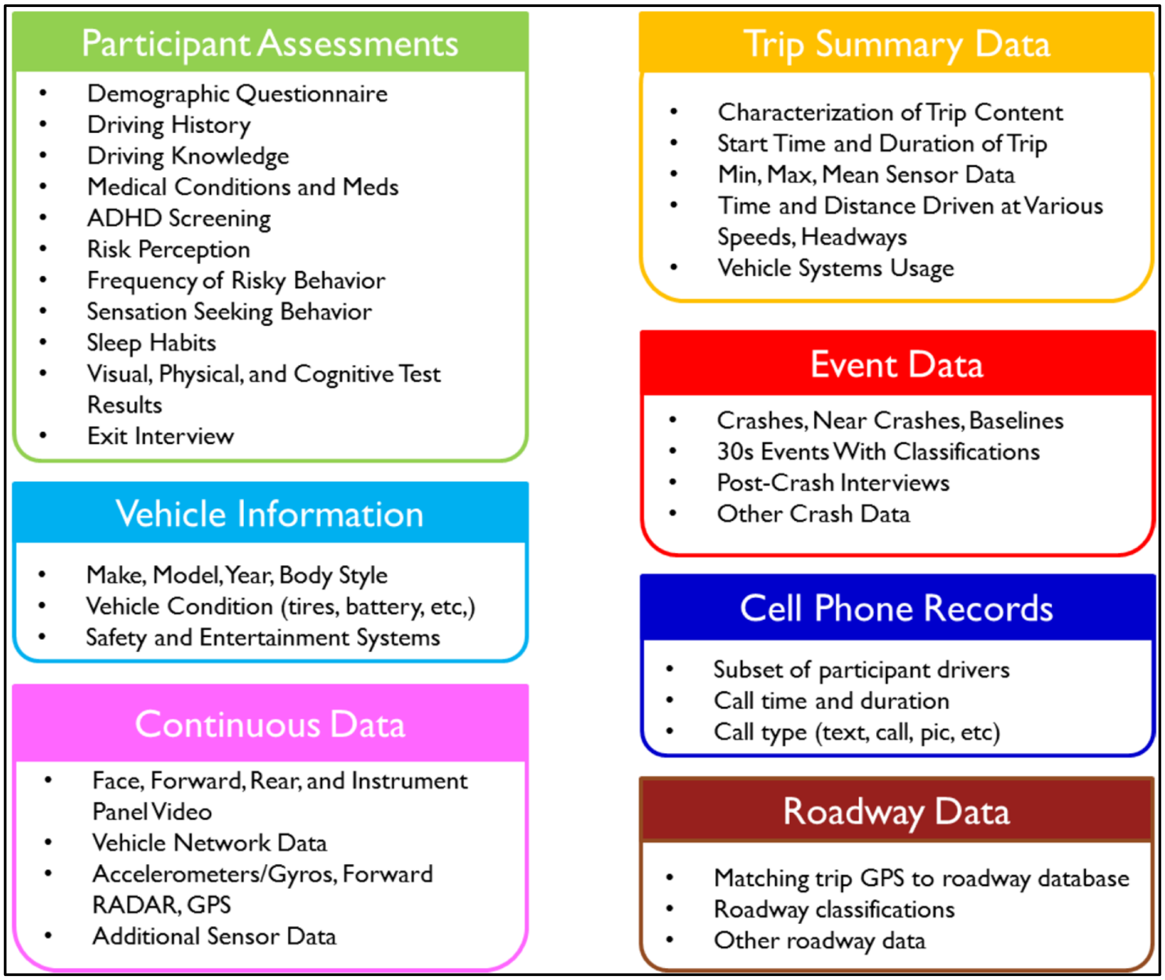
The SHRP 2 NDS took place between 2010 and 2013 to investigate driver behavior and performance relevant to safety during real-world scenarios.(14) More than 3,500 participant drivers were recruited from all age groups (Figure 4) at six sites across the country:

- Bloomington, Indiana
- Central Pennsylvania
- Tampa Bay, Florida
- Buffalo, New York
- Durham, North Carolina
- Seattle, Washington



Source: (12).

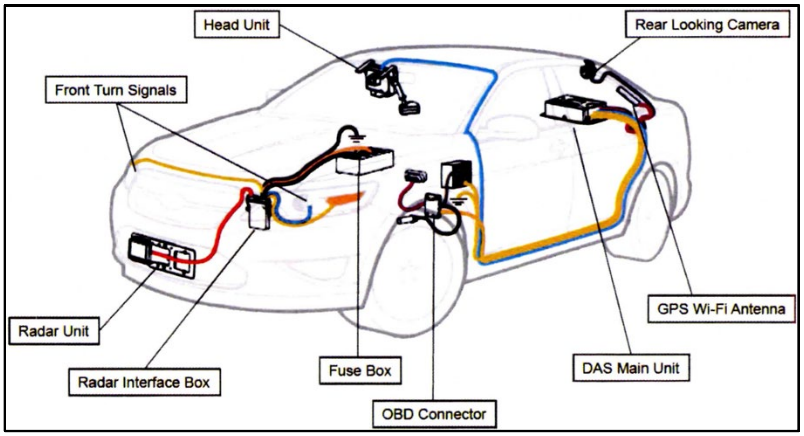
Figure 3. Bar graph. SHRP 2 NDS participants by gender and age group.



Source: (15).

Figure 4. Text graphic. Data categories collected in the SHRP 2 project.

The SHRP 2 NDS used onboard DASs for vehicle kinematic and driver behavior data collection. Each DAS consisted of a forward radar, four video cameras (observing driver's face and hands, passenger side, forward view, and rear roadway view), accelerometers, GPS receivers, computer vision lane-tracking capability, and data storage equipment, as shown in Figure 5.



Source: (16).

Figure 5. Graphic. DAS components.

The final NDS database contained information for more than 5 million trips and 41,000 events, with additional events and data being added as data processing continues.(17) SHRP 2 defined three types of events: crashes, near-crashes, and baseline events. Crashes and near-crashes in the NDS database are also collectively referred to as safety-critical events (SCEs).(13) SHRP 2 classified crashes into four different severity levels:(15)

- Level 1 (Severe crash): These are crashes that involved an airbag deployment, a vehicle rollover, vehicle towing, a change in speed in any direction greater than 20 mph (excluding curb strikes), or acceleration greater than ±2 g (excluding curb strikes) during the impact, or that caused any injury to the driver or any other roadway users. If the injury was present, it should be sufficient to warrant a doctor's visit, including those self-reported and those observed from video.

- Level 2 (Police-reportable crash): These crashes did not meet Level 1 crash criteria but caused sufficient property damage that was police reportable (minimum of $1,500 worth of damage, as estimated from video), reached an acceleration on any axis greater than ±1.3 g (excluding curb strikes), or there was a police report completed for the crash. Most large animal strikes and sign strikes, for example, were considered Level 1 crashes.

- Level 3 (Minor crash): These are crashes involving physical conflicts with another object, but with minimal damages that do not meet Level 1 and Level 2 criteria. Most road departures, small animal strikes, all curb and tire strikes potentially in conflict with oncoming traffic, and other curb strikes with an increased risk element were considered Level 3 crashes.

- Level 4 (Low-risk tire strike): These crashes only involved minimal tire strikes with little/no risk elements (e.g., clipping a curb during a tight turn). The distinction between Level 3 and Level 4 is that Level 3 crashes would lead to worse conditions if the curb had not been there, but Level 4 crashes would not due to limited risk present.

In the SHRP 2 NDS database, near-crashes were events that involved a rapid evasive maneuver by the subject vehicle or other involved roadway users. The maneuver performed was not premeditated and did not result in a roadway departure. During the evasive maneuver, the subject vehicle made no physical contact with other objects. Baseline events were sample epochs of trips that represented normal driving and typical driver behavior that were identified using a case-cohort sampling method.[15] During the sampling, balanced sample baseline events were randomly selected for the population, controlling for a number of factors, such as time, weather, and roadway condition. The case-cohort sampling method was relatively efficient and less resource-demanding considering the large number of variables relevant to drivers, environment, traffic, and roadways involved in the large-scale NDS. However, the resulting sample baselines may be less powerful for certain studies involving factors that were not well controlled during the sampling.

The NDS database contained 8,758 SCEs, 19,998 balanced sample baseline events, and 12,583 random baseline events (analyzed for all participants regardless of whether they were involved in an SCE or not) at the time that this roadway object study was conducted.[12]

To complete the NDS data, the Roadway Information Database (RID) was also developed as part of SHRP 2. The RID provides relatively detailed traffic and roadway information for the six NDS sites. The linkages between the SHRP 2 driving and roadway data allowed researchers to effectively identify driving data on particular roadway segments of interest.[18] The database incorporated both data originated at state departments of transportation (DOTs) and data collected by instrumented vehicles on selected routes:

- Detailed roadway data for a selected number of roadways, such as horizontal and vertical curvature, grade, cross-slope/superelevation, travel lanes, shoulder, and the presence of certain traffic control measures. Most such data was collected during the SHRP 2 NDS study with instrumented vehicles.
- Basic roadway and traffic information for state-maintained roadways at all six NDS states. This data mostly originated at state DOTs.
- Historical crash data and crash-data-related documents.
- Historical transportation project data for Washington only.
- List of safety-related traffic laws for all SHRP 2 states.
- Aerial imagery data between 2011 and 2013 for all SHRP 2 states.
- Weather-related data (e.g., daily/hourly precipitation and weather station locations) for all SHRP 2 states.
- List of safety campaigns conducted by state DOTs during the SHRP 2 NDS study in Indiana, North Carolina, Pennsylvania, and Washington.
- Work zone and lane use information for Florida and New York.

ROADWAY AND ROADSIDE DESIGN PRACTICES RELEVANT TO ROADWAY OBJECT CRASHES

General Considerations

Ideally, high-speed roadways should be designed with clear zones on both sides to allow errant vehicles to recover safely during roadway departures. The American Association of State Highway Transportation Officials' (AASHTO's) *Roadside Design Guide* (RDG)[19] specifies the procedure to determine clear-zone widths, taking into consideration traffic volumes, roadside characteristics, and speed limits. For example, the RDG recommends a 30- to 32-ft clear zone for straight highway segments with a 60-mph posted speed, 6,000 annual average daily traffic (AADT), and level terrain for which the side slope is equal or flatter than 1V:6H. For steeper slopes on a 70-mph section, the clear zone width increases to 38 to 46 ft. For low-speed roadways, the guide typically recommends that a minimum clear zone width of 10 ft should be maintained. The clear zone width can be increased by up to 50% if horizontal curves are present.

In many circumstances, however, a continuous clear zone is impractical due to right-of-way restraints, appurtenances associated with the roadway or utilities (e.g., traffic control devices, light/power poles, and drainage structures), and/or existing objects (e.g., trees or bushes). For those hazards within the clear zone distance, RDG[19] recommends the following solutions in order of preference to reduce the severity of potential crashes:

- Remove the obstacle
- Redesign the obstacle to make it traversable
- Relocate the obstacle to a point where it is less likely to be struck
- Reduce impact severity by using appropriate breakaway devices
- Shield the obstacle with a longitudinal traffic barrier and/or crash cushion if it cannot be removed, relocated, or redesigned
- Delineate the obstacle if all above alternatives are inappropriate

Trees Within Clear Zones

Trees with an expected mature size of, or larger than, 4 inches in diameter are treated as hazards, while trees with thinner stumps can break away or bend over when struck by most motor vehicles. Typical treatments for trees within clear zones include removal, relocation, shielding, and delineating.[20] For safety purposes, it is best to remove or relocate large trees whenever possible. When removal of some large trees may result in significant disturbance to the landscape, the RDG recommends cutting or grinding them to a traversable height. In many cases, tree removals can be cost prohibitive and associated with environmental concerns. Public sentiment also often favors preserving trees for their aesthetic and historic values. In such cases, shielding trees with barriers or delineating them with retroreflective panels should be considered.

Poles/Posts Within Right of Way

Poles and posts are commonly used along roadways as part of traffic control devices or are required for utilities and signage. The RDG requires the use of breakaway posts or poles whenever possible to reduce crash severity. The Manual on Uniform Traffic Control Devices

(MUTCD) further requires that all signs within roadway clear zones of 50 mph or higher use breakaway structure or be shielded with crashworthy barriers.[21] The following are types of signposts that are commonly used in the country:[22]

- **Wood posts**. These are the most frequently used type of poles due to their low costs. Wood posts range from 4 × 4 to 6 × 8 inches in size and should be buried about 30 to 36 inches deep. Wood posts larger than 4 × 4 inches can be made breakaway by reducing the cross-section area (e.g., drilling holes) near the base (Figure 6).

- **U-channel steel posts**. Posts weighing 3 pounds-per-foot or less are considered breakaway. For heavier posts, slip plane connected with bolts can be used near the base to make them breakaway.

- **Steel posts**. Square steel tube posts that are 2.25 inches wide or less are considered breakaway. Larger steel posts and I-beam steel posts should be installed with sleeve assemblies for the base or slip coupling near the base to make them breakaway.

Source: (22).

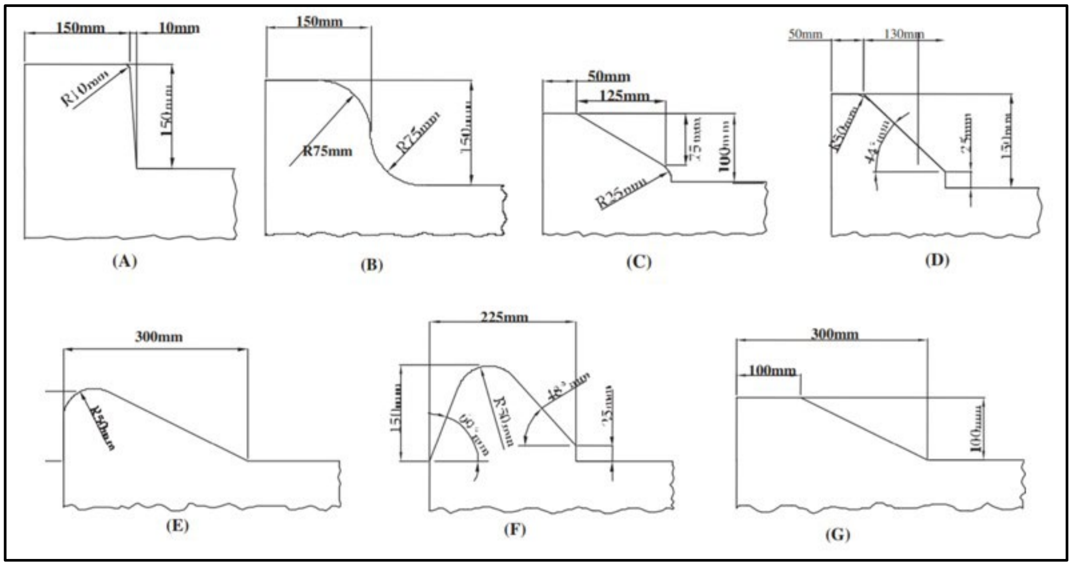
Figure 6. Photographs. Examples of breakaway mechanisms for signposts.

Most light poles are installed with slip bases, cast aluminum transformer bases, or slip couplings to provide a breakaway mechanism. For utility poles, the most effective solution is to remove those poles and place utility lines underground. Other alternatives to avoid or mitigate crash risks involving utility poles include increasing pole lateral offset, increasing pole spacing, using breakaway devices (e.g., steel reinforced safety poles), shielding poles, or delineating poles.[23]

Note that breakaway poles/posts may fall into travel lanes, endangering bypassing vehicles when struck. Due to this, such poles should not be used in certain locations (e.g., concrete median barriers). Some states have used fiberglass reinforced composite poles to replace breakaway poles. Such poles are designed to absorb energy upon impact and therefore tend to collapse rather than break when struck by a vehicle.[24,25]

Curbs

There are generally two types of curb designs used across the country: vertical and sloping. Vertical curbs have a vertical or nearly vertical face with a height of 6 to 8 in. They are designed to discourage vehicles from leaving the roadway deliberately. Sloping curbs are those with a sloping face and a height of 4 to 6 in. The sloping faces allow vehicles to traverse them without causing tire blowouts or damages to vehicle suspensions. AASHTO lists seven types of common curb designs, all of which are sloping, with the exception of type A, which is vertical (Figure 7).[26]



Source: (26).

Figure 7. Diagrams. AASHTO typical highway curb design.

When a well-designed curb is hit by an errant vehicle from a small angle, the impacting wheel will be steered by the curb in a direction parallel to the travel lane. This steering action may be sufficient to prevent low-speed vehicles from leaving the roadway with relatively low risk of losing control. At higher speeds and impacting angles, vehicles may be more likely to lose control or roll over when hitting a curb. In addition, studies showed that vehicles were much more likely to lose control and roll over when traversing taller and/or steeper-faced curbs.[27] Drivers' different steering reactions before, during, and after hitting a curb make it more difficult to understand the likelihood of the vehicle losing control or rolling over. For these reasons, curbs are usually restricted from high-speed highways or freeways. At high-speed roadway segments where the installation of curbs is necessary for drainage, countermeasures like locating curbs at the outside edge of the shoulder or installing curbs with guardrails may help with this problem.

Ditches and Culverts

Ditches and culverts are commonly used along roadways for drainage purposes and can also be roadside hazards for vehicles when a roadway departure occurs. The RDG(19) recommends a number of general solutions to mitigate the crash risks associated with drainage features:

- Eliminate non-essential drainage features
- Make drainage structures traversable
- Shield drainage structures with barriers

Culverts and pipes are designed to carry water underneath the embankment. Their size varies from 18 inches in diameter for small pipes to 10 ft for large box culverts. The RDG(19) recommends the following to mitigate crash risks involving culverts or pipes:

- Large culverts should be installed to match the ends to embankment slopes. Culvert openings wider than 1 m should be installed with bar grates to prevent vehicles from trapping.
- Small pipes or culverts whose inlets and outlets are not traversable should be extended to outside of the clear zone.
- At locations where the embankment is not traversable (i.e., the slope is steeper than 1V:3H) or the extension is not practical due to roadside terrain or economic considerations, a traffic barrier should be used to shield the obstacles.

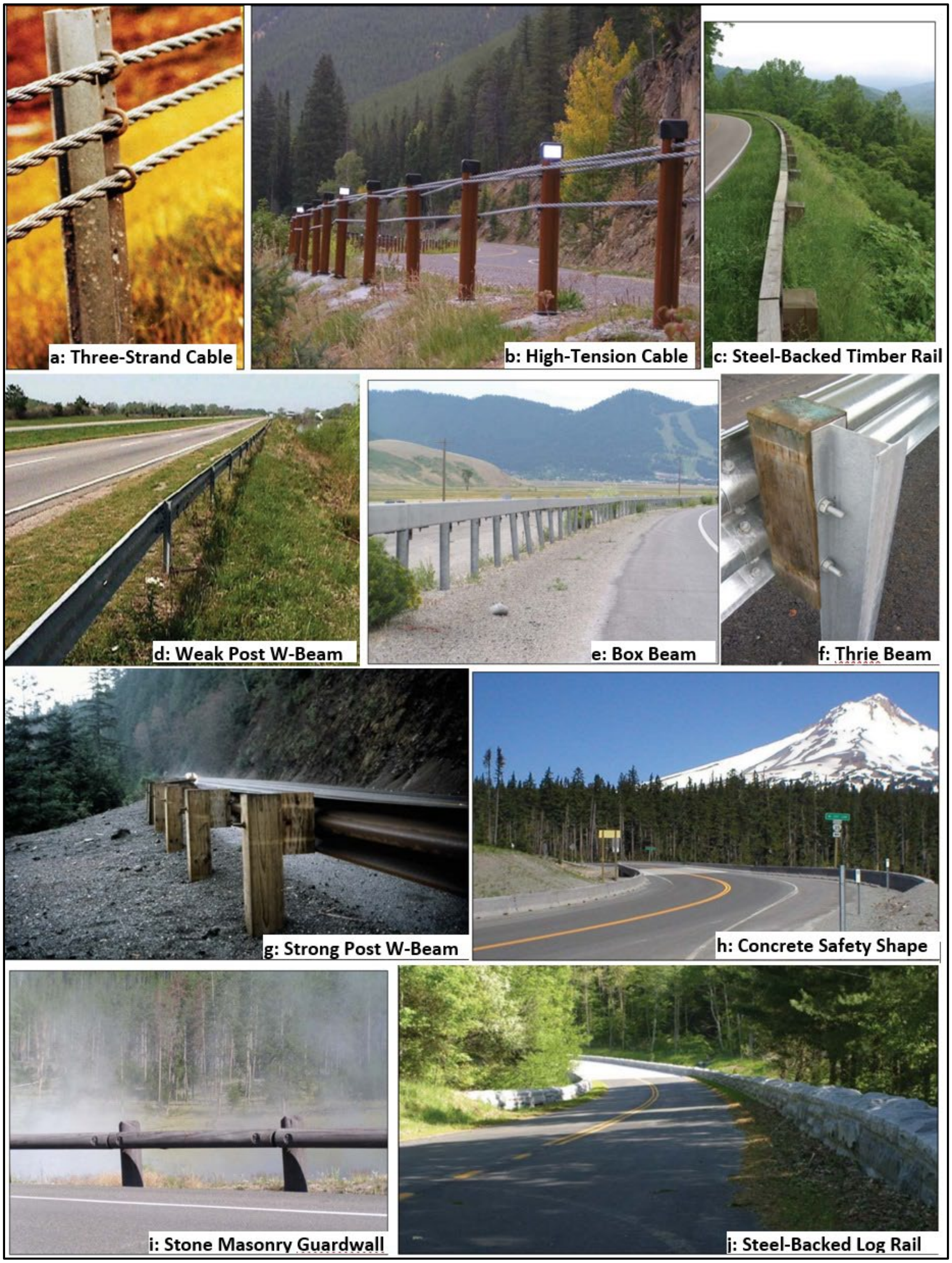
Safety Barriers

Safety barriers are widely used along roadways to shield roadside objects that may cause severe injuries when involved in crashes. Different types of barriers vary in performance, costs, maintenance requirements, and aesthetic characteristics, but can be broadly categorized as flexible, semi-rigid, and rigid based on their deflection characteristics upon impact. National Cooperative Highway Research Program Report 350(28) recommends crash test procedures for barrier performance at different test levels defined by impact conditions and test vehicles. Table 1 lists some commonly used barriers and their approved test levels, and Figure 8 lists examples of common safety barriers.

Table 1. Frequently used roadside barrier types.

Barrier Type	Barrier System	Approved Test Level
Flexible	Three-Strand Cable	TL-3
	High-Tension Cable	TL-3
	Weak Post W-Beam	TL-2
Semi-Rigid	Box Beam	TL-3
	Thrie-Beam	TL-3
	Modified Thrie-Beam	TL-4
	Steel-Backed Timber Rail	TL-3
	Strong Post W-Beam	TL-3
Rigid	Concrete Safety Shape	TL-4
	Stone Masonry Wall	TL-3
	F-Shape Barrier (810 mm, 1070 mm)	TL-4,5
	Vertical Concrete Barrier (810 mm, 1070 mm)	TL-4,5

Source: (19, 29)



Source: (29).

Figure 8. Photos. Examples of commonly used barriers.

Barriers are continuous and closer to the roadway and are therefore more likely to be hit by errant vehicles than other roadside hazards. Flexible barriers are more forgiving since much of the impact energy will be dissipated by the deflection of the barrier, and lower impact forces will be imposed on vehicles. The RDG provides detailed guidance for determining proper barrier lengths and recommends that agencies avoid excessive use of traffic barriers.

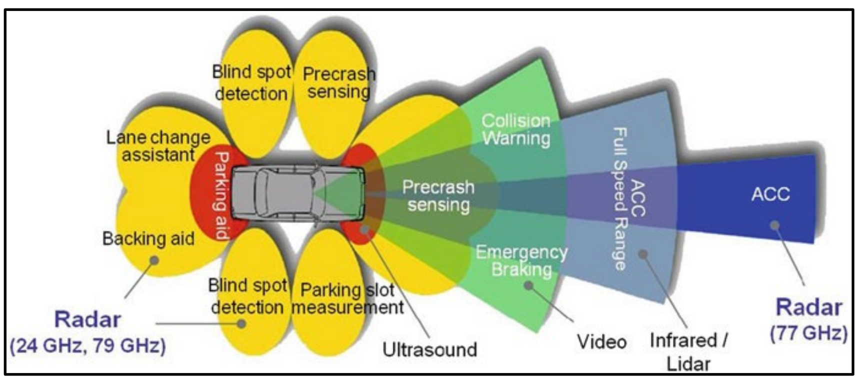
On-Road and Roadside Debris

In addition to roadside features, debris and objects on roadways such as rocks, blown tires, fallen branches, and dead animals are also potential hazards that may cause roadway object crashes. Although debris are frequently removed on well-maintained roadways, it is not uncommon for large pieces of debris to remain on roadways for hours or days.

VEHICLE VISION IMPLICATIONS FOR ROADWAY OBJECT CRASHES

Sensors Used for Vehicle Vision

Vehicle vision utilizes a variety of sensors to detect, recognize, and track obstacles surrounding a vehicle. Vehicle vision technologies have been vital for many automated vehicle functions, such as adaptive cruise control, blind spot detection, lane departure warning, lane keeping assistance, parking assistance, and collision avoidance. Recent advances in software and hardware technologies combined with increasingly affordable costs have enabled a boom in vehicle vision applications, propelling the development of HAVs. Currently (and within the foreseeable future), most vehicle vision systems rely on a combination of technologies, such as camera-, LiDAR-, and radar-based systems (Figure 9).



Source: (30).

Figure 9. Diagram. Vehicle vision sensors and corresponding functions.

Following are brief descriptions of these vehicle vision technologies.

- **Camera-based vehicle vision**. Cameras are common vehicle vision devices due to their relatively low costs, low operating power, and the fact that they are passive noninvasive sensors. Modern cameras use an aperture or lens to sample the light from objects, then expose the sampled light to a sensor chip made with semiconductor materials with photoelectric effects.

- **Infrared cameras.** Infrared cameras detect the thermal radiation sent by objects. Near infrared can often be detected with the same camera used for visible light.

- **LiDAR.** A typical LiDAR system for vehicle vision consists of a laser scanner emitting and receiving a laser pulse, a precise timing unit recording the time lapse, a GPS, and an inertial measurement unit tracking the vehicle's position.

- **Radar**. Many radar systems are small and inexpensive and are widely used by automated vehicle features for object detection. Radar systems use radio waves to detect the range, shape, angle, or velocity of objects.

- **Ultrasonic sensor**. Ultrasonic sensors detect objects using ultrasonic waves and determine the distance of a detected object based on the time-of-flight principle. Sound waves travel much slower than electromagnetic waves and have longer wave lengths.

Vehicle Vision Data Processing and Object Recognition

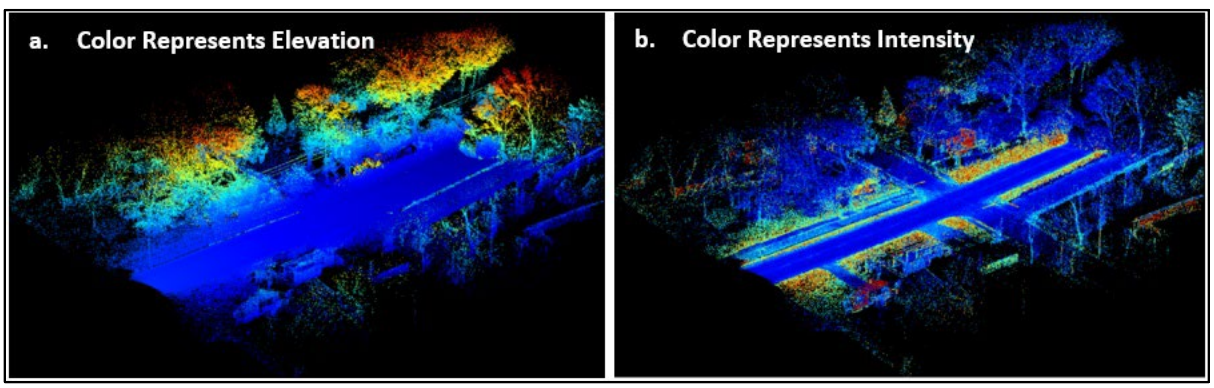
Different sensing technologies frequently result in large amounts of data that require significant efforts to process and interpret. While vehicle vision tasks require less sophisticated information from sensors used for short-range detections, such as radar and ultrasound systems, data collected by camera and LiDAR systems needs to be well processed to extract useful information.

Digital images can be represented by matrices of numerical values describing red, green, and blue colors for color images or light intensity for grayscale images. Such values are the basis for image processing and recognition algorithms, including those used for object detection in automated vehicles. Based on the algorithm used, there can be two types of image recognition methods: non-learning and learning. The former identifies objects by comparing their unique characteristics with predefined features in the algorithms. For example, vehicles can be detected from their shadows on the road surface,(31,32) shapes and headlights,(33) and/or tires and roadway surface interaction.(34,35) Such methods are straightforward and effective in some cases, but it can sometimes be challenging to find robust features for target objects that work well under all conditions.

Machine learning methods use sophisticated algorithms to identify features that can be learned by computers. Usually, feature extraction methods are used to highlight object features, such as contours, texture/patterns, or color/lighting intensities, then algorithms are trained with positive and negative data sets consisting of such extracted features, and the object features are learned during the training process. When a new image is input, the same feature extraction method is applied, and the new extracted features are submitted to the trained algorithm for detection. Feature vectors/descriptors can be constructed or computed using different methods such as Haar-like(36,37) features and histograms of oriented gradients,(38,39,40) depending on the nature of the tasks. Commonly used feature learning algorithms include AdaBoost, support vector machine (SVM), decision tree, and convolutional neural network. Previous applications suggested a correct detection rate greater than 90% for most learning-based methods: 93% for vehicle detection,(37) 99.94% for traffic sign recognition (at a distance up to 50 m),(41) 99% for pedestrian recognition,[39] and 95% for human face recognition.[36] Mobileye, a leading camera-based vehicle vision system manufacturer, claimed that their systems could reach a detection accuracy of 99% for a collection of vehicles, pedestrians, cyclists, lane markings, and speed limit signs.[42]

For efficiency and accuracy, users frequently preprocess the images prior to applying the object detection process. Image preprocessing techniques may include contrast enhancement, size compression, noise reduction, image restoration, and image segmentation. To reduce computing demand, many applications also convert color images to grayscale during this process.

LiDAR data includes 3D point clouds depicting object surfaces and the amount of light they reflect. Like 2D images, the data processing methods to recognize objects from 3D point clouds can also be categorized as non-learning or learning based. Examples of non-learning methods include identifying vehicles and pedestrians from the dimension of fitted rectangles,[43] detecting the road edge or curbs through height variance,[44] and determining lane markings based on differences in the reflected laser intensity.[45] Learning methods involve sliding a bounding box across the point clouds and training classifiers with features extracted from the point clouds. Unlike 2D images, for which the feature extraction methods are widely researched and tested, there is no established, widely accepted feature extractor for 3D point clouds. Example learning and non-learning algorithms showed correction detection rates for fixed objects, such as electrical poles, signs, and trees, ranging from 58% to 98% based on different conditions and data.[46]



Source: (data from 47).

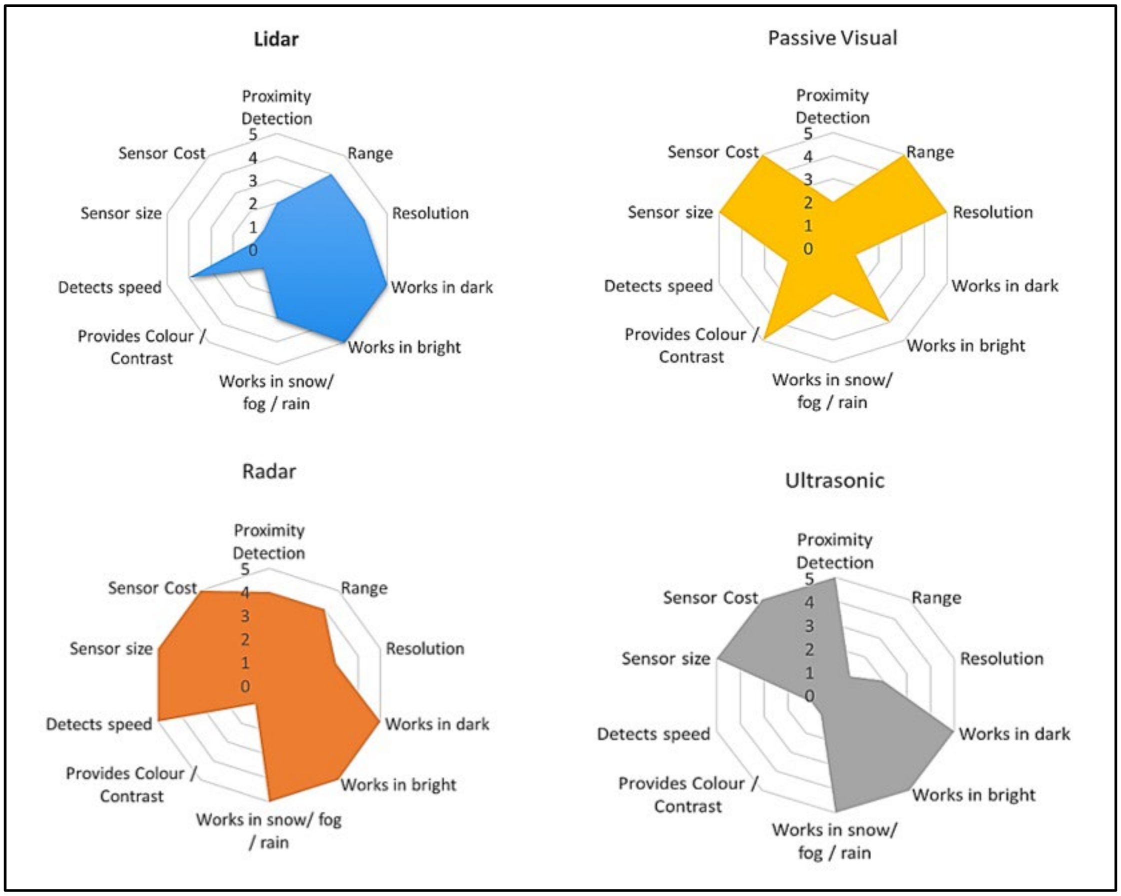
Figure 10. LiDAR scans. 3D point clouds of a street view scanned by a LiDAR sensor mounted on an SUV.

Compared to LiDAR, radar gives low directional resolution in the scanning results. Hence, the sampled points cannot precisely unveil the shape or size of detected objects. Radar systems may recognize certain large objects, however, based on the information indicated through radar cross-sections.[48,49] In addition, radar is very effective in detecting the speeds of objects by measuring the changed frequency of returned signals caused by the Doppler effect. For example, 77-GHz radar has been widely used to detect vehicles for adaptive cruise control at a range of 200 m.[50] Example applications showed an accuracy rate of 95% for radar systems in detecting pedestrians under optimal conditions.[51]

Application and Reliability

To improve reliability, most technology manufacturers use a combination of sensing technologies. Weather condition, lighting condition, and algorithm design are among some of the most common factors that play a critical role in HAV function reliability. Although there is little doubt that vehicle vision and HAV systems will significantly improve traffic safety in the future, current data and studies suggest a need for significant improvements. Figure 11, for example, compares the performance reliabilities of LiDAR, camera, radar, and ultrasonic sensors in adverse weather and lighting conditions. LiDAR systems, for instance, work well in all lighting conditions but can be vulnerable to adverse weather conditions. Studies showed that fog could significantly block LiDAR signals,(52) while rain could considerably reduce the received signal intensity and number of points received for LiDAR systems, especially on asphalt pavement.(53) Cameras are capable of providing long-range and high-resolution information in ideal weather and illumination conditions, but the image quality can severely degrade during low-visibility conditions. In addition, dirt, dust, precipitation, and fog on windshields have a considerable effect on camera performance as most forward-facing cameras are installed inside windshields. Vehicle vision systems also have difficulties operating during snow conditions, as they cannot identify some vital navigation features, such as pavement markings and edges/curbs.(54)

Although infrared cameras are relatively resistant to inclement weather and low lighting conditions, adverse weather conditions such as fog and rain can considerably worsen the attenuation rate of thermal radiation during transmission due to increased air moisture and therefore adversely affect their performance.(55) Compared to LiDAR systems and cameras, the performance of radar and ultrasonic sensors is less affected by the environment. In the case of radar systems, for example, studies showed that the effects of adverse weather were negligible for radio waves with a frequency lower than 10 GHz, but the effects increased with the increase of frequency and air moisture, and adverse effects were most evident in heavy rains and dense fog.(56)



Source: (57).

Figure 11. Graphic. A comparison of the characteristics of LiDAR, visual cameras, radar, and ultrasonic sensors.

Insufficient vehicle vision system reliability combined with potential limitations in the associated algorithms can result in significant safety concerns for HAVs. Such concerns have recently raised public attention following a number of severe crashes involving HAV functions developed/tested in real-world travel conditions.(58,59) Figure 12 shows the dashboard camera images from a self-driving vehicle involved in a fatal pedestrian crash. The video suggests that the crash occurred during nighttime on a lighted roadway with the vehicle having low-beam front lighting. There were no adverse weather conditions during the crash and very little vehicular and pedestrian traffic at the scene. As the figure shows, the time difference between the first image where the pedestrian was barely visible and the last image when the pedestrian was struck was approximately 2 seconds. Assuming a speed of 40 mph, the 2-second period translates to approximately 120 ft.

Source: (59).

Figure 12. Camera stills. Dashboard camera images from Uber pedestrian fatal crash.

Studies based on HAV on-road testing data in California showed a crash rate of 2.38×10^{-5} crashes per vehicle mile of travel (VMT), one magnitude higher than the 2.0×10^{-6} crashes per VMT estimated for conventional vehicles.(60,61) Among the crashes recorded for HAVs, rear-end crashes were the most common crash type (62% or twice that for human drivers), and 89% of all crashes happened at intersections. The studies also found that system failures accounted for 52% of all reported disengagements (i.e., when autonomous systems experienced a failure or the driver intervened in vehicle operation when they felt uncomfortable), of which software-related failures exceeded hardware-related failures at a ratio of 11:1. The studies also identified roadway and environmental conditions, such as poorly marked lanes, construction zones, heavy pedestrian traffic, and adverse weather conditions, as other major causes for HAV system failures.

CHAPTER 3. DATA COLLECTION AND METHODOLOGY

SHRP 2 DATA COLLECTION

This project focused on the following data sets in the SHRP 2 NDS database:

- SHRP 2 event data, including event detail data and the associated video data
- Time series data for events, including variables depicting the location, travel speed, longitudinal acceleration, and alcohol usage of each analyzed SHRP 2 event
- Driver age from the SHRP 2 driver demographic questionnaire data for all analyzed SHRP 2 events
- Driving history questionnaire data, including average annual mileage, years driving, and number of previous violations for drivers involved in all analysis events
- RID data, including roadway alignment (i.e., curve versus tangent), speed limit, number of lanes, grade, and AADT for locations where the analyzed SHRP 2 events took place

Identification of SHRP 2 Events

The research team requested data for all SHRP 2 crashes and near-crashes meeting the following criteria:

- Event Severity = crash or near-crash
- Event Nature = conflict with parked vehicle, conflict with animal, conflict with obstacle/object in roadway, and single-vehicle conflict

The initial data request resulted in 2,304 crashes and near-crashes. However, after a quick review of the initial data, researchers eliminated the following events from analysis:

- Events where subject vehicles were parking or starting in a parking lot. These events typically involved slow-moving vehicles colliding with parked cars and parking lot appurtenances, such as parking blocks, columns/walls, and bollards. These events represent a different causation than that of roadway object crashes involving moving vehicles.

- Events occurring when the subject vehicle was backing up. Most of these events occurred within parking lots, with the rest occurring at driveways or streets with on-street parking spots.

- Single-vehicle conflicts that did not involve fixed objects. For example, events involving vehicles losing control, rotating in the road, or stopping due to vehicle failure.

At the end of this process, the researchers kept a total of 1,639 SCEs for analysis (Table 2 and Figure 13). Note that, although the focus of this project was roadway object crashes, the researchers included crashes involving animals in the study. Animal-related crashes frequently involve high-speed vehicles and can cause roadway departures leading to secondary crashes involving roadside objects.

Table 2. Analyzed SHRP 2 crashes and near-crashes.

Type	Crash	Near-crash	Total
Conflict with parked vehicle	5	52	57
Conflict with animal	64	301	365
Conflict with obstacle/object in roadway	59	65	124
Single-vehicle conflict*	901	192	1,093
Total	1,029	610	1,639

*Events involving a single vehicle running off the road, or a single vehicle conflicting with roadside objects that were not included in the above types.

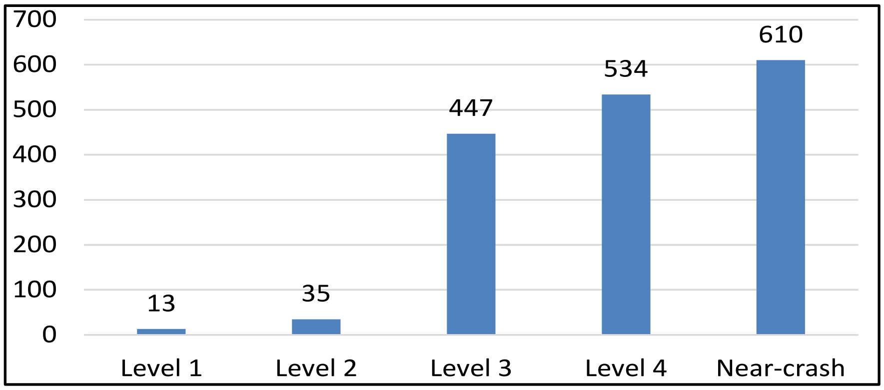


Figure 13. Bar graph. SCEs by SHRP 2 crash severity level.

The research team also requested 1,050 balanced baseline events for comparison purposes.

DATA PROCESSING AND INTEGRATION

The research team obtained the requested SHRP 2 data sets in the following formats:

- Event detail table with linked driver demographic and driving history data in a tabular format. The event detail data contained detailed and comprehensive information about each SCE collected by SHRP 2 data reductionists based on time series and event video data. The SHRP 2 team also extracted the driver demographic and driving history data for the studied drivers and provided it in conjunction with the event data.
- Time series data for SCEs in a tabular format. Time series data was provided at a 1-Hz frequency. The data items were linked through timestamps, which can be further linked to event detail data using the event ID field.
- RID data. The research team obtained roadway information data in a geographic information system (GIS) format. The roadway information data did not contain a linking field that would allow the integration of the GIS roadway data and the tabular event data.

For this project, the research team collected a number of additional data elements that were not previously available in the event detail table and matched the RID data with the event data using a GIS-based process.

Additional Event Data Collection

The researchers collected the following vehicle vision data elements for the SCE events:

- **Critical speed**. To understand driver behavior prior to, during, and after each event, it was necessary to accurately gauge the travel speeds of the subject vehicles involved. The SHRP 2 event data included a 30-second epoch for each SCE and 10 seconds for each baseline event. Vehicle dynamics variables, such as speed and acceleration, varied throughout each epoch. After a careful review of the event videos and the associated time series data, the project team decided to use the maximum speed for the following three timestamps for each SCE, referred to as the critical speed, to represent the pre-event speed:

    - **Event start**: the timestamp that was identified as the point of time in the video when the sequence of events defining the occurrence of the incident, near-crash, or crash began. Event starts were identified by the SHRP 2 data reduction team based on analyses of event videos.

    - **Subject reaction start**: the timestamp at the point the driver is seen to recognize and begin to react to the event, defined as the first change in facial expression or the first movement of a body part in a way indicating awareness and/or the start of an evasive maneuver, whichever occurs first.

    - **Impact proximity**: the timestamp at the point the subject vehicle makes physical contact with the object of conflict. In the case of a near-crash, it is the timestamp when the subject vehicle is at the closest distance to the object of conflict. If more than one incident type occurs, the impact proximity time is coded for the most severe or the first incident type if both are of the same severity.

- **Additional information for involved fixed objects**. To thoroughly understand fixed objects involved in the SHRP 2 events and their implications for vehicle vision technologies, the research team collected several additional data elements that described fixed objects in a greater level of detail:

    - **Object type**. Categories included tree/shrub, pole/posts, barrier, ditch, curb, pavement edge, median island, debris, animal, and other.

    - **Object dimension.** Dimensions included height and diameter. The object dimensions were estimated and rounded to the nearest 10 cm (5 cm for objects less than 10 cm) based on the event videos. Note that the object dimensions reflected researchers' best estimates and were based primarily on nearby objects of known dimensions, such as vehicle tires, curbs, pavement markings, and traffic signs.

- **Longitudinal and lateral distances to object at the critical timestamp**. For each event, researchers determined a critical timestamp, which was defined as the timestamp when the driver was expected to start reacting to safely avoid colliding with the object. In the case of fixed-object events, the critical timestamps of many events were the timestamp when the involved objects first became visible on the event videos. For example, Figure 14 shows a screenshot of a SHRP 2 event taken at the critical timestamp, when an object on the roadway becomes identifiable by researchers. The following sections include more detailed information on how distances were determined based on the event videos.

Figure 14. Camera still. Pre-crash scenario – crash with a small animal on the roadway.

- **Color contrast between the object and its surrounding background**. This was measured based on both grayscale and RGB values (Figure 15). These values were collected using the MATLAB® Image Viewer Application for a total of 158 cases (excluding cases involving turning movements where direct sightline to object was obstructed).

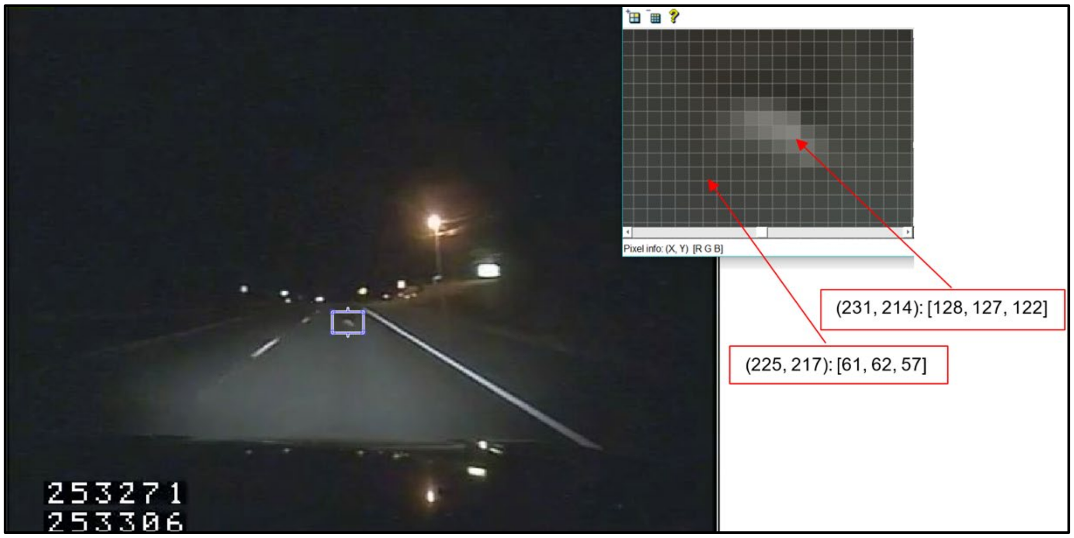


Figure 15. Camera still. Example of applying bird's-eye-view transformation – pixel value contrast collection.

  - **Moving direction if the object was a live animal.**

- **Additional information for vehicle maneuver and driver actions** (Table 3):

  - **Safe evasive maneuver based on researcher judgement**. For comparison with actual evasive maneuver taken by the subject vehicle driver.

  - **Vehicle reaction after incident**. The reaction of the subject vehicle after the event regardless of driver action. This variable captured information about if and how the vehicle lost control and reacted to the events.

  - **Post-event maneuver.** The action taken by the subject vehicle driver. This information may provide insights on how drivers react to an event of a particular nature that may lead to the cause or avoidance of secondary events.

  - **Safe post-event maneuver based on researcher judgement**. The maneuver after the event that would be safe to take to avoid secondary events based on researchers' judgement.

  - **Driver reaction time**. The time spent by the subject driver to make the evasive maneuver, determined as the time difference between impact proximity and subject reaction start. In the case that the driver reacted after striking the object, or did not react to the event, driver reaction time was considered zero.

  - **Machine vision reaction time**. The time from the critical timestamp to the moment when the vehicle collides with the object, assuming travel at the critical speed.

- **Additional information for roadway and environment**. In viewing the event, data was also collected about potential conflicting objects in the vicinity of the subject vehicle during the event, which described surrounding objects/vehicles in the near vicinity that may have been in conflict with the subject vehicle for certain evasive maneuvers (Table 3). An example is a vehicle closely following the subject vehicle approaching a large piece of debris on a freeway. The vehicle would conflict with the subject vehicle if it decided to stop to avoid colliding with the debris.

- **Critical event images**. For each SCE, the research team extracted the image frame of the forward-facing video at the critical timestamp.

Table 3. Variables collected for additional vehicle maneuver and driver action information.

Variable	Observation
Safe Evasive Maneuver	No evasive maneuver executed
	Accelerate
	Accelerate and steer left
	Accelerate and steer right
	Brake
	Brake and steer left
	Brake and steer right
	Steer left
	Steer right
	Release brake
	Increase turning radius
	Decrease turning radius
Vehicle Reaction	Stopped
	Roadway departure to the right
	Roadway departure to the left
	Deviate to the right
	Deviate to the left
	Continue previous trajectory
	Lose control, rotated
	Lose control skidded
	Decelerated
Post Event Maneuver	Accelerate and steer left
	Accelerate and steer right
	Brake and steer left
	Brake and steer right
	Steer to the left
	Steer to the right
	Roll over the object
	Stop in the road
	Stop in the roadside
	Continue previous trajectory

Variable	Observation
	Reverse from the object
Variable Object of Potential Conflict - Type	Observation
	Fixed object
	Vehicle
	Pedestrian
	Animal
	Other
Object of Potential Conflict - Location	In front of the SV*
	In front and to the right of the SV
	In front and to the left of the SV
	On the right side of the SV
	On the left side of SV
	Behind and to the right of the SV
	Behind the SV
	Behind and to the left of the SV
	On the left oncoming lane
Object of Potential Conflict - Maneuver	Stationary
	Braking
	Going straight
	Crossing the road
	Stopped in roadway
	Stopped in roadside
	Turn right
	Turn left
	Merging lanes
	Pulling out/backing from parking space
Safe Post-Event Maneuver	Brake and steer to left
	Steer to the left
	Steer to the right
	Brake and steer to right
	Brake
	Roll over
	Reverse off the object
	Accelerate and steer right
	Stop in the roadside

*SV = subject vehicle

The additional event data collection was mostly based on event videos. To the extent necessary, the research team also used satellite images and Google® Maps. All data collection involving personally identifying information (PII) was conducted in the Virginia Tech Transportation Institute's secure enclave designated for PII access and processing for the SHRP 2 NDS data.

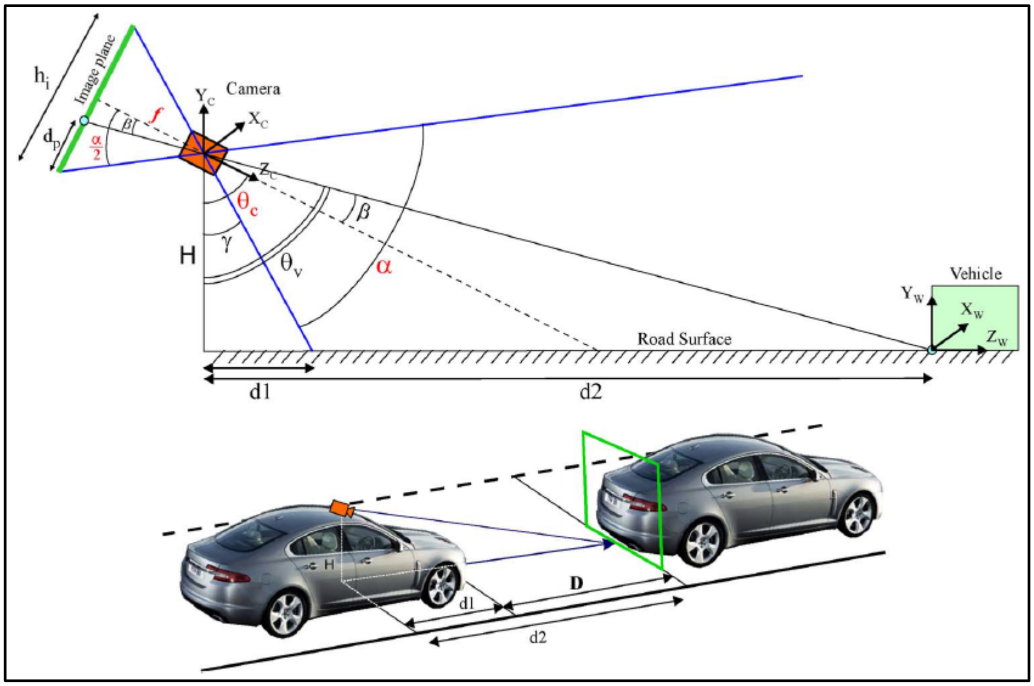
Object Distance Estimation

To improve the accuracy of the distance estimation based on the event videos, the research team used three methods to estimate the distance between the subject vehicle and the involved object:

- **Bird's-eye-view transformation**. Bird's-eye-view transformation, also referred to as inverse perspective mapping, generates a top-view perspective from an image taken from another perspective. Due to image quality and roadway conditions, the research team was only able to use this method for 158 events.

- **Integral of distance over time between the critical timestamp and impact proximity**. The integral was computed assuming a linear deceleration between each pair of adjacent data points. The time series data points were collected at a 10-Hz frequency. This method was used for all events for which detailed time series data was provided (i.e., 825 SCEs). Note that the distance determined this way reflects the total distance traveled by the vehicle during the time period, which in some cases was not the linear distance (i.e., shortest distance) between the subject vehicle and the object.

- **Manual estimation**. The research team also estimated the vertical and lateral distance to the objects from videos based on nearby objects of known dimensions. Figure 16 illustrates the basic theories of the bird's-eye-view transformation method. The distance to the object on the roadway could be estimated based on the pixel distance captured in the 2D image and by transforming the captured image to an orthogonal top-down view of the scene. A pixel in the two different perspectives can be converted through rotating, translating, and scaling based on the camera position, orientation, and optical specifications,[62,63] which can be described mathematically by Equation 1:[62]:



Source: (63).

Figure 16. Mathematical diagram. Real-world intervehicle distance estimation based on pixel distance from 2D image plane.

$$\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \boldsymbol{KTR} \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix} \quad (1)$$

where *u* and *v* specify the location of the target pixel in the image plane; *x*, *y*, and *z* define the real-world location of the object in a 3D coordinate system; and **K**, **T**, and **R** are matrices depicting camera parameters, translation, and rotating.

The researchers used the MATLAB Autonomous Driving Toolbox for the bird's-eye-view transformation and distance estimation. Based on conversations with the SHRP 2 hardware team and observations of three testing vehicles instrumented in a similar manner as the SHRP 2 participant vehicles, the research team used the following camera specifications and installation parameters during the distance estimation:

- Focal length: 3.6 mm
- Camera installation height: 1,300 mm
- Offset (camera lateral position offset from the center of the vehicle): zero
- Pitch: zero initially and then adjusted to ensure that the longitudinal lane markings were parallel in generated bird's-eye-view image

Note that the inaccuracies of camera configurations due to the large number of participating vehicles in the SHRP 2 study could result in bias of distance estimate. Studies also showed that the level of estimation error could increase with increased distance.(63) In addition, the research team faced the following challenges when estimating the distances:

- For continuous objects such as curbs, medians, and barriers, it was difficult to determine the exact impact point.
- Some objects were invisible in the front view videos, such as those close to the vehicle and animals colliding with the vehicle on the side.
- Small, flat objects were also difficult to identify from the videos.
- Some videos were of low quality due to adverse weather conditions and/or dirty windshields.

Figures 17–19 demonstrate the process of the bird's-eye-view transformation from object identification to resultant output in MATLAB.

Figure 17. Camera stills. Example of applying bird's-eye-view transformation – pre-crash scenario and drawing bounding box.

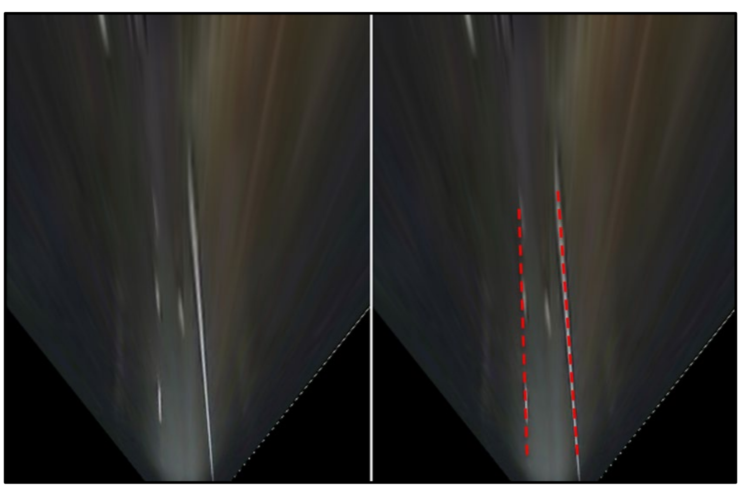


Figure 18. Camera still and generated image. Example of applying bird's-eye-view transformation – generated bird's-eye-view image.

Figure 19. Camera still. Example of applying bird's-eye-view transformation – estimation results.

When comparing the distance estimation results of the three methods, researchers found that the results of manual estimation were generally comparable to the mathematical estimation, but the results of birds'-eye-view estimation often underestimated the distances. Manual estimation was more accurate for cases where objects were are at a relatively close distance, and the distances estimated based on speed were more accurate for medium and long ranges. During this study, the research team decided to use averages of the distances estimated by the three methods:

- For distances less than 5 m, the detection distance was the average of manual estimates and bird's-eye-view estimates.
- For distances between 5 and 15 m, the detection distance was the average of the estimates of the three methods.
- For distances more than 15 m, the detection distance was the average of the speed and manual estimates.

Roadway Data Collection and Integration

The integration of event and RID data was achieved by spatially joining the events with the needed GIS feature classes in RID. During this data matching process, the researchers faced the following challenges and considerations:

- **Events were linear instead of point features**. The research team obtained latitude-longitude coordinates for the study events along with the associated time series data. The coordinates, however, were provided for the entire lengths of events at a frequency of 1 Hz. The lengths of events varied significantly, with many lasting approximately 30 seconds. At a speed of 30 mph, a 30-second epoch translates to a distance traveled of 1,320 ft. Over this distance, subject vehicles frequently changed roadways (particularly for events at intersections) or traversed multiple roadway sections with different traffic and roadway characteristics.

- **Some events took place at locations with densely located streets**. Urban areas frequently had densely located roadways and side streets. Divided roadways, in addition, were represented by two closely located lines due to the two different directions of traffic. Multiple roadways closely situated in the vicinity of an event resulted in challenges to correctly locating the event on the right roadway solely based on spatial relationships.

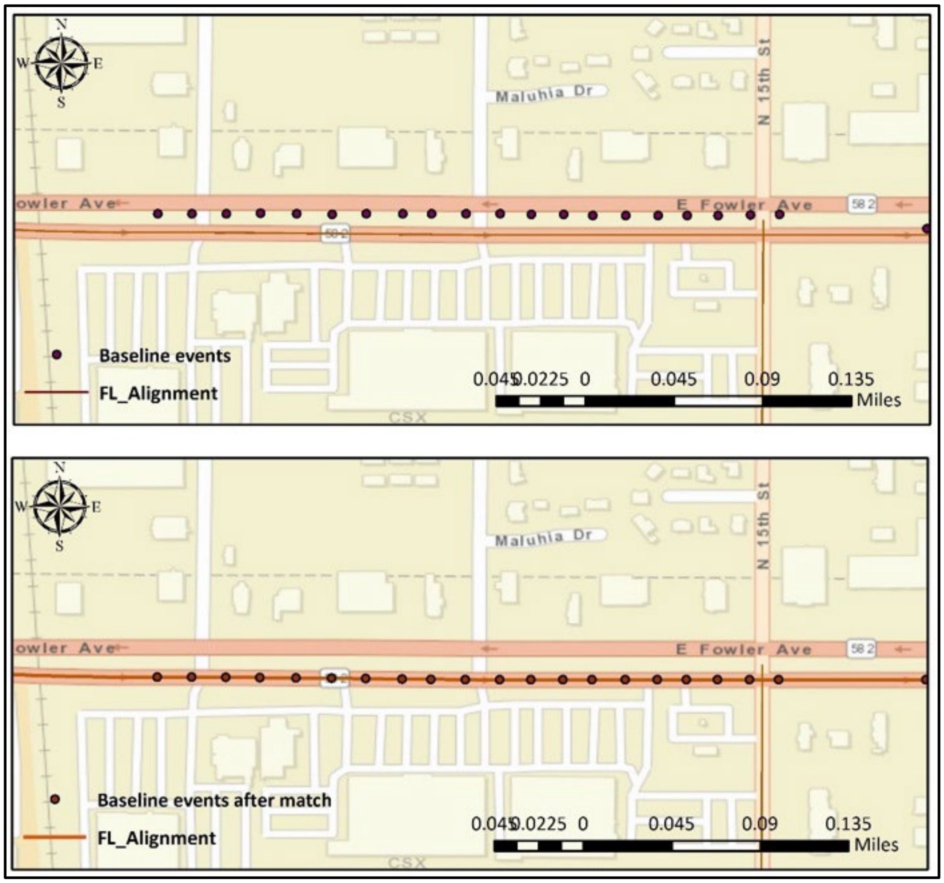


Figure 20. Map. An example of mismatching due to densely located streets.

In the case presented in Figure 20, the trip happened on densely situated streets. The trip should have been matched to the top route as the vehicle traveled west. However, as there was no corresponding RID feature for the top street, the trip was automatically matched to the bottom direction, traveling east, resulting in a mismatch.

- **The NDS GPS sensors in some cases performed erratically** near bridges, tunnels, or high-rise buildings, or when traveling at low speeds. The erratic GPS coordinates for certain data points of some events added further challenges for data matching.

- **The RID did not include data for many rural and local roadways**. RID included data from two sources: state transportation agency-generated data (e.g., AADT and speed limit) and SHRP 2-collected data (e.g., curvature). State-generated data only included detailed information on state-maintained roadways. SHRP 2 roadway data only covered a relatively small number of roadways, with focuses on roadways with higher NDS trip densities (e.g., freeways and major arterials) in areas in and surrounding major metropolitan regions.

- **Many events occurred at or near intersections**. Events occurring at or near intersections traverse multiple roadways with different traffic and roadway characteristics. Different portions of the event epochs would be located on different roadways strictly following spatial relationships.

Figure 21 presents the case of matching a trip turning at intersections where the GPS points were matched to two separate routes.

Figure 21. Map. An example of matching a trip turning at an intersection.

To address these challenges, and for efficiency, the following GIS-based approach was used to match the data:

- **Identify data points representing event locations**. For crash and near-crash events, the research team used the coordinates between the last data point before the event start and the first data point after the impact proximity, which in most cases corresponded to a period between 1 to 5 seconds (two to six GPS data points at the frequency of 1 Hz). Most baseline events were approximately 10 seconds long, and therefore all data points for baseline events were used to represent their locations.

- **Insert intermediate location points for crash and near-crash events**. To improve the number of data points representing the location of each crash or near-crash, the research team inserted nine intermediate points between each pair of adjacent GPS points based on a linear relationship and equal distance. The larger number of points helped the spatial join process to better determine the roadway segment corresponding to the largest portion of each event.

- **Map event data points into feature classes**. Researchers used the Display XY data tool in the ArcGIS® software to perform this task.

- **Join events with RID data**. The research team performed this task using the ArcGIS Near tool, which spatially matched each event data point with the nearest roadway feature within a 75-ft search radius. This process was performed for the multiple RID data layers containing the needed roadway and traffic information and by state. Note that the same data layers in RID for the six NDS sites contained inconsistent data formats, including different attribute names for the same variables. This inconsistency required the data-matching process to be performed separately by state.

- **Determine correct matches of roadway segments for events.** For each event, the research team selected the roadway segment to which the greatest number of data points were matched. This segment was considered the location where the event took place (e.g., the roadway segment corresponding to the largest proportion of the event). This step ensured that each event was only matched to one link segment.

- **Perform quality assurance/quality control.** After the automated data matching process, researchers performed quality assurance/quality control by manually reviewing the matching results on the ArcGIS platform with original event locations and roadway feature classes overlaid. This process focused on events at locations that were more likely to be subject to the previously described challenges.

At the end of this process, researchers were able to match RID roadway and traffic information with 1,538 events, including 694 SCEs and 844 baseline events. The RID did not contain the needed data for the remaining events. Note that this data matching for most crashes was conducted in the Virginia Tech Transportation Institute's secure enclave due to the involvement of PII information (in these cases, trip origins and destinations).

Appendix A includes detailed counts of the analyzed events by variable.

DATA ANALYSIS METHODOLOGY

The research team addressed these objectives using a three-pronged approach. The research team first conducted a detailed engineering study of the roadway object events to identify and quantify effects of a large number of relevant variables. A machine-vision-oriented study was then performed to document the implications of the roadway object events on machine vision performance. To develop a complete understanding of roadway object crashes, the research team also conducted detailed case study analyses of representative roadway object events. The case studies provide further qualitative results on how and why roadway object crashes occur and what potential actions can be effectively taken to prevent such events.

To understand factors that significantly contribute to roadway object crashes and quantify risks due to such factors, the engineering study employed both logistic regressions and SVMs. The former are inferential statistical methods frequently employed for discrete/categorical data analyses in traffic safety studies.(7,8,10,12,13,64) Variations of logistic regression methods are flexible enough to analyze binary outcomes, ordinal outcomes, and non-ordinal discrete outcomes. Common statistical software tools frequently output odds ratios (ORs) as an effective measure to quantify how strongly the presence of a factor is associated with an outcome. The latter are machine learning methods that are frequently used for pattern classification and regression analyses.(65,66) Compared to logistic regression methods, SVMs do not require beforehand knowledge of data distributions and can be more robust in some cases, particularly when the data is not regularly distributed.

During the engineering study, the research team considered the following scenarios for data analysis:

- Binary logistic regressions of event occurrence and severity, including the following:
  - Comparison between SCEs and baselines.
  - Comparison between Level 1–3 crashes and near-crashes. This analysis addressed the possibility that the limited baseline events may not correctly describe the exposures associated with the crashes and near-crashes. It also allowed the researchers to filter out potential bias associated with the Level 4 crashes (low-risk tire strike events).
- Ordinal logistic regression for event severity, which compared the crash risks between all SCE severity levels, including Level 1–4 crashes and near-crashes.
- SVM analyses for binary event occurrence and severity, including:
  - SCEs against baselines.
  - Level 1–3 crashes against near-crashes.
- SVM analysis for multi-class event severity based on comparisons between all SCE severity levels, including Level 1–4 crashes and near-crashes.

The machine-vision-oriented study mostly utilized a variety of correlation analysis methods and descriptive statistics to understand the implications of the SHRP 2 roadway object events on machine vision performance. The study analyzed in detail a number of machine-vision-related performance metrics, such as reaction time, detection distance, and driver reactions relevant to machine vision algorithms pertaining to different event scenarios and roadway/visibility conditions.

The following section describes the basic theories of the logistic regression and SVM methods used in the engineering study.

OR and Logistic Regression

ORs measure the association between explanatory variables and responses, which are calculated by comparing the odds of an event occurrence with and without the particular exposure condition. An OR greater than 1 suggests that the factor contributed to the event occurrence. ORs are calculated as in Equation 2 (Table 4).

$$\mathrm{OR} = \frac{a/c}{b/d} \tag{2}$$

where:

a = Number of exposed cases
b = Number of exposed non-cases
c = Number of unexposed cases
d = Number of unexposed non-cases

Table 4. Typical 2 × 2 frequency table for calculating ORs.

		Exposure Status	
Outcome Status		With	Without
	Yes	a	b
	No	c	d

The 95% confidence interval for a given set of observations can be calculated as:

$$95\%\mathrm{CI} = \exp\left(\mathrm{In}(\mathrm{OR}) \pm 1.96 \times \mathrm{sd}\right) \tag{3}$$

where sd is the standard deviation calculated with the following equation:

$$\mathrm{sd} = \left(\frac{1}{a} + \frac{1}{b} + \frac{1}{c} + \frac{1}{d}\right)^{0.5} \tag{4}$$

Binary logistic regression models the log odds of event occurrence as a response of explanatory variables:

$$\mathrm{logit}(P(\mathrm{Y}=1)) = \log\left(\frac{P(\mathrm{Y}=1)}{1-P(\mathrm{Y}=1)}\right) = \beta_0 + \beta_1 X_1 + \cdots + \beta_k X_k \tag{5}$$

or

$$P(\mathrm{Y}=1) = \frac{1}{1+e^{-(\beta_0+\beta_1 X_1+\cdots+\beta_k X_k)}} \tag{6}$$

where:

P is the probability of the event occurrence
β_0 is the intercept
β_i is the estimated parameter for explanatory factor X_i

Similarly, ordinal logistic regression takes the following form for event severity outcome *j*:

$$\text{logit}(P_j) = \log\left(\frac{P_j}{1-P_j}\right) = \beta_{0j} + \beta_1 X_1 + \cdots + \beta_k X_k \quad (7)$$

or

$$P_j = \frac{1}{1+e^{-(\beta_{0j}+\beta_1 X_1+\cdots+\beta_k X_k)}} \quad (8)$$

where:

j is the event outcome
P_j is the probability of events with outcome level $\leq j$

By assigning severity level values of 1–5 to SHRP 2 Level 1–4 crashes and near-crashes sequentially (i.e., Severity Level 1 = Level 1 [most severe crashes] and Severity Level 5 = near-crashes), the probability for each response level can be calculated as:

$$Prob(\text{Y} = 1) = P_1$$

$$Prob(\text{Y} = 2) = P_2 - P_1$$

$$Prob(\text{Y} = 3) = P_3 - P_2$$

$$Prob(\text{Y} = 4) = P_4 - P_3$$

$$Prob(\text{Y} = 5) = 1 - P_4 \quad (9)$$

In the context of logistic regression, the OR can be calculated with parameter estimates (β_i) as follows (Equation 10):

$$\text{OR} = e^{\beta_i} \quad (10)$$

This study used the SAS® Studio software package[(67)] to conduct the logistic regressions. All significant models and variables were selected at a 0.1 level of significance.

SAS uses maximum likelihood estimation to calculate the model parameters and outputs the following statistics for model goodness of fit:

- **-2 log likelihood, AIC (Akaike's information criterion), SC (Schwarz criterion)**. The -2 log likelihood statistic was used to test the global null hypothesis that all parameters associated with covariates were zero (under the null hypothesis, the -2 log likelihood statistic has a chi-square distribution). The AIC and SC statistics adjusted the -2 log likelihood statistic for the number of terms in the model and the number of observations used. These statistics are used when comparing different models for the same data, and lower values of these statistics indicate a model with better goodness of fit.[67,68]

- **Likelihood ratio test, Score test, and Wald test results**. These three statistical methods test the global null hypothesis that $\beta = 0$. Each statistic is assumed to have a chi-square distribution. The likelihood ratio test compares the deviation of the log likelihood function of models with estimated parameters to the null hypothesis. The Wald test is based on the Gaussian distribution and is obtained by comparing the maximum likelihood estimate of the slope parameter β_1 to an estimate of its standard error. The score test is based on the distribution theory of the derivatives of the log likelihood and is obtained as the value of the first score function (first derivative of likelihood function) at β. Higher values of these statistics indicate lower probability of a null hypothesis, and hence better model goodness of fit. The Wald test is also used in testing the significance of single parameters, where the comparison is made between maximum likelihood estimate of slope parameter β_i and standard error.[67,68]

Readers should note that this project also attempted to use multinomial (non-ordinal) logistic regression to model the event crash severity outcomes. However, the resulting multinomial models included a limited number of variables, many of which had *p*-values greater than 0.1. The models were considered not powerful enough to explain the risk factors and therefore are not discussed further.

SVM Theories and Events Analysis

SVM is a machine learning method primarily developed to perform binary classification with a hyperplane constructed in a multidimensional space that separates cases of different class labels.[69] It can be easily extended to multi-class classifiers using methods such as one-against-all and one-against-one:[70]

- The one-against-all method constructs k SVM classifiers for k categorical classes, where the mth SVM is trained with all the examples in mth class with positive labels and all other examples with negative labels.

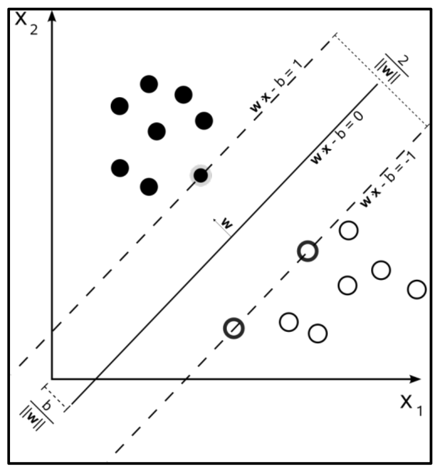
- The one-against-one method constructs $\frac{k(k-1)}{2}$ classifiers, where each classifier is trained on data from two different classes.[70]

In this study, three SVM classifiers, two binary classifiers, and a multi-class classifier were constructed for event occurrence and event severity levels. The following describes the basic theories and procedures for the SVM analyses.

In a binary SVM classifier, each selected event can be represented as a vector: $\{(x_i, y_i), i = 1, \dots, N\}$, where y_i is the class label and x_i is the feature vector used to describe the event. The hyperplane $w \cdot x + b = 0$ is then learned from the training data so that:

- Samples with labels $y = +1$ and $y = -1$ are located on different sides of the hyperplane.
- The accumulative distance of the closest samples to the hyperplane on each side is maximized.

The closest events are also called support vectors, and the distance between support vectors to the hyperplane is the optimal margin, as shown in Figure 22. Note that the optimal margin can be calculated as $\frac{2}{\|w\|}$. Hence, the problem of maximizing the optimal margin becomes minimizing $\|w\|$, subject to $y_i(w \cdot x_i - b) \geq 1$.



Source: (71).

Figure 22. Diagram. Hyperplane and margins for an SVM trained with two classes.

In many cases, samples cannot be linearly separated, or it is hard to find a hyperplane to separate all samples into different sides at a satisfactory level of accuracy. In such cases, the performance of SVMs may be improved by adopting transformation kernels such as the following:[(72)]

- Linear: $K(x_i, x_j) = x_i^T x_j$.
- Polynomial: $K(x_i, x_j) = \left(x_i^T x_j + 1\right)^\rho, \rho > 0$, where ρ is the order of the polynomial.
- Radial Basis Function (RBF): $K(x_i, x_j) = exp\left(-\gamma \|x_i - x_j\|^2\right), \gamma > 0$, where γ is a parameter for the classifier, controlling the influence of a single training example.
- Gaussian: $K(x_i, x_j) = exp\left(-\frac{1}{2\sigma^2}\|x_i - x_j\|^2\right), \sigma > 0$. Note that Gaussian kernel is another form of RBF kernel with γ replaced by $\frac{1}{2\sigma^2}$, and σ is the kernel width parameter.

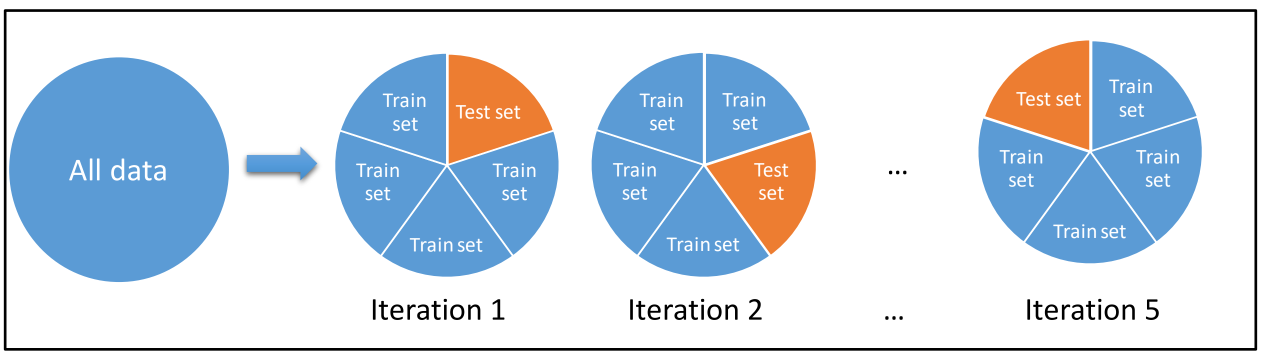
In practice, a slack variable ξ_i is frequently used to allow a certain degree of misclassification when using SVMs. The hyperplane for two classes would then become $w \cdot x + \mathrm{b} = \pm(1 - \xi_i)$. The optimized hyperplane can be determined based on a trade-off between maximizing the margin range and minimizing the misclassification rate by solving the following constrained optimization problem:

$$\text{Minimization: } \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{k}\xi_i, \text{ subject to } y_i(w \cdot x_i - b) \geq 1 - \xi_i, i = 1, \ldots, k, \xi_i > 0$$

where C is a regularization parameter used to control the magnitude of allowing violation of the margin. It defines the trade-off between the rate of misclassification in the training data and the maximization of the margin. In practice, the regularization parameter is selected by trial and error. When a new feature vector of a testing event is input, its classification outcome is defined as

$$\mathrm{f(x) = sgn(w \cdot x + b)}$$

During this study, researchers used the cross-validation method to avoid overfitting during the SVM analyses. Overfitting is a modeling error that occurs when the trained model is able to closely fit the limited training data but would fail to predict new input data. A k-fold cross validation, for example, partitions the entire data set into k roughly equal subsets. During each iteration, one subset is used as a validation set while the other $k - 1$ subsets are used as the training set. This process is repeated k times, and the average result of the k repetitions is used as the final analysis result.(73) Figure 23 graphically illustrates this process with k = 5.



Source: (73).

Figure 23. Diagram. A *k*-fold cross validation, with *k* = 5.

For the analysis of the SHRP 2 events, the response variables were as follows:

- Binary classifiers: −1 for baseline events and 1 for SCEs, or −1 for near-crashes and 1 for Level 1–3 crashes.
- Multi-class classifier: Level 1–4 crashes and near-crashes.

Researchers used the following rules to code the feature vectors:

- Binary explanatory variables were coded as 0 and 1.

- Ordinal explanatory variables were assigned with discrete ordinal integers.
- Categorical variables were assigned with a vector.
- Continuous variables used their original values.

Appendix A includes a detailed listing of the variables and feature vectors. Note that the SVM analyses did not use RID data because the SVM classifiers did not allow missing values. As previously noted, the RID data elements, such as AADT, speed limit, and alignment, were missing for several events.

The results of the feature vector composition were 85 and 99 numeric features for crash occurrence and severity level classifiers, respectively. The researchers performed the training and validation of SVM classifiers with the MATLAB Classification Learner Toolbox (Figure 24).[74]

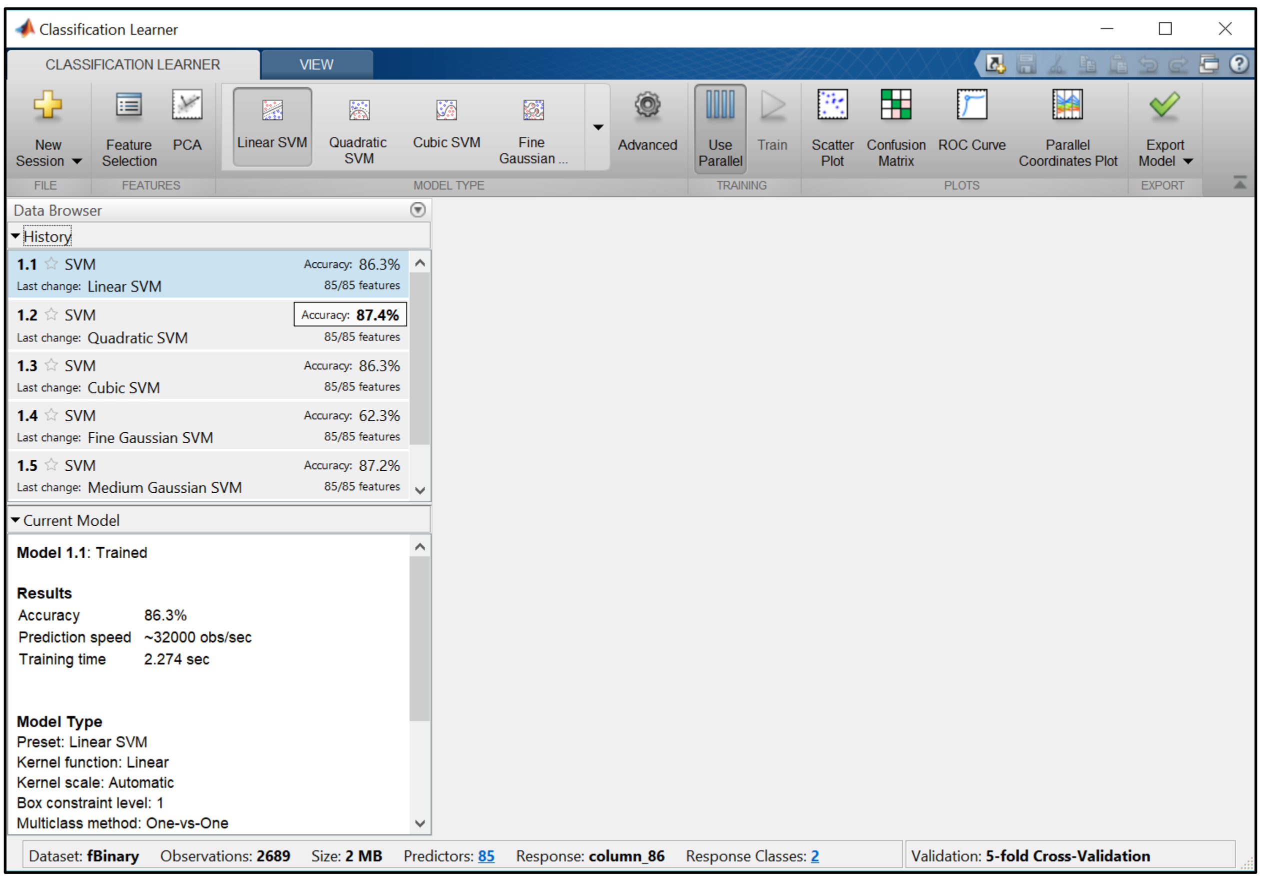


Figure 24. Screenshot. Classification learner toolbox in MATLAB.

A main drawback of SVM classifiers is their black-box-like performance, which means no interpretable parameters for each explanatory variable compared to logistic regression models. In order to mitigate this deficiency, previous researchers have used sensitivity analysis to explain the correlations between predictors and responses.[75,77] The original sensitivity analysis proposed by those researchers evaluated the output variances with investigated variables added by a user-controlled amount of change while other variables remained unchanged. This study adopted that sensitivity analysis concept to demonstrate the effects of explanatory variables. However, instead of introducing the changes to existing features, researchers removed individual input features from the models and trained new SVM classifiers. The changes in predictive performance of the new classifiers were then used to quantitatively imply the impacts of the removed variables.

CHAPTER 4. ENGINEERING ANALYSIS FINDINGS AND RISK FACTORS

SCE-BASELINE COMPARISON ANALYSIS RESULTS

Binary Logistic Regression Model and Goodness of Fit

This binary logistic regression analysis modeled the variable effects on the probability of an event being a crash or near-crash given an event based on a comparison between SCEs and baseline events. Table 5 lists the significant variables and associated statistical test results of the fitted binary logistic regression model. Table 6 further lists the estimated parameters of the significant variables and variable values along with their ORs for the logistic regression model. Note that Table 6 only includes significant variable values with a *p*-value smaller than 0.1. Variable values with a *p*-value larger than 0.1 were excluded, although the associated variables were tested for significance.

Table 5. Significant explanatory variables for SCE probability modeling.

Effect	DF	Wald Chi-square	Pr > ChiSq
Pre-incident Maneuver	5	34.3704	<.0001
Maneuver Judgment	3	16.0199	0.0011
Driver Behavior	9	39.7489	<.0001
Passenger Existence	1	2.9601	0.0853
Secondary Task	10	53.0622	<.0001
Hands on the Wheel	2	10.1661	0.0062
Lighting	3	13.6342	0.0034
Surface Condition	1	3.4882	0.0618
Traffic Density	4	21.9477	0.0002
Contiguous Travel Lanes	5	13.7778	0.0171
Traffic Control	4	9.851	0.043
Grade	3	6.5556	0.0875
Locality	7	36.7197	<.0001
Critical Speed	1	60.5405	<.0001
AADT	8	76.1996	<.0001
IRI	6	46.0758	<.0001

*DF = Degree of freedom; AADT = Average annual daily traffic; IRI = International roughness index.

- In the model, a reference level was set for each unordered categorical variable. Parameter estimates and ORs of other values were calculated by comparing them against the reference level. The reference levels were determined to reflect normal/optimal driving conditions if applicable.

- An OR for an unordered categorical variable reflects the odds of an event being a crash or near-crash when the variable value was present compared to the odds when the reference value was present instead.

- An OR calculated for a continuous variable is the odds of the event being a crash or near-crash compared to those for a variable value that is one unit lower.

- An OR calculated for ordinal variables reflects the odds of the event being a crash or near-crash compared to the odds for a variable value that is one ordinal level lower. Hence, the interpretation of ORs for ordinal values should be multiplied over the lowest level. For example, in Table 6, the ORs 4.233 and 0.068 for variable values "IRI: ≤ 20" and "IRI: 20–50" suggest that the presence of these variables increases and reduces the risk of fixed object events when compared to their one ordinal lower values—"IRI: missing" and "IRI: ≤ 20," respectively. The presence of variable value "IRI: 20–50" is still beneficial when compared to average IRI conditions ("IRI: missing"), as the multiplied OR 0.288 (4.233*0.068) is less than 1.

- A positive parameter for a continuous variable or unordered categorical variable suggests that the increased level or presence of that variable contributes to increased risks of the event being a crash or near-crash.

- A positive parameter for an ordinal variable indicates that the presence of that ordinal level contributes to increased risks of the event being a crash or near-crash compared to those for a variable value that is one unit lower. Hence, the interpretation of parameters for ordinal values should be accumulated over the lowest level. For example, the parameters of ordinal values "IRI ≤ 20" and "IRI: 20–50" are 1.4439 and -2.6842, indicating that the presence of these two variables increases and reduces the risk of fixed object events when compared to their one ordinal lower values—"IRI: missing" and "IRI: ≤ 20," respectively. The presence of variable value "IRI: 20–50" is still beneficial when compared to average IRI conditions ("IRI: missing"), as the accumulated parameter—1.2413 (1.4429-2.6842)—is negative.

Table 6. Significant variables and ORs for binary logistic regression model (SCE vs. baseline).

Variable	Values	Parameter	Chi-square	Pr > Chi Sq	OR (95% CI)
Intercept		13.9110	0.0004	0.9846	
Driver Behavior Factors					
Pre-Incident Maneuver	Changing lanes	0.9423	7.1918	0.0073	2.566 (1.289-5.109)
	Going straight - unintentional "drifting"	1.3933	5.4315	0.0198	4.028 (1.248-13.002)
	Making a turn	2.2989	20.7979	<.0001	9.963 (3.709-26.759)
	Going straight (accelerate, decelerate, constant speed)	Reference			
Maneuver Judgement	Unsafe and illegal	1.1902	4.4044	0.0358	3.288 (1.082-9.991)
	Unsafe but legal	2.4294	13.6215	0.0002	11.352 (3.124-41.243)
	Safe and legal	Reference			
Driver Behavior	Avoiding animal or other vehicle	3.6471	18.6589	<.0001	38.362 (7.332-200.715)
	Failed to signal, improper signal	1.8436	2.7283	0.0986	6.319 (0.709-56.33)
	Improper turn	4.4753	17.9293	<.0001	87.82 (11.065-697.012)
	Other	0.9841	3.5164	0.0608	2.675 (0.956-7.483)
	Sign, signal violation	1.671	2.8814	0.0896	5.318 (0.772-36.615)
	None	Reference			
Secondary Task	Adjusting/monitoring vehicle devices	0.878	4.1228	0.0423	2.406 (1.031-5.615)
	Personal hygiene	0.8268	4.1371	0.042	2.286 (1.031-5.071)
	Reaching, moving object in vehicle	3.3542	41.7081	<.0001	28.624 (10.343-79.218)
	No secondary tasks	Reference			
Hands on the Wheel	None or at least one hand off	-1.907	8.9612	0.0028	0.149 (0.043-0.518)
	Both hands	Reference			
Critical Speed	-	-0.0244	89.946	<.0001	0.976 (0.971-0.981)
Passenger Existence	Yes	-0.3237	2.9601	0.0853	0.723 (0.5-1.046)
	No	Reference			
Roadway and Traffic Variables					
Traffic Density	LOS A2	-0.6545	13.1572	0.0003	0.52 (0.365-0.74)
	LOS B	-0.3569	3.4302	0.064	0.7 (0.48-1.021)
	LOS D/E/F	-3.8469	10.1675	0.0014	0.021 (0.002-0.227)
	LOS A1	Reference			
Contiguous Travel Lanes	1	-13.2558	0.0003	0.9854	NA
	2	0.1449	0.1332	0.7151	1.156 (0.531-2.517)
	3	-0.6208	8.6733	0.0032	0.537 (0.356-0.812)
	4	0.0858	0.1052	0.7456	1.090 (0.649-1.830)
	5 and 5+	-0.2246	0.5641	0.4526	
	0	Lowest level			
	Other	1.757	5.5092	0.0189	5.795 (1.336-25.132)

Variable	Values	Parameter	Chi-square	Pr > Chi Sq	OR (95% CI)
Traffic Control	Sign control	0.5333	4.3504	0.037	1.705 (1.033-2.814)
	No traffic control	Reference			
Grade	Dip, hillcrest	1.3454	3.5741	0.0587	3.84 (0.952-15.492)
	Grade Up	0.3754	3.0712	0.0797	1.456 (0.957-2.215)
	Level	Reference			
Locality	Business/Industrial	0.8187	13.3666	0.0003	2.268 (1.462-3.517)
	Open Country	1.084	5.4653	0.0194	2.956 (1.191-7.336)
	Residential area	1.3483	35.9477	<.0001	3.851 (2.478-5.984)
	School/church/playground	0.7997	6.4612	0.011	2.225 (1.201-4.122)
	Interstate/Bypass/Divided-no signals	Reference			
AADT	≤5,000	-1.2394	21.66	<.0001	0.290 (0.172-0.488)
	5,000-10,000	0.0306	0.0088	0.9254	1.031 (0.543-1.956)
	10,000-15,000	-0.1253	0.1268	0.7218	0.882 (0.443-1.759)
	15,000-20,000	0.2026	0.2411	0.6234	1.225 (0.545-2.750)
	20,000-30,000	0.2493	0.3321	0.5644	1.283 (0.550-2.996)
	30,000-50,000	0.2295	0.3212	0.5709	1.258 (0.569-2.782)
	50,000-100,000	0.6368	2.1943	0.1385	1.890 (0.814-4.390)
	≥100,000	1.2827	8.9248	0.0028	3.605 (1.555–8.367)
	Missing	Lowest level			
IRI	≤20	1.4429	10.9066	0.001	4.233 (1.798-9.966)
	20-50	-2.6842	17.539	<.0001	0.068 (0.019-0.240)
	50-100	0.4296	0.6645	0.4150	1.537 (0.547-4.317)
	100-150	-0.00318	0.0001	0.9922	0.997 (0.527-1.887)
	150-200	0.9646	3.6997	0.0544	2.624 (0.982-7.011)
	>200	1.2233	3.4779	0.0622	3.398 (0.940-12.291)
	Missing	Lowest level			
Environmental Factors					
Lighting	Darkness, lighted	0.6621	11.0242	0.0009	1.939 (1.312-2.866)
	Darkness, not lighted	0.459	4.5099	0.0337	1.583 (1.036-2.417)
	Daylight	Reference			
Surface Condition	Icy/snowy/wet	0.3492	3.4882	0.0618	1.418 (0.983-2.046)
	Dry	Reference			

1. LOS = level of service.
2. NA in OR presented when one cell of the two-by-two calculation table is zero.

The model optimization and variable selection were based on maximum likelihood estimation. SAS provides several model fitness statistics, including -2 Log L (−2 log likelihood), AIC, and SC, as shown in Table 7. Readers should note that these goodness-of-fit measures are generally useful when comparing different models developed for the same data set. The measure values themselves may not provide significant information for how well the model describes the original data. SAS also outputs statistics of the likelihood ratio test, Wald test, and score test, indicating the significance of the constructed model (Table 8). To better understand how well the model describes the data and compare the prediction performance of logistic regression analysis with later SVM analysis, the research team applied the logistic regression model to the original data set. Among the 2,689 SCE and baseline events used, the regression model correctly described the outcomes of 89% of the events (Table 9).

Table 7. Goodness-of-fit measures for binary logistic regression model (SCE versus baseline).

Type	Intercept Only	Intercept and Covariates
AIC	3599.679	1588.039
SC	3605.576	2018.514
-2 Log L	3597.679	1442.039

Table 8. Test of global null hypothesis (SCE versus baseline).

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	2155.6398	72	<.0001
Score	1523.5849	72	<.0001
Wald	512.1695	72	<.0001

Table 9. Model prediction results with original data (SCE versus baseline).

Total Events = 2,689			Actual	
			SCE	**Baseline**
			1,639	1,050
Predicted	**SCE**	1,559	1,455	114
	Baseline	1,120	184	936

$$Accuracy = \frac{1455 + 936}{2689} \times 100\% = 88.9\%$$

SCE-Baseline Comparison Findings

Impacts of Driver Behavior Factors on Event Outcome

The model included seven driver behavior-related factors with significant influence on SCE occurrence (Table 6). The following summarizes the findings relevant to driver behavior-related variables:

- **Pre-incident maneuver**. Pre-incident maneuver describes the last driving maneuver the subject driver performed prior to the precipitating event. The results indicated that drivers were more likely to be involved in roadway object crashes when or after making a turn, drifting unintentionally while driving straight, or changing lanes. The ORs associated with these three types of pre-incident maneuvers were approximately 10, 4, and 2.6, respectively, compared to going straight.

- **Maneuver judgement**. This variable depicts the SHRP 2 data team's judgement on the safety and legality of the pre-incident maneuver based on vehicle position and vehicle dynamics. An example of an unsafe but legal maneuver is a vehicle traveling at the speed limit on slippery pavement. Compared to safe and legal maneuvers, the results showed that unsafe maneuvers were significantly more likely to be a contributing factor for roadway object crashes and near-crashes. This was true in particular for unsafe but legal maneuvers associated with an OR of 11, indicating a risk level for roadway object crashes and near-crashes more than 11 times higher than for safe and legal maneuvers.

- **Driver behavior**. The driver behavior variable depicts driver errors that led to or contributed to the occurrence of the event. The results showed that a number of driver behaviors were identified as contributing factors for roadway object crashes. Avoiding animals or other vehicles (OR = 38) and turning improperly (OR = 88) were particularly risky in terms of causing roadway object crashes.

- **Secondary task**. Generally, the involvement of secondary tasks while driving significantly increased the risk of roadway object crashes and near-crashes. Reaching and moving objects in the vehicle were associated with an OR of almost 30, indicating the significant contribution of such secondary tasks to roadway object crashes. Other tasks, such as personal hygiene-related activities (e.g., putting on makeup or cutting nails) and adjusting/monitoring vehicle devices also significantly increased roadway object crash risks.

- **Hands on the wheel**. The model suggests that drivers were less likely to be involved in roadway object crashes and near-crashes when they had one hand or no hands on the steering wheel. This outcome does not necessarily indicate that driving with one or no hands on the wheel is safer. Driving with one hand on the wheel, however, is commonly considered to be a surrogate for a less risky and relaxed driving environment (e.g., straight alignment with no or little traffic).

- **Critical speed**. The negative parameter for the critical speed variable suggested that roadway object crashes were more likely to occur while traveling at lower speeds. This is plausible since roadway object crashes are more common on local roads and/or at intersections compared to freeways and continuous segments on arterial roads.

- **Passenger presence**. The results showed that the presence of passengers in a vehicle reduced the risks of roadway object crashes and near-crashes. One explanation for this outcome is that passengers, particularly front seat passengers, could help reduce driver inattention and fatigue and help drivers identify risky fixed objects. Interaction with passengers, identified in the secondary task group, however, was found to contribute to roadway object crashes and near-crashes, though the effect was less significant.

Effects of Roadway- and Traffic-related Factors

The results showed the following significant roadway- and traffic-related variables relevant to roadway object crashes and near-crashes (Table 6):

- **Traffic density**. This variable depicts the SHRP 2 data team's perception of traffic density, based on the event video data, where level of service (LOS) A1 is no leading traffic in any lanes and LOS F is stop-and-go or severe congestion. The regression model showed that the presence of traffic was generally beneficial for reducing the risk of roadway object crashes. This is consistent with common observations that vehicles following other vehicles are less likely to collide with fixed objects.

- **Contiguous travel lanes**. Contiguous travel lanes include all lanes on the roadway that the subject vehicle can move into at the time of the precipitating event, including auxiliary lanes. The results showed that the presence of other lanes that were available for drivers to maneuver into was associated with lower risks of roadway object crashes and near-crashes.

- **Traffic control**. The results suggested that traffic control devices, such as traffic signs and other devices, significantly increased the risks of roadway object crashes, except for lane markings. Traffic control devices, while intended to improve traffic safety overall, result in fixed objects in the roadway environment and therefore could potentially increase the risks of roadway object crashes. The category of "other" under this variable includes traffic control measures that are not commonly seen on roadways, such as toll booths, parking gates, traffic circles, or roundabouts.

- **Grade**. The results showed that uphill inclines, dips, or hillcrests increased risks of fixed object-crashes and near-crashes.

- **Locality**. The locality variable describes the surroundings of the event roadway location. The results showed that more complex surroundings (possibly with more roadside objects or curbs/channelization devices) such as business/industrial, residential, and school/church/playground areas were associated with significantly higher risks of roadway object crashes. Note that roadways characterized as open country had an OR of about 3.

- **AADT and IRI**. Note that AADT in this analysis did not reflect actual traffic conditions during the events (see the traffic density variable). Rather, it was considered a surrogate for certain roadway types. The results indicated a roughly direct correlation between AADT and roadway object crash probability. The results suggested that roadways with an IRI between 20 and 150 had lower odds for roadway object crashes and that either smoother or rougher pavement increased the likelihood of roadway object crashes. Both AADT and IRI were obtained from RID for only a portion of the events. In addition, a number of AADT and IRI levels were not significant in the model.

Effects of Environment-related Factors

The binary logistic regression model suggested that lighting and surface condition were significant variables contributing to the occurrence of roadway object crashes and near-crashes.

- **Lighting conditions**. Both darkness lighted and darkness not lighted conditions had an OR higher than 1 compared to the daylight condition. The OR for the former was 1.9 and for the latter was 1.6. Note that the OR for darkness lighted was actually higher than for darkness not lighted, which could be due to some or all of the following:[78]

  - A large proportion of the events analyzed in this study occurred at or near intersections in urban areas. Street lighting is more likely to be present at such locations, and therefore the lighting variable in this context is merely a surrogate for the location conditions where lighting was present and does not account for any variation in the lighting level or the lighting uniformity.

  - Roadway lighting, when designed/installed improperly, results in poor uniformity across the roadway surface. Brighter areas in some cases may attract driver attention from darker areas on the roadway surface and therefore help hide fixed objects if they happen to be located in those darker areas.

  - When lighting levels are inadequate to light on-road/roadside objects, the presence of lighting becomes irrelevant to the risk levels of roadway object crashes.

  - Lighting infrastructure (i.e., light poles) can also create additional risks for roadway object crashes if not properly placed.

Note that during this project, the research team did not further analyze the events by grouping them based on roadway configurations due to the limited sample sizes.

- **Surface condition**. The results suggested that icy/snowy/wet pavement surfaces had an OR of 1.4 for roadway object crashes compared to the dry pavement condition.

RESULTS OF EVENT SEVERITY ANALYSIS BASED ON CRASHES AND NEAR-CRASHES

Ordinal Logistic Regression for Event Severity

The research team used ordinal logistic regression to model the effects of risk factors on the probability of increased severity levels based on the SHRP 2 SCEs. During this analysis, the research team assigned a severity level ranging from 1 to 5 to each SCE type, with Level 1 being severe crashes and Level 5 being near-crashes. In addition to the variables used in the binary logistic regression model, SCE severity level modeling also included variables such as driver reaction time and struck object type, which were not available for baseline events.

Model Parameters and Goodness of Fit

Tables 10–12 list the significant variables, model goodness-of-fit measures, and global null hypothesis tests, respectively. This analysis used 0.1 as the level of significance. Verification of the logistic regression model using the original data showed that the model was able to correctly describe 70% of the analyzed events (Table 13). Table 14 lists the significant variables and their associated values, parameters, and ORs in detail.

Table 10. Significant explanatory variables for ordinal event severity modeling.

Effect	DF	Wald Chi-square	Pr > ChiSq
Number of Violation	3	6.0748	0.108
Pre-incident Maneuver	5	13.0414	0.023
Driver Behavior	9	107.2417	<.0001
Weather	1	2.9861	0.084
Traffic Density	4	12.3309	0.0151
Locality	6	36.3792	<.0001
Critical Speed	1	3.7883	0.0516
Radius	6	21.7426	0.0013
Struck Object Type	12	266.8916	<.0001
Reaction Time	1	84.523	<.0001

Table 11. Model fitness measures for ordinal event severity modeling.

Criterion	Intercept Only	Intercept and Covariates
AIC	3968.104	3293.890
SC	3989.711	3585.590
-2 Log L	3960.104	3185.890

Table 12. Testing global null hypothesis: β=0 for ordinal event severity modeling.

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	774.2134	50	<.0001
Score	558.8899	50	<.0001
Wald	574.0044	50	<.0001

Table 13. Confusion matrix of ordinal event severity logistic prediction.

<table>
<tr><td colspan="3" rowspan="3">Total SCEs = 1,639</td><td colspan="5">Counts by Actual Severity</td></tr>
<tr><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td></tr>
<tr><td>13</td><td>35</td><td>447</td><td>534</td><td>610</td></tr>
<tr><td rowspan="5">Counts by Predicted Severity</td><td>1</td><td>1</td><td>1</td><td>0</td><td>0</td><td>0</td><td>0</td></tr>
<tr><td>2</td><td>0</td><td>0</td><td>0</td><td>0</td><td>0</td><td>0</td></tr>
<tr><td>3</td><td>373</td><td>5</td><td>12</td><td>236</td><td>77</td><td>43</td></tr>
<tr><td>4</td><td>698</td><td>3</td><td>9</td><td>140</td><td>440</td><td>106</td></tr>
<tr><td>5</td><td>567</td><td>4</td><td>14</td><td>71</td><td>17</td><td>461</td></tr>
</table>

$$Accuracy = \frac{1 + 0 + 236 + 440 + 461}{1639} \times 100\% = 69.43\%$$

Table 14. Significant variables and values for ordinal logistic regression model.

Variable	Variable Value	Parameter	Chi-square	Pr > Chi Sq	OR (95% CI)
Intercept 1	-	-5.645	67.0434	<.0001	-
Intercept 2	-	-4.236	43.2149	<.0001	-
Intercept 3	-	-1.051	2.8298	0.0925	-
Intercept 4	-	0.9066	2.1018	0.1471	-
Driver Behavior Factors					
Number of violations in past 3 years	0	-0.9412	4.2593	0.039	0.390 (0.160-0.954)
	1	0.0429	0.1112	0.7388	1.044 (0.811-1.343)
	2 and 2+	0.1834	1.0579	0.3037	1.201 (0.847-1.704)
	Missing	Lowest Level			
Pre-incident Maneuver	Going straight but unintentionally drifted	0.4981	3.2443	0.0717	1.646 (0.957-2.83)
	Making a turn	0.3062	2.6188	0.1056	1.358 (0.937-1.968)
	Going straight	Reference			
Driver Behavior/Error	Apparent unfamiliarity with roadway	1.3754	14.6353	0.0001	3.957 (1.956-8.005)
	Avoiding animal, or other vehicle	-1.1367	3.5268	0.0604	0.321 (0.098-1.051)
	Distracted	1.089	39.1993	<.0001	2.971 (2.113-4.178)
	Drowsy, sleepy, asleep, fatigued	1.2856	10.703	0.0011	3.617 (1.674-7.813)
	Exceeded safe speed, or speed limit	1.3257	40.4204	<.0001	3.765 (2.502-5.665)
	None	Reference			
Critical Speed (km/h)	-	0.00622	3.7883	0.0516	1.006 (1-1.013)
Reaction Time (s)	-	-0.5962	84.523	<.0001	0.551 (0.485-0.626)
Roadway and Traffic Factors					
Traffic Density	LOS A2	-0.3368	6.1728	0.013	0.714 (0.547-0.931)
	LOS B	-0.3219	4.5792	0.0324	0.725 (0.54-0.973)
	LOS C	-0.8883	6.7163	0.0096	0.411 (0.21-0.805)
	LOS A1	Reference			
Locality	Business/Industrial	0.8038	8.8657	0.0029	2.234 (1.316-3.792)
	Bypass/Divided Highway with traffic signals	0.8137	3.2428	0.0717	2.256 (0.931-5.47)
	Church/school/playground	1.0214	11.5393	0.0007	2.777 (1.54-5.007)
	Open Country	2.8109	33.7909	<.0001	16.624 (6.444-42.888)
	Residential area	0.8056	9.1334	0.0025	2.238 (1.327-3.774)
	Urban	0.642	2.7473	0.0974	1.9 (0.889-4.06)
	Interstate/Bypass/Divided Highway with no traffic signals	Reference			
Curve Radius (ft)	≤500	0.3594	0.7040	0.4014	1.433 (0.619-3.317)
	500-1000	-0.1376	0.0672	0.7955	0.871 (0.308-2.467)
	1000-2000	0.0884	0.0295	0.8636	1.092 (0.398-2.995)
	2000-5000	-1.5421	7.0451	0.0079	0.214 (0.069-0.668)
	>5000	2.1959	15.2680	<.0001	8.988 (2.988-27.042)
	No curvature	-0.5585	2.1021	0.1471	0.572 (0.269-1.217)
	Missing	Lowest Level			

Variable	Variable Value	Parameter	Chi-square	Pr > Chi Sq	OR (95% CI)
Struck Object Type	Animal	-2.2632	102.4069	<.0001	0.104 (0.067-0.161)
	Ditch	3.0768	32.6201	<.0001	21.688 (7.545-62.341)
	Roadway debris	0.919	10.1226	0.0015	2.507 (1.423-4.415)
	Stopped, backing, pulling out car	-3.2329	45.9126	<.0001	0.039 (0.015-0.1)
	Tree/shrub	1.4932	3.6178	0.0572	4.451 (0.956-20.737)
	Utility/light pole	2.1344	6.6982	0.0097	8.452 (1.679-42.551)
	Curb	Reference			
Environmental Factors					
Weather	Adverse Weather	0.2642	2.9861	0.084	1.302 (0.965-1.757)
	No adverse weather	Reference			

*LOS = level of service.

Effects of Driver Behavior Factors on Event Outcome

The results showed five driver behavior-related factors with significant influence on SCE severity level outcomes. The following summarizes the findings relevant to driver-behavior-related variables (Table 14):

- **Number of violations in past 3 years**. The number of violations in the past can be an indicator of driving habits to some extent. The results indicated that drivers with fewer violations in the past generally had a higher likelihood of having a lower severity roadway object conflict than those with more violations.

- **Pre-incident maneuver**. Results suggested that drivers were more likely to be involved in a more severe roadway object crash during or after drifting when going straight or making a turn.

- **Driver behavior/error**. Results showed that most identified driver behavior factors contributed to the increase of event severity upon occurrence of a roadway object event. The presence of factors such as unfamiliarity with roadway, distraction, drowsiness/fatigue, and speeding was associated with an OR ranging from 3 to 4, indicating significantly higher levels of risks for a more severe roadway object crash. Avoiding animals or other vehicles, however, was found to be associated with lower odds of more severe roadway object event outcomes, possibly because this driver action is an evasive maneuver and therefore is more likely to cause near-crashes compared to crashes.

- **Critical speed**. The positive parameter for the critical speed suggested that increased travel speeds correlated with higher severity roadway object event outcomes. The results showed that an increase of 10 mph in speed increased the likelihood of a more severe roadway object event by 1.1 times.

- **Reaction time**. The negative parameter for the reaction time indicated that drivers were often able to avoid severe roadway object crash outcomes given enough reaction time. An extra 1-second reaction time could reduce the risk of more severe roadway object event outcomes by 1.8 times.

Effects of Roadway- and Traffic-related Factors

The results showed that the following significant roadway- and traffic-related variables were relevant to the severity outcomes of roadway object SCEs (Table 14):

- **Traffic density**. The ordinal regression model showed that the presence of traffic was generally beneficial for reducing the risks of more severe roadway object event outcomes. In particular, drivers were least likely to be involved in a severe roadway object crash when traveling in LOS C density (stable flow, restricted maneuverability and speed), which had the lowest OR of 0.411.

- **Locality**. The results showed that locations with more complex surroundings, such as business/industrial, residential, urban, bypass/divided highway with traffic signals, and school/church/playground areas, were significantly associated with higher likelihoods of more severe roadway object event outcomes, with ORs ranging from 2 to 3. Note that roadways characterized as open country were particularly correlated with more severe roadway object event outcomes, with an OR as high as 16.6.

- **Curve radius**. This variable was obtained from the RID for only a portion of the events. The analysis of curve radius showed that a radius of 2,000–5,000 ft had an OR lower than 1, while curves with radii greater than 5,000 ft had an OR larger than 1 (i.e., 9.0). These results seem to contradict prevailing wisdom, which might be due to the limited sample sizes.

- **Struck object type**. Curbs were the most frequently struck objects and were often associated with low-risk tire strikes (used as the reference level for this variable). Comparatively, conflicts with animals and vehicles had a significantly lower likelihood of more severe roadway object event outcomes judging from the low ORs (i.e., 0.1 and 0.04), which might indicate that many animal-vehicle encounters end up being near-crashes. Encounters with other objects, such as roadway debris, trees/shrubs, and utility/light poles, generally had higher probability of more severe roadway object event outcomes, with ORs of 2.5, 4.5, 8.5, and 21.7, respectively.

Effects of Environmental Factors

The analysis results showed that driving in adverse weather conditions such as fog, rain, and snow tended to be correlated with higher risks of more severe roadway object event outcomes (OR of 1.3).

Binary Logistic Regression Model Comparing Level 1–3 Crashes and Near-crashes

In addition to the ordinal logistic regression modeling of all SCE levels, a binary logistic regression model was developed to compare SHRP 2 Level 1–3 crashes and near-crashes. This comparison was made to address the limited sample sizes of Level 1 and Level 2 crashes and the potentially low risk levels associated with Level 1 crash events. This analysis was aimed at identifying factors that influenced drivers when making a successful evasive maneuver in crash scenarios and validating and comparing the results with those of the ordinal regression analysis.

Model Parameters and Goodness of Fit

Tables 1517 list the significant variables, model goodness-of-fit measures, and global null hypothesis tests. The constructed model was applied to original data, which showed that the model was able to correctly describe 80% of the analyzed events (Table 18). Table 19 lists the significant variables and their associated values, parameters, and ORs in detail.

Table 15. Significant explanatory variables for binary event severity modeling.

Variable	DF	Wald Chi-square	Pr > ChiSq
Pre-incident Maneuver	5	12.4392	0.0292
Driver Behavior	9	39.6921	<.0001
Traffic Density	4	9.9685	0.041
Locality	6	17.9676	0.0063
Radius	6	17.8147	0.0067
Struck Object Type	12	101.2866	<.0001
Reaction Time	1	47.4715	<.0001

Table 16. Model fitness measures for binary event severity modeling.

Criterion	Intercept Only	Intercept and Covariates
AIC	1521.865	980.929
SC	1526.873	1206.271
-2 Log L	1519.865	890.929

Table 17. Testing global null hypothesis: β=0 for binary event severity modeling.

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	519.3224	45	<.0001
Score	430.5521	45	<.0001
Wald	293.8899	45	<.0001

Table 18. Confusion matrix of binary event severity prediction.

Total Events = 1,105			Actual: Crash	Actual: Near-crash
			495	610
Predicted	Crash	499	388	111
	Near-crash	606	107	499

$$Accuracy = \frac{388 + 499}{1105} \times 100\% = 80.27\%$$

Table 19. Significant variables and values for Level 1–3 crash and near-crash modeling.

Variable	Value	Parameter	Chi-square	Pr>ChiSq	OR
Intercept	-	0.9651	4.7213	0.0298	-
Driver Behavior Factors					
Pre-incident maneuver	Making a turn	0.5955	4.3342	0.0374	1.814 (1.035-3.177)
	Going straight	Reference			
Driver behavior/error	Apparent unfamiliarity with roadway	1.4035	7.6453	0.0057	4.069 (1.505-11.005)
	Distracted	0.827	10.927	0.0009	2.287 (1.4-3.734)
	Drowsy, sleepy, asleep, fatigued	1.4702	6.586	0.0103	4.35 (1.415-13.37)
	Exceeded safe speed, or speed limit	1.2035	19.8686	<.0001	3.332 (1.963-5.656)
	Improper turn	0.6892	2.9	0.0886	1.992 (0.901-4.403)
	Sign, signal violation	1.4035	7.6453	0.0057	4.546 (1.241-16.651)
	None	Reference			
Reaction time		-0.5953	47.4715	<.0001	0.551 (0.466-0.653)
Roadway and Traffic Variables					
Traffic density	LOS A2	-0.5985	6.4761	0.0109	0.55 (0.347-0.871)
	LOS B	-0.6051	5.8869	0.0153	0.546 (0.335-0.89)
	LOS C	-1.0458	3.9919	0.0457	0.351 (0.126-0.98)
	LOS A1	Reference			
Locality	Church/school/playground	0.7093	3.368	0.0665	2.033 (0.953-4.336)
	Open Country	2.2271	12.9324	0.0003	9.273 (2.755-31.216)
	Interstate/Bypass/Divided Highway with no traffic signal	Reference			
Curve Radius (ft)	0-500	-0.0789	0.0152	0.9018	0.924 (0.264-3.238)
	500-1000	0.0208	0.0017	0.9667	1.105 (0.244-5.002)
	1000-2000	0.6345	0.8708	0.3507	1.847 (0.385-8.856)
	2000-5000	-1.4748	4.4028	0.0359	0.121 (0.019-0.777)
	>5000	1.1423	4.9548	0.026	1.055 (0.282-3.950)
	No curvature	0.6881	7.5464	0.006	0.635 (0.243-1.661)
	Missing	Lowest Level			
	Others	-0.9103	6.907	0.0086	0.402 (0.204-0.793)

Variable	Value	Parameter	Chi-square	Pr>ChiSq	OR
Struck Object Type	Raised median	-0.6873	4.2444	0.0394	0.503 (0.262-0.967)
	Animal	-2.3576	53.2448	<.0001	0.095 (0.05-0.178)
	Pavement edge/ edge line	-0.8956	9.302	0.0023	0.408 (0.23-0.726)
	Stopped, backing, pulling out car	-3.3244	38.522	<.0001	0.036 (0.013-0.103)
	Curb	Reference			

The following conclusions can be made based on the results shown in Table 19.

Effects of Driver Behavior Factors on Event Outcome

- **Pre-incident maneuver**. Results suggested that roadway object crashes that occurred during or after making a turn were less likely to be avoided. Events in this category often occurred at intersections and involved vehicles colliding with curb corners, median ends, or other roadside infrastructure.

- **Driver behavior/error**. Results showed that the involvement of driver behavior or errors increased the likelihood for an event to be a crash rather than a near-crash. The presence of factors such as unfamiliarity with the roadway, distraction, drowsiness/fatigue, speeding, improper turn, and sign/signal violation was associated with an OR ranging from 2 to 4.5, suggesting that engagement in those driver behaviors decreased the probability of drivers avoiding a crash.

- **Reaction time**. The negative parameter for the reaction time indicated that drivers were often able to successfully evade a crash given enough reaction time. One extra second of reaction time could increase the probability of turning a roadway object crash event into a near-crash event by 1.8 times.

Effects of Roadway and Traffic-related Factors

- **Traffic density**. The binary regression model showed that the presence of traffic made it more likely for drivers to make successful evasive maneuvers. In particular, the identified LOS A2, LOS B, and LOS C conditions were able to reduce the probability of a vehicle making physical contact with fixed objects by 1.8 to 2.8 times.

- **Locality**. According to the results, it was less probable that drivers would avoid a crash in a locality characterized as church, school, playground, and open country, with an increased crash risk of 2 and 9.2 times, respectively.

- **Curve radius**. The analysis results of curve radius showed that roadways with curve radii ranging from 2,000–5,000 ft were particularly beneficial for preventing an event from becoming a roadway object crash, while events occurring on straight roadways were less likely to be avoided. The benefit of the curve is unclear; however, it can be surmised that the long radius curve is not as complicated a driving task as a short radius curve, and the presence of the curve would assist in the perception of objects in the roadway, particularly when following another vehicle, as the object would not be aligned with the leading vehicle.

- **Struck object type**. The negative parameters for struck object types suggested a higher probability for the associated events being near-crashes than crashes. In other words, events involving vehicles conflicting with curbs were more likely to result in crashes.

SVM ANALYSIS RESULTS

SVM Classifier Development and Accuracy

During this study, the research team developed three SVM classifiers to complement the previous logistic regression analyses:

- A binary SVM classifier for comparing SCEs against baseline events
- A multi-class SVM classifier for all SCE severity levels (Level 1–5)
- A binary SVM classifier for comparing Level 1–3 crashes against near-crashes

For completeness and accuracy, the research team used five different kernels for each SVM classifier, as listed in Table 20. To understand the weight of the significant factors identified by the classifiers, the research team also conducted a sensitivity analysis for each SVM classifier.

Table 20. List of kernels used for binary and ordinal SVM classifiers.

Kernel Type	Kernel Function
Linear	$K(x_i, x_j) = x_i^T x_j$
Quadratic	$(x_i, x_j) = \left(x_i^T x_j + 1\right)^2$
Cubic	$(x_i, x_j) = \left(x_i^T x_j + 1\right)^3$
Fine Gaussian (σ = 2.5)	$K(x_i, x_j) = exp\left(-\frac{1}{2\sigma^2}\left\|x_i - x_j\right\|^2\right)$
Medium Gaussian (σ = 10)	
Coarse Gaussian (σ = 40)	

Note that the purpose of the SVM analyses in this study was to identify significant risk factors and understand their associated risk levels based on the current SHRP 2 event data. It was not the goal of these analyses to develop SVM classifiers with strong prediction powers for identifying roadway object crashes from other data sets. Therefore, other than the sensitivity analyses, the research team did not use additional data to verify/validate the SVM classifiers developed during this study. Table 21 lists the accuracy rates for the three SVM classifiers with different kernel functions. The results indicate that the highest accuracy rates for these three classifiers were 87.4%, 74.7%, and 78.3%, respectively. Tables 22–24 are the associated confusion matrices for the three classifiers with the highest accuracy rates.

Table 21. Accuracy rates for binary and ordinal SVM classifiers with different kernels.

Kernel Type	SVM Accuracy		
	(SCE vs. Baseline)	(Five Severity Levels)	(Level 1–3 Crashes vs. Near-crashes)
Linear	86.3%	74.7%	76.3%
Quadratic	87.4%	74.2%	78.3%
Cubic	86.3%	72.8%	76.4%
Fine Gaussian	63.3%	39.4%	55.2%
Medium Gaussian	87.2%	73.6%	77.6%
Coarse Gaussian	85.6%	72.2%	75.6%

Table 22. Confusion matrix for binary SVM with quadratic kernel (baseline vs. SCE).

Total Events = 2,689			Actual	
			SCE	**Baseline**
			1,639	1,050
Predicted	**SCE**	1,520	1,410	110
	Baseline	1,169	229	940

$$Accuracy = \frac{1410 + 940}{2689} \times 100\% = 87.4\%$$

Table 23. Confusion matrix for multi-class SVM with linear kernel.

Total SCEs = 1,639			Counts by Actual Severity				
			1	2	3	4	5
			13	35	447	534	610
Counts by Predicted Severity	1	0	0	0	0	0	0
	2	5	1	2	1	0	1
	3	417	2	5	267	69	74
	4	551	1	0	67	452	31
	5	666	9	28	112	13	504

$$Accuracy = \frac{0 + 2 + 267 + 452 + 504}{1639} \times 100\% = 74.7\%$$

Table 24. Confusion matrix for binary SVM with quadratic kernel (crash vs. near-crash).

Total Events = 1,105			Actual	
			Level 1-3 Crash	**Near-crash**
			495	610
Predicted	**Level 1-3 Crash**	483	369	114
	Near-crash	622	126	496

$$Accuracy = \frac{369 + 496}{1105} \times 100\% = 78.3\%$$

The receiver operating characteristic (ROC) curve is a frequently employed tool to illustrate the diagnostic ability of an SVM classifier by plotting the true positive rate against the false positive rate. The former is computed as the ratio of true positives to total positives, which can be considered as an indicator of model sensitivity. The latter is the ratio of false negatives to true negatives and can be considered as an indicator of model specificity. Note that a threshold is used to make continuous output values into dichotomous classification outcomes. By changing the threshold for classification gradually, a curve of a series of points representing the corresponding sensitivity and specificity values is formed. ROC curves are insensitive to classification distribution, classification priori probability, and misclassification cost, and therefore are widely used for evaluating the performance of machine-learning-based classifiers.[(79)] On an ROC curve plot, the top left corner, which suggests a false positive rate of zero, and a true positive rate of 1, is the ideal point for a classifier. In addition, a larger area under the curve is usually better.

Figures 25–27 show the ROC curves for the three SVM classifiers with the highest accuracy rates, respectively. In general, the plots show that all three classifiers performed reasonably well for the SHRP 2 roadway object event data. For the multi-class SVM classifier, the plots indicate that the classifier performed better for Level 4 crash events, near-crash events, and, to a lesser degree, Level 3 crash events. The poor performance for Level 1 and 2 crash events was most likely due to the limited sample sizes.

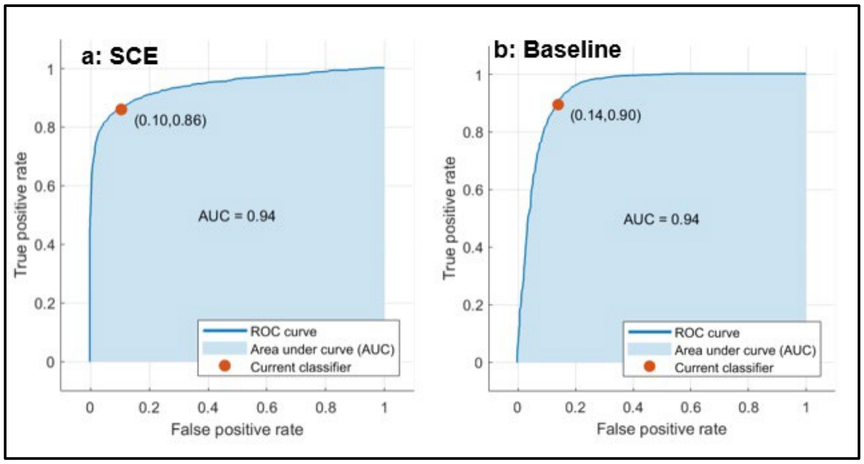


Figure 25. Line graphs. ROC curves for binary SVM classifier with quadratic kernel (baseline vs. SCE).

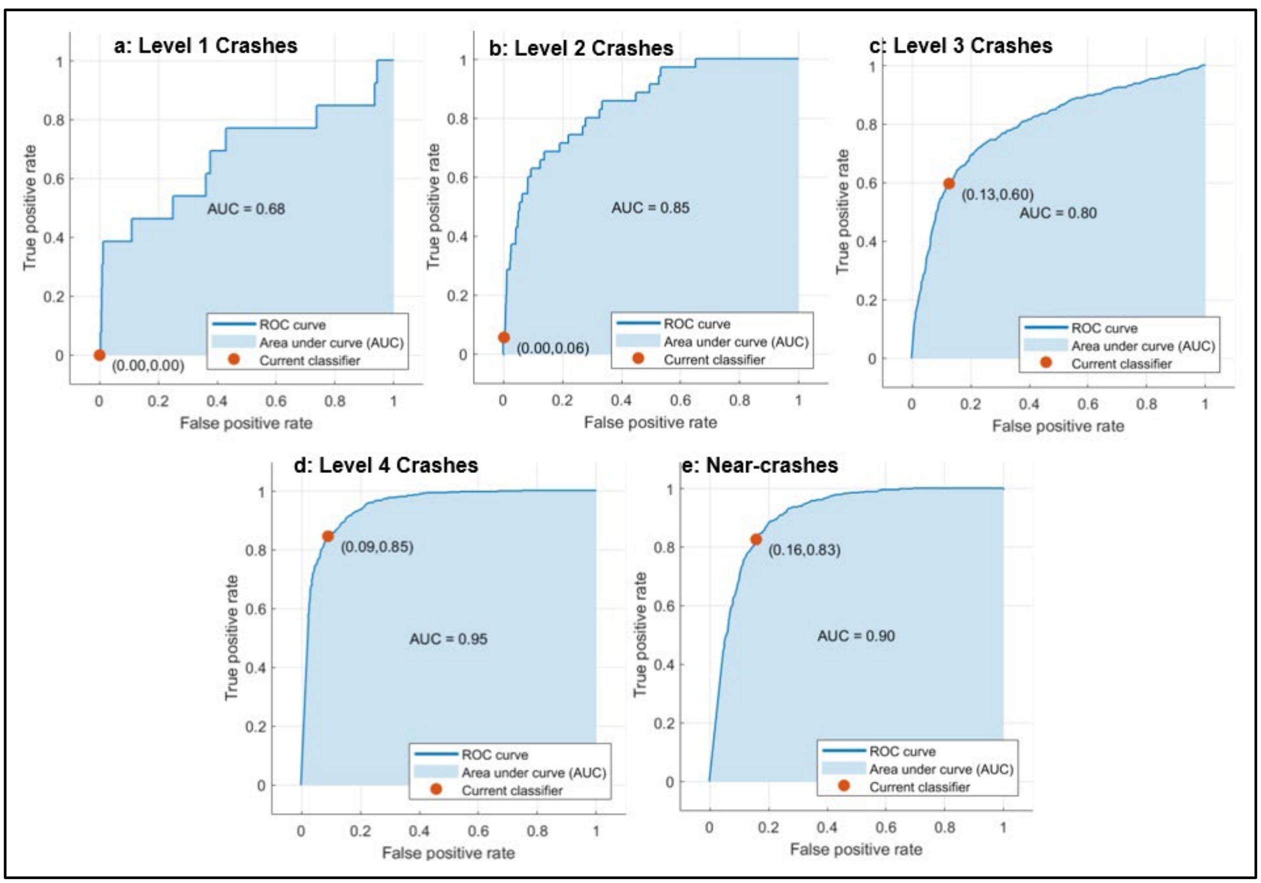


Figure 26. Line graphs. ROC curves for multi-class SVM classifier with linear kernel.

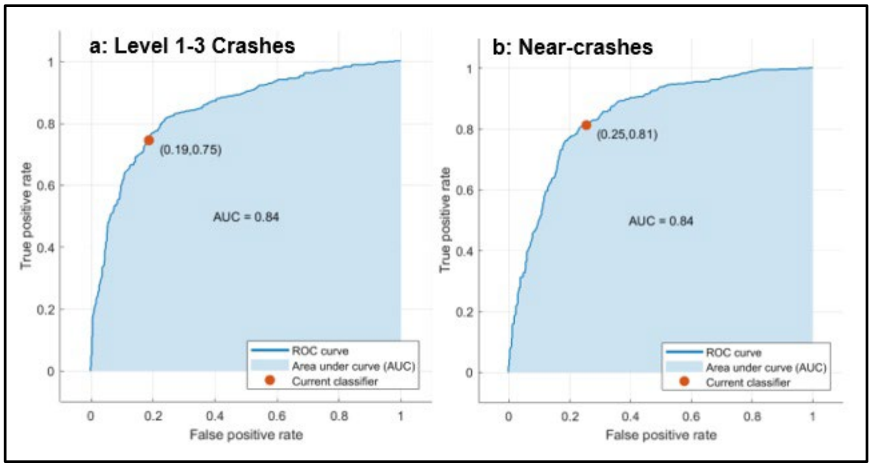


Figure 27. Line graphs. ROC curves for binary SVM classifier with quadratic kernel (Level 1–3 crashes vs. near-crashes).

Sensitivity Analysis Results

Figures 28–30 show the sensitivity analysis results for three SVM classifiers with the highest accuracy rates. As previously discussed in the methodology section, SVM classifiers work as "black boxes." The sensitivity analysis results provide insights on the level of contribution that variables have to the overall performance of the classifiers.

As the figures illustrate, driver behavior and critical speed played the most significant roles in the binary classifier for roadway object event occurrence, indicating their significant correlation with roadway object crashes. When analyzed for more detailed severity levels, the SVM analysis indicates that driver behavior, struck object type, and reaction time contributed the most to the increase of event severity for roadway object events. When excluding low-risk tire strikes, the SVM analysis results showed that struck object type and reaction time contributed the most to event severity.

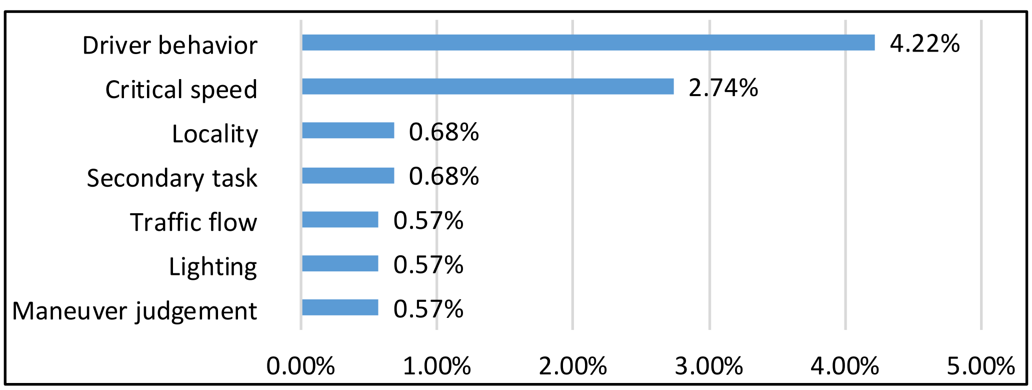


Figure 28. Bar graph. Sensitivity analysis results of binary SVM classifier (baseline vs. SCE).

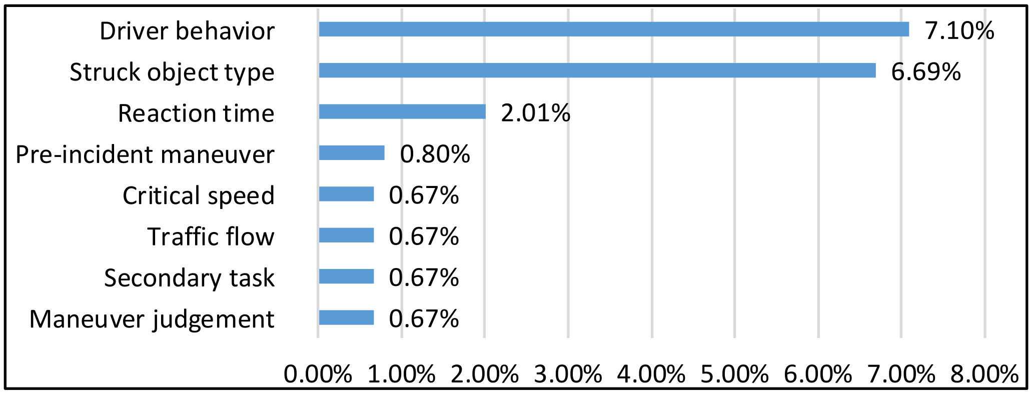


Figure 29. Bar graph. Sensitivity analysis results of multi-class SVM classifier.

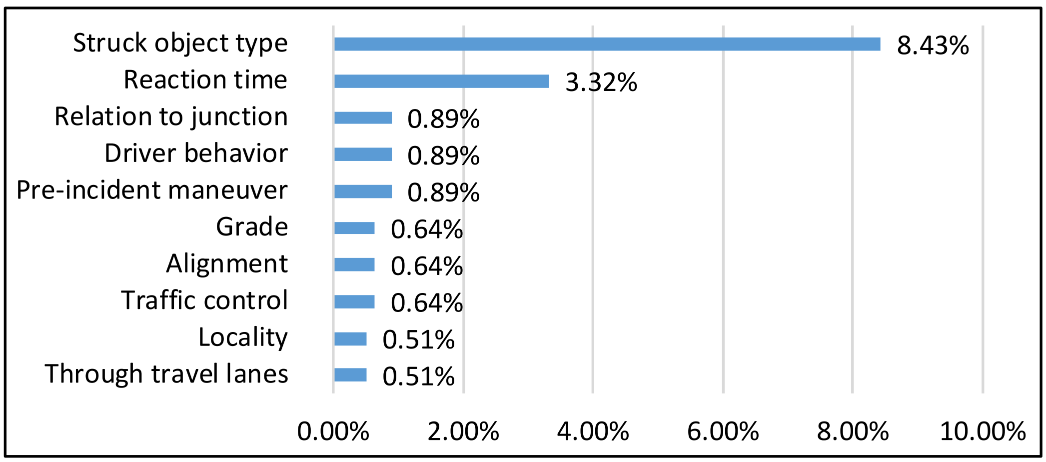


Figure 30. Bar graph. Sensitivity analysis results of binary SVM classifier (crash vs. near-crash).

SUMMARY AND DISCUSSION

Table 25 summarizes the role that identified major significant variables played in different models.

Table 25. Influences of variables on roadway object crashes and near-crashes.

Variable	Values	Binary Occurrence	Multi-Class Severity	Binary Severity
Driver Behavior Factors				
Pre-incident Maneuver	Changing lanes	↑ (2.566)	-	-
	Going straight - unintentional "drifting"	↑ (4.028)	↑ (1.646)	-
	Making a turn	↑ (9.963)	↑ (1.358)	↑ (1.814)
	Going straight	Reference		
Driver Behavior	Apparent unfamiliarity with roadways	-	↑ (3.957)	↑ (4.069)
	Avoiding animal or other vehicle	↑ (38.362)	↓ (0.321)	-

Variable	Values	Binary Occurrence	Multi-Class Severity	Binary Severity
	Distracted	-	↑ (2.971)	↑ (2.287)
	Drowsy, sleepy, asleep, fatigued	-	↑ (3.617)	↑ (4.350)
	Failed to signal, improper signal	↑ (6.319)	-	-
	Exceeded safe speed, or speed limit	-	↑ (3.765)	↑ (3.332)
	Improper turn	↑ (87.82)	-	↑ (1.992)
	Other	↑ (2.675)	-	-
	Sign, signal violation	↑ (5.318)	-	↑ (4.546)
	None	Reference		
Secondary Task	Adjusting/monitoring vehicle devices	↑ (2.406)	-	-
	Personal hygiene	↑ (2.286)	-	-
	Reaching, moving object in vehicle	↑ (28.624)	-	-
	No secondary tasks	Reference		
Critical Speed		↓ (0.976)	↑ (1.006)	-
Reaction Time		-	↓ (0.551)	↓ (0.551)
Roadway and Traffic Variables				
Traffic Density	LOS A2	↓ (0.52)	↓ (0.714)	↓ (0.55)
	LOS B	↓ (0.7)	↓ (0.725)	↓ (0.546)
	LOS C	-	↓ (0.414)	↓ (0.351)
	LOS D/E/F	↓ (0.021)	-	-
	LOS A1	Reference		
Locality	Business/Industrial	↑ (2.268)	↑ (2.234)	-
	Divided highway with traffic signals	-	↑ (2.256)	-
	Church/school/playground	↑ (2.225)	↑ (2.777)	↑ (2.033)
	Open Country	↑ (2.956)	↑ (16.624)	↑ (9.273)
	Residential area	↑ (3.851)	↑ (2.238)	-
	Urban	-	↑ (1.900)	-
	Freeway/Divided Highway - no signals	Reference		
Struck Object Type	Animal	-	↑ (2.225)	↓ (0.095)
	Ditch	-	↑ (21.688)	-
	Pavement edge/edge line	-	-	↓ (0.408)
	Raised median	-	-	↓ (0.503)
	Roadway debris	-	↑ (2.507)	-
	Stopped, backing, pulling out car	-	↓ (0.039)	↓ (0.036)
	Tree/shrub	-	↑ (4.451)	-
	Utility/light pole	-	↑ (8.452)	-
	Others	-	-	↓ (0.402)
	Curb	Reference		

Variable	Values	Binary Occurrence	Multi-Class Severity	Binary Severity
Environmental Factors				
Lighting	Darkness, lighted	↑ (1.939)	-	-
	Darkness, not lighted	↑ (1.583)	-	-
	Daylight	Reference		
Surface Condition	Icy/snowy/wet	↑ (1.418)	-	-
	Dry	Reference		
Weather	Adverse weather	-	↑ (1.302)	-
	No adverse weather	Reference		

↑ = the presence of this variable contributes to roadway object crashes occurrence or more severe outcome.
↓ = the presence of this variable reduced probability of roadway object events, or associated severity levels.
Numbers in parentheses are associated ORs.

The following summarizes the major findings of the logistic regression and SVM analyses.

Effects of Driver Behavior Factors on Roadway Object Crashes

- **Pre-incident maneuver**. Pre-incident maneuver played a more significant role in the occurrence of a roadway object event than the severity outcome. Drifting when going straight and making a turn were identified as significant contributors that increased the odds of roadway object event occurrence by 4 and 10 times, respectively. However, these two factors only increased the risk of a more severe outcome by 1.6 and 1.3 times. Drifting when going straight is often due to driver inattention, frequently resulting in roadway departures and collisions with roadside infrastructure. Making a turn is frequently required at intersections and therefore has a higher likelihood of resulting in a crash with objects at intersections such as curb corners, raised medians, and other channelization and delineation devices.

- **Driver behavior/errors**. Driver behavior or errors played a critical role in both roadway object occurrence and severity level, but the identified values and significance levels were different among models. In particular, the event occurrence analysis identified behaviors such as failed or improper signal, sign/signal violation, and improper turn to be significant contributors to the probability of a roadway object crash, while the severity analysis showed that these behaviors had little contribution to crash severity outcomes. Distraction, drowsiness, fatigue, and speeding correlated with increased severity outcomes when a roadway object crash took place. Interestingly, avoiding animals/vehicles was found to be associated with higher probability of an SCE occurrence, but the severity analysis indicated that this action tended to correspond to less severe events. The comparison analysis of Level 1–3 crashes and near-crashes indicated that all these driver behavior/errors increased the odds of a roadway object crash by 2.0 to 4.5 times when a roadway object event occurred.

Both binary SVM analysis comparing SCEs and baseline events and the multi-class SVM analysis confirmed that driver behavior/errors were the most significant factor affecting event occurrence and severity outcomes.

- **Critical speed**. The event occurrence analysis showed that roadway object crashes and near-crashes were more likely to occur on low-speed roadways. This finding was consistent with the analysis results of locality, which suggested that roadway object events were more likely to take place on local roadways than on freeways and continuous divided highway segments. The results of event severity analysis indicated that increased speeds led to increased risk of a more severe crash. Critical speed was not a significant variable in the model developed for the Level 1–3 crash versus near-crash comparison. The SVM analysis also showed that critical speed was a significant variable distinguishing SCEs and baseline events.

- **Reaction time**. It was not surprising that sufficient driver reaction time was beneficial for successful crash evasion. The results showed that each extra second reduced the likelihood of an event being a Level 1–3 crash as opposed to a near-crash by a factor of 0.55. Driver distraction, engagement in secondary tasks, and impairments (drowsiness, fatigue, sleepiness, etc.) could all potentially reduce driver reaction time when a conflict occurs, which can explain the findings that these factors were significant for increasing the probability of roadway object crash occurrence. Reaction time was found to be a significant variable affecting event severity outcomes during the SVM analyses.

- **Secondary tasks**. This variable was only identified as significant in the event occurrence analysis. Involvement in secondary tasks, such as reaching/moving objects in the vehicle, personal hygiene-related activities, and adjusting/monitoring vehicle devices, increased the risks of roadway object crashes, with ORs of 28.4, 2.6, and 2.2, respectively.

Effects of Roadway and Traffic-related Factors on Roadway Object Crashes

- **Traffic density**. The results of all three logistic regression models showed that LOS A1 (free flow, with no leading traffic) was the most hazardous traffic condition and associated with significantly higher risks of both roadway object event occurrence and more severe outcomes. This finding is consistent with the "cooperative safety" concept, which posits that vehicles following other vehicles tend to be safer since leading vehicles can help show following vehicles safe paths. This phenomenon is particularly evident during nighttime or at locations with complex roadway features with the potential to cause traffic conflicts.

- **Locality**. The results showed that more roadway object events and more severe roadway object crashes occurred on local roads (business/industrial, residential, urban, and open country) compared to freeways and continuous divided highway segments. In particular, roadways characterized as open country were found to be 3 times more likely to involve an SCE with a roadway object or 16.6 times more likely to involve an event having a more severe outcome. Open country was assigned to roadways where only vegetation was visible on the roadside. Events falling into this category were commonly characterized as no leading traffic, rural two-lane road, and involving conflicts with animals such as deer. Note that this study only analyzed 23 SCEs and 19 baseline events in the "open country" category.

- **Struck object type**. The results showed that struck objects, such as ditches, utility/light poles, trees/shrubs, and roadway debris, generally increased the probability of severe roadway object crash outcomes compared to curb strikes, but events involving animals and vehicles tended to be associated with less severe outcomes. A potential explanation was that drivers were more vigilant when encountering those objects than curbs, and hence were more likely to make successful evasive maneuvers that resulted in near-crashes instead of crashes. The significantly low odds radios and negative parameters associated with vehicle and animal conflicts suggested that these were the two objects that drivers wanted to strike the least.

Both SVM classifiers for event severity outcomes suggested that struck object type was a significant factor for event severity outcomes.

- **AADT and IRI**. These two variables were only significant in the model comparing SCEs and baselines. Note that AADT in that analysis did not reflect actual traffic condition during the events (see the traffic density variable). It was considered more as a surrogate for certain roadway types. The results indicated a roughly direct correlation between AADT and roadway object crash probability. While the results suggested that roadways with an IRI between 20 and 150 had lower odds for roadway object crashes, either smoother or rougher pavement increased the likelihood of roadway object crashes. Both AADT and IRI were obtained from RID for only a portion of the events. In addition, a number of AADT and IRI levels were not significant in the model.

Effects of Environment-related Factors on Roadway Object Crashes

- **Lighting conditions**. During the modeling of roadway object SCEs versus baseline events, both darkness lighted and darkness not lighted conditions correlated with risk levels of roadway object crash occurrence that were almost 2 times higher than risk levels for daytime. It is noteworthy that the OR for the darkness lighted was higher than for darkness unlighted. This is likely due to the categorization of lighting as a single variable. There is no consideration for the type of lighting installed or the lighting level; this is further confounded by the use of lighting in more complex and incident-prone areas.

- **Roadway surface**. According to the results, slippery roadway surface significantly contributed to the severity outcomes of roadway object crashes based on the ordinal severity modeling, but it did not significantly affect the occurrence probability of roadway object crashes.

- **Adverse weather**. The results showed that the presence of adverse weather contributed to roadway object crashes with higher severity, but this factor did not influence event occurrence.

SVM Analysis Results and Significance

The sensitivity analysis of the three SVM classifiers confirmed that driver behavior/errors, critical speed, struck object type, and reaction time were major factors affecting roadway object event occurrence and severity outcomes. The SVM analyses demonstrated that the effects of these factors were significantly higher than those of other factors (Figure 28–Figure 30).

CHAPTER 5. VEHICLE VISION IMPLICATIONS OF SHRP 2 ROADWAY OBJECT EVENTS

The data analyses in Chapter 4 revealed that roadway- and driver-related variables played critical roles in roadway object crash occurrence and severity outcomes. Emerging advanced safety functions are widely recognized to have the potential to significantly reduce crashes. Although there have been debates regarding whether HAVs can replace human drivers,[60,61] vehicles with advanced functions such as blind spot warning, lane keeping assistance, collision warning, and object detection are expected to be particularly effective in preventing roadway object crashes. This chapter aims to identify and document the implications of SHRP 2 roadway object events on the performance and potential improvements of vehicle vision systems and algorithms.

The research team used mixed methods, including both descriptive analysis and statistical testing, in an attempt to understand how machine vision performance differed from human driver performance and what implications it has for vehicle vision development. The chapter is presented in four sections:

- Characteristics of objects involved in SHRP 2 roadway object events and how they affect machine vision detection distance
- Lighting effects on object detection
- Comparison of machine vision reaction time and driver reaction time
- Driver reactions during roadway object events

CHARACTERISITICS OF OBJECTS INVOLVED AND THEIR IMPLICATIONS FOR MACHINE VISION

Overview of Object Characteristics

Table 26 lists the types of objects involved in the analyzed crash and near-crash events, followed by the detailed listings of animals and roadway objects/debris in Table 27 and Table 28. As demonstrated by the tables, the SHRP 2 data indicates that animals, curbs/medians, pavement edge/edge lines, roadway debris/objects, and stopped cars were the most common objects involved in the studied events.

Among the animals involved in the SHRP 2 events, deer, dog, and squirrel/possum/rabbit were the most common animal types. The heights of the animals ranged from 5 cm (~ 2 in) to 1.2 m (47 in), and their gray contrast values ranged from 0.7 to 133.6. For passenger vehicles, in general, animals with heights lower than 15 cm may be considered traversable (i.e., traversable without losing control of the vehicle). However, the event videos showed that many drivers' instincts were to take sudden evasive maneuvers to avoid the animals, thereby creating risks of secondary crashes.

Table 28 lists the roadway debris/objects involved in the SHRP 2 crashes and near-crashes in more detail. The SHRP 2 event data showed a range of on-road objects with the potential to be involved in crashes. Among the objects, traffic cone/construction barrels, tire/tire pieces, wood pieces/tree branches, and cases/boxes were most common. The heights of such objects ranged from approximately 5 to 100 cm, and their gray contrast values ranged from 1.0 to 199.2.

Table 26. Types of struck objects by frequency.

Struck Object Type	Frequency	Percent
Animal	365	33.73
Curb	251	23.2
Pavement edge/edge line	121	11.18
Roadway debris/objects	95	8.78
Others	79	7.3
Raised median	66	6.1
Stopped car	52	4.81
W-beam barrier	17	1.57
Ditch	12	1.11
Concrete barrier	7	0.65
Tree/shrub	6	0.55
Utility/light pole	6	0.55
Signpost	5	0.46
Total	1,082	100

Table 27. Animals involved in the studied events.

 **Deer** Frequency: 108, 29.59% Height (cm): Mean: 99.4 Min: 40.0 Max: 120.0 Gray value contrast: 47.0	 **Dog** Frequency: 52, 14.25% Height (cm): Mean: 38.5 Min: 20.0 Max: 100.0 Gray value contrast: 26.4	 **Squirrel/possum/rabbit** Frequency: 28, 7.67% Height (cm): Mean: 21.8 Min: 10.0 Max: 30.0 Gray value contrast: 65.6
 **Cat** Frequency: 47, 12.88% Height (cm): Mean: 12.3 Min: 5.0 Max: 25.0 Gray value contrast: 102.8	 **Bird** Frequency: 27, 7.40% Height (cm): Mean: 30.6 Min: 10.0 Max: 100.0 Gray value contrast: 53.0	**Other Small Animal** Frequency: 27, 7.40% Height (cm): Mean: 30.6 Min: 10.0 Max: 100.0

Table 28. Types of roadway debris/objects involved in the analyzed events.

Traffic cone/construction barrel
Frequency: 22, 23.16%
Height (cm):
Mean: 67.4
Min: 2.0
Max: 100.0
Gray value contrast: 199.2

Tire/tire piece
Frequency: 21, 22.11%
Height (cm):
Mean: 17.6
Min: 5.0
Max: 50.0
Gray value contrast: 49.0

Wood piece/tree branch
Frequency: 12, 12.63%
Height (cm):
Mean: 24.6
Min: 5.0
Max: 100.0
Gray value contrast: 2.1

Case/box
Frequency:7, 7.37%
Height (cm):
Mean: 34.3
Min: 5.0
Max: 100.0
Gray value contrast: 12.6

Struck Object Type	Frequency	Percent	Height (cm)		
			Mean	Min	Max
Ladder	3	3.16%	13.3	10.0	20.0
Trash can	3	3.16%	50.0	50.0	50.0
Falling sign	2	2.11%	17.5	5.0	30.0
Rock	2	2.11%	22.5	15.0	30.0
Trash bag	2	2.11%	25.0	20.0	30.0
Bucket	1	1.05%	30.0	30.0	30.0
Concrete block	1	1.05%	25.0	25.0	25.0
Flying paper	1	1.05%	20.0	20.0	20.0
Hubcap	1	1.05%	30.0	30.0	30.0
Jacket	1	1.05%	5.0	5.0	5.0
Mattress	1	1.05%	20.0	20.0	20.0
Blowing plastic bag	1	1.05%	30.0	30.0	30.0
Snow pile	1	1.05%	15.0	15.0	15.0
Other/unknown	13	13.68%	-	-	-

Object Types and Detection Distance

Figure 31 presents the detection distances of some common roadway objects involved in the SHRP 2 events in different environmental and lighting conditions. The detection distances were determined based on the critical image of each event video when the object first became identifiable by the research team. Objects such as traffic cones and construction barrels were generally found to have the longest detection distance among the identified object types, largely due to their bright color and high retroreflectivity. Consequently, these objects may be detected and identified by machine vision mechanisms more reliably and at a greater distance, especially during nighttime and adverse weather conditions. In terms of animals, small animals, such as squirrels, possums, and rabbits, were difficult to detect due to their size. In contrast, large animals, such as deer, were relatively easy to identify from a further distance, but their higher moving speeds may increase the difficulty of crash avoidance.

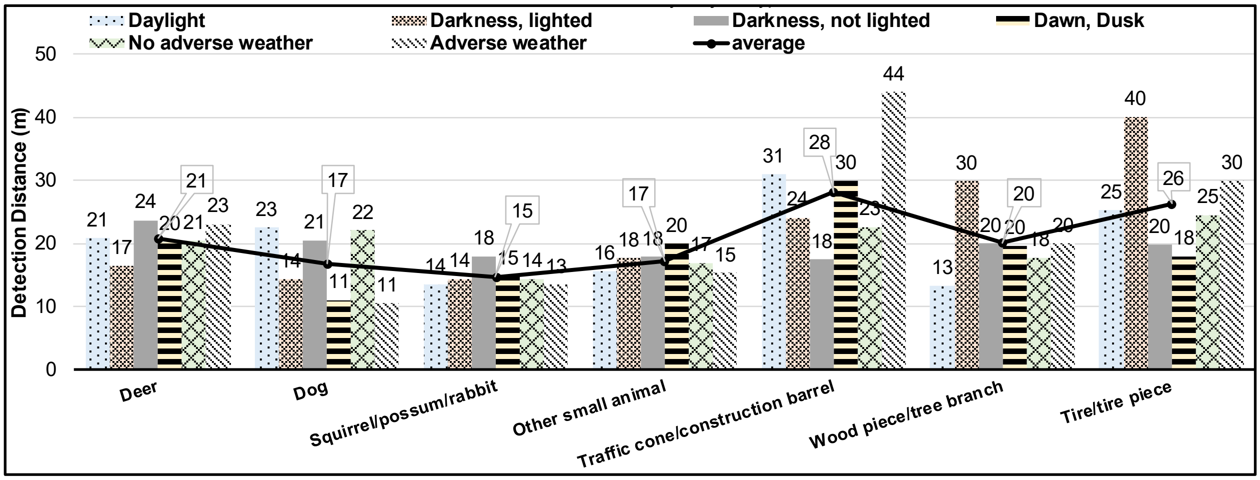


Figure 31. Bar graph. Detection distance by object type and weather/lighting condition.

Figure 32 further illustrates the machine vision reaction time (i.e., time available for driver reaction based on video detection distance) by types of objects and weather/lighting conditions. It appears that, on average, the available reaction time for most events involving animals and roadway debris/objects was below 2 seconds. Available reaction times for tires/tire pieces during dawn/dusk and darkness without lighting were among the lowest, possibly because such objects commonly appear on high-speed roadways (e.g., freeways) and are relatively hard to identify during poor lighting conditions. In addition, the figure suggests that roadway lighting is particularly beneficial for identifying static roadway debris such as wood pieces/tree branches and tires/tire pieces, with a 2.6- and 2.2-second available reaction time, respectively, for the darkness with lighting condition.

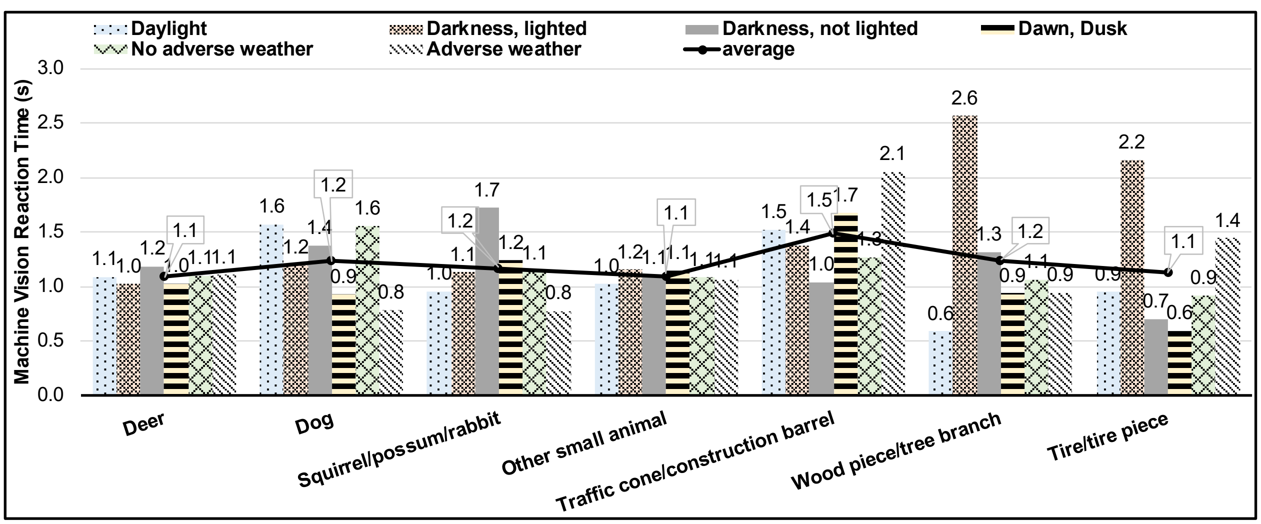


Figure 32. Bar graph. Machine vision reaction time by object type and weather/lighting condition.

Effects of Contrasts on Object Detection

The research team analyzed the correlations of both gray value contrasts and color contrasts with object detection distance and machine vision reaction time. Gray value contrast was calculated as the numerical difference of gray values between the object of conflict and the background. The correlations between detection distance and gray value contrast were analyzed with a variety of linear and non-linear models, among which the linear regression model had the best performance, as shown in Table 29. The small *p*-value (0.0372) in Table 29 suggests a significant association between higher gray value contrast and increased detection distance.

Table 29. Modeling results of detection distance by gray value contrast.

Variable	DF	Parameter Estimate	Standard Error	t-Value	Pr > |t|
Intercept	1	19.52820	2.16094	9.04	<.0001
Gray Value Contrast	1	0.07571	0.03590	2.11	0.0372
Goodness of Fit					
Root MSE: 12.96301, R-Square: 0.0385; Adj R-Sq: 0.0299, Coeff Var: 55.65854					

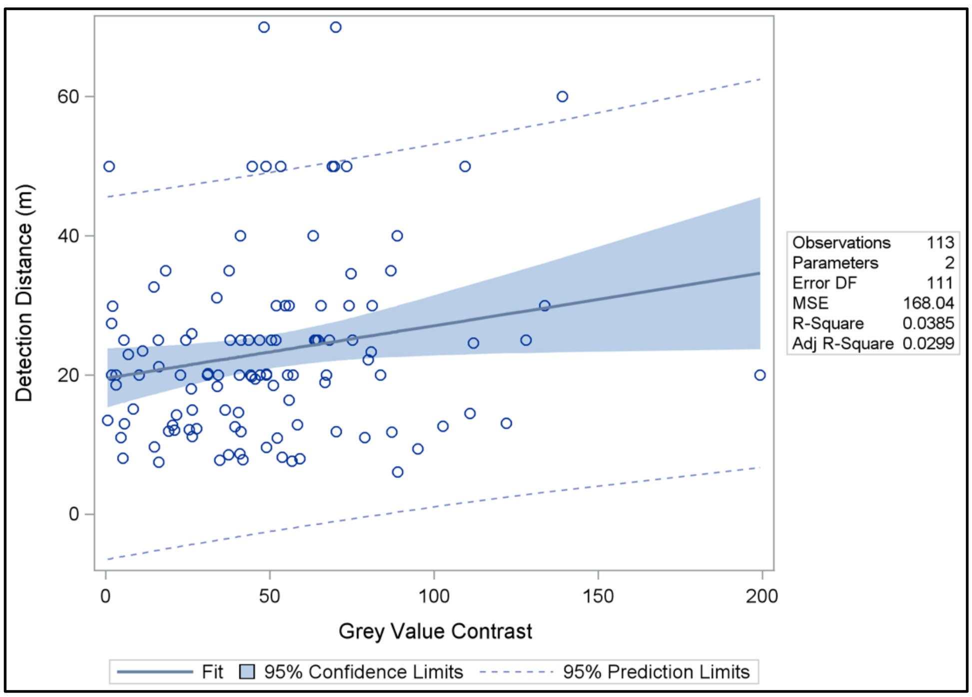


Figure 33. Scatter plot. Linear regression model of detection distance by gray value contrast.

According to this model, an increase of 10 in gray value contrast for the object would result in an increase of approximately 0.8 m (or 30 in) in detection distance by the video cameras used in the SHRP 2 study. However, this did not translate to a statistically significant correlation between the gray value contrast and the machine vision reaction time, as none of the models fitted had a *p*-value lower than 0.1.

In addition to the gray value contrast, the research team also analyzed the correlation between color contrast ratio and object detection distance. In this study, the research team adopted the World Wide Web Consortium's Web Content Accessibility Guidelines[80] color contrast ratio concept, which uses a special calculating process based on RGB values stipulated for webpage visual presentation of text. Note that this concept was developed to target human eye reactions instead of machine vision performance. The research team was not able to identify a color contrast ratio calculation method widely accepted for machine-vision-based object detection, as most previous studies and applications were focused on gray value contrasts only.

For the correlation between color contrast ratio and detection distance, the data suggested that a generalized linear model with a logarithmic function performed best among the different models (Table 30). This model had a *p*-value of 0.02, suggesting that the detection distance improved significantly as the color contrast ratio increased.

Table 30. Modeling results of detection distance by color contrast ratio.

Variable	DF	Parameter Estimate	Standard Error	t-Value	Pr > |t|
Intercept	1	19.03783	2.17144	8.77	<.0001
Color Contrast Ratio	1	6.32121	2.67672	2.36	0.0199
Goodness of Fit					
Root MSE: 12.90004, R-Square: 0.0478; Adj R-Sq: 0.0393, Coeff Var: 55.38815					

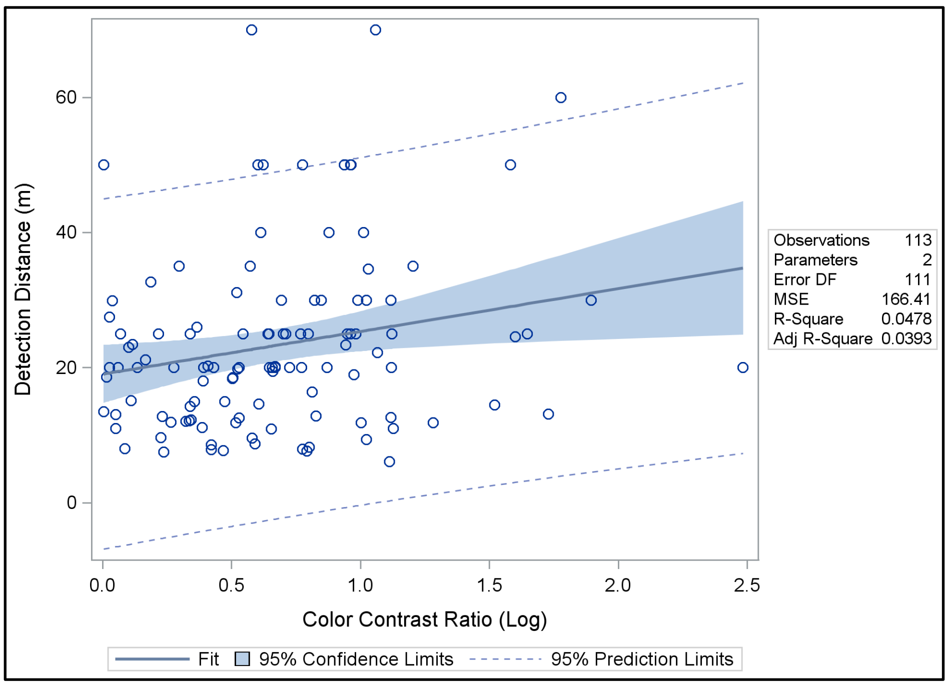


Figure 34. Scatter plot. Generalized linear model regression model of detection distance by logarithm of color contrast ratio.

Similarly, the correlation analysis between color contrast ratio and machine vision reaction time did not yield any significant results.

LIGHTING EFFECTS ON OBJECT DETECTION

Table 31 summarizes the frequency of events under different lighting conditions.

Table 31. Frequency of lighting condition.

Lighting Condition	Overall		Animals and Roadway Debris	
	Frequency	Percent	Frequency	Percent
Darkness, lighted	234	21.63%	108	23.48%
Darkness, not lighted	134	12.38%	87	18.91%
Dawn, Dusk	59	5.45%	34	7.39%
Daylight	655	60.54%	231	50.22%
Total	**1,082**	**100.0%**	**460**	**100.0%**

Detection Distance and Lighting Condition for Animal and Roadway Debris

The following box plot (Figure 35) and Table 32 show the Tukey test results of detection distance of animals and roadway debris under different lighting conditions. With a small *p*-value of 0.04, a significant difference was found between detection distances in daylight and in darkness with lighting. The detection distance was on average 3.9 m farther when vehicles were traveling in daylight versus traveling on lighted roadways at nighttime.

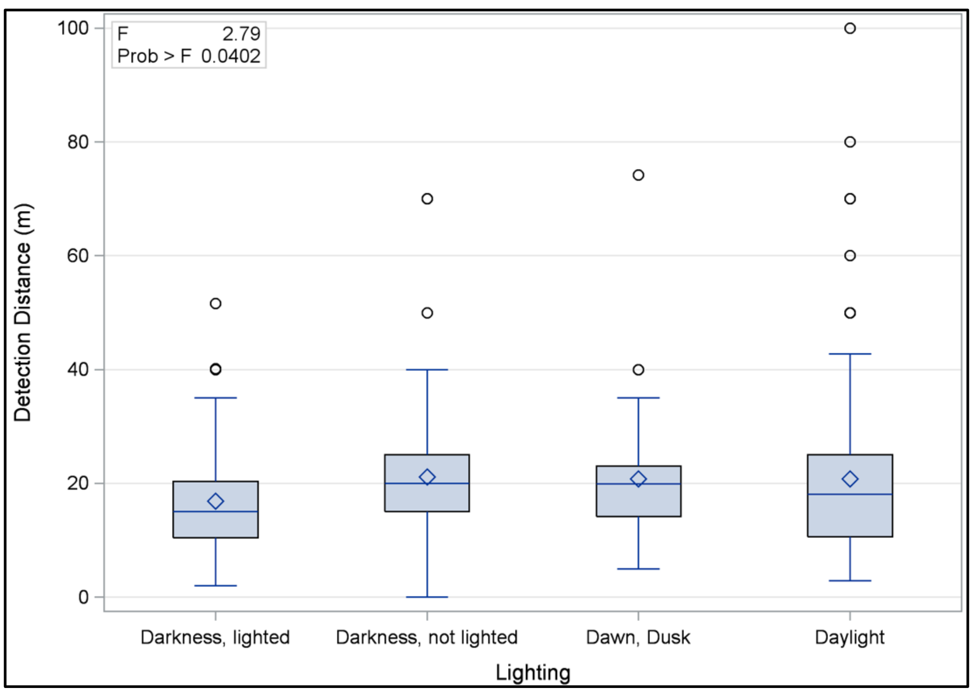


Figure 35. Box plot. Detection distance by lighting condition for animal and roadway debris.

Table 32. Tukey test results of detection distance by lighting condition for animals and roadway debris.

Lighting Comparison	Difference Between Means	Simultaneous 90% Confidence Limits		
Darkness, not lighted - Darkness, lighted	4.207	0.062	8.352	***
Daylight - Darkness, lighted	3.905	0.551	7.259	***

Mean: 19.9245, F Value: 2,79, Pr > F: 0.0402
Comparisons significant at the 0.1 level are indicated by ***.

The research team tested correlations between lighting conditions and machine vision reaction time but did not find statistically significant results.

MACHINE VISION REACTION TIME AND DRIVER REACTION TIME

Accumulated Reaction Time for Animals and Roadway Debris

Figure 36 shows the accumulated reaction time for events involving animals and roadway debris. The machine vision reaction time for animals and roadway debris was shorter than the overall driver reaction time and the driver reaction time for near-crash events, but it was still a bit longer than the driver reaction time for crashes. These findings suggest that machine vision detection distances are generally shorter than human vision detection distances. However, machine vision systems may be well suited to provide a layer of safety redundancy in case human drivers are distracted.

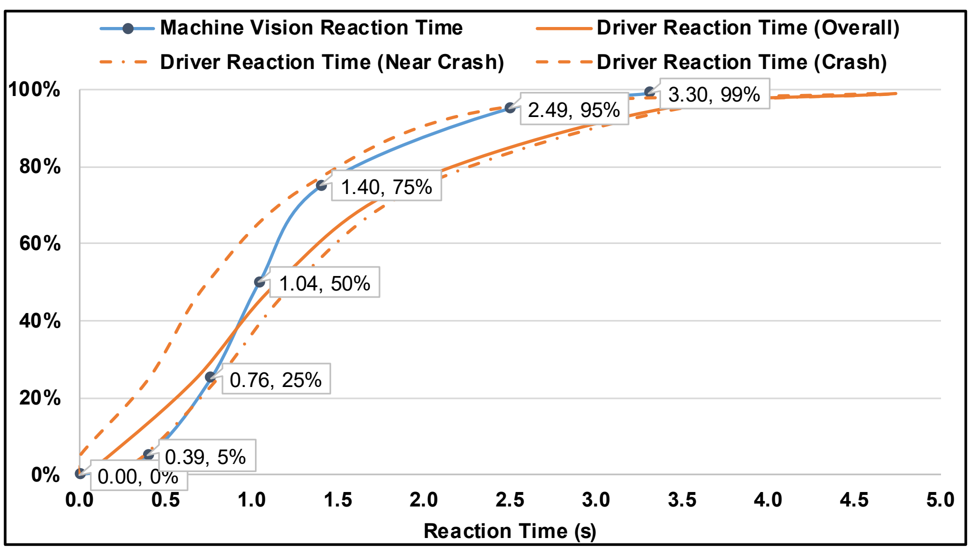


Figure 36. Line graph. Accumulated driver reaction time and machine vision reaction time (for animal and roadway debris).

Influence of Lighting Condition on Reaction Time for Animal and Roadway Debris

Figure 37 compares the average driver reaction time and machine vision reaction time for roadway objects under different lighting and weather conditions. The data showed that the machine vision reaction time was generally shorter than the driver reaction time in all conditions. In addition, the reaction times were roughly equal for daylight and darkness without lighting conditions, slightly lower for dawn and dusk, and the lowest for darkness with lighting.

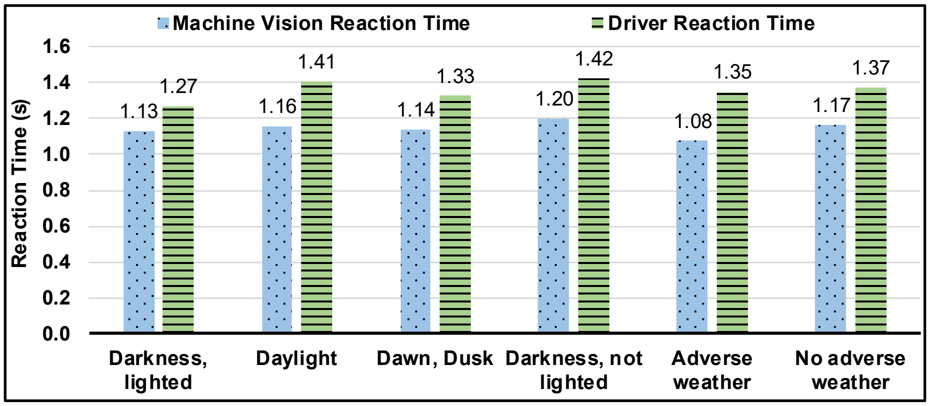


Figure 37. Bar graph. Average reaction time by lighting/weather condition (for animal and roadway debris).

DRIVER REACTIONS DURING ROADWAY OBJECT EVENTS

This section considers driver reactions during roadway object events and how such reactions affected event outcomes. Vehicle vision systems and safety features based on such systems have great potential to assist drivers or take over control for safer decisions when encountering immediate crash risks. Better understanding when and how drivers make unsafe reactions to roadway hazards may provide valuable information for vehicle vision systems and associated algorithm development. Driver reactions for all fixed object events as well as events that involved roadway debris and animals were examined.

Driver Reactions for All Roadway object Events

Table 33 summarizes the frequency of the actual evasive maneuvers taken by drivers and the evasive maneuvers considered "safe" in each crash scenario (see Table 33. Frequency of driver evasive maneuvers.

Evasive Maneuver Type	Driver Evasive Maneuver		Safe Evasive Maneuver	
	Frequency	Percent	Frequency	Percent
Accelerate	2	0.18%	1	0.09%
Accelerate and steer left	3	0.28%	0	0.00%
Accelerate and steer right	2	0.18%	2	0.18%
Brake	307	28.37%	289	26.71%
Brake and steer left	206	19.04%	228	21.07%
Brake and steer right	193	17.84%	235	21.72%
No evasive maneuver executed/required	239	22.09%	21	1.94%
Other actions	5	0.46%	0	0.00%
Release brake	4	0.37%	0	0.00%
Steer left	93	8.60%	239	22.09%
Steer right	28	2.59%	59	5.45%
Total	1082	100%	1074	99.26%
Note: there are eight events that could not be avoided at the time that the object appeared in videos.				

Table 34 for some examples of crash scenarios).

Table 33. Frequency of driver evasive maneuvers.

Evasive Maneuver Type	Driver Evasive Maneuver		Safe Evasive Maneuver	
	Frequency	Percent	Frequency	Percent
Accelerate	2	0.18%	1	0.09%
Accelerate and steer left	3	0.28%	0	0.00%
Accelerate and steer right	2	0.18%	2	0.18%
Brake	307	28.37%	289	26.71%
Brake and steer left	206	19.04%	228	21.07%
Brake and steer right	193	17.84%	235	21.72%
No evasive maneuver executed/required	239	22.09%	21	1.94%
Other actions	5	0.46%	0	0.00%
Release brake	4	0.37%	0	0.00%
Steer left	93	8.60%	239	22.09%
Steer right	28	2.59%	59	5.45%
Total	1082	100%	1074	99.26%
Note: there are eight events that could not be avoided at the time that the object appeared in videos.				

Table 34. Examples of scenarios where the driver made an unsafe evasive maneuver.

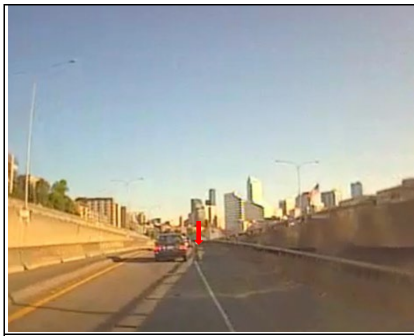
		
In this example, the subject vehicle steered right to avoid colliding with the leading braking vehicle, hitting the end of a raised curb on the right side. In this scenario, braking following the leading vehicle is considered the safer maneuver.	In this example, the leading vehicle decelerated while running over a piece of blown tire. Instead of slowing down and running over the tire piece, the subject vehicle steered left without deceleration to avoid the blown tire, nearly colliding with the guardrail.	The subject vehicle was traveling on a freeway during nighttime. The driver steered left intuitively to avoid a shredded tire piece, nearly colliding with a car on the left. In this scenario, due to vehicles around the subject vehicle at the scene and the high speed, running over the tire piece without abruptly steering or braking is considered the least risky maneuver.

Figure 38 shows the percentage of events for which drivers' evasive maneuvers were considered safe compared to unsafe maneuvers. As shown in the figure, drivers made safe evasive maneuvers for 56% of all roadway object events. Among the different maneuver types, drivers were more likely to make a safe maneuver in scenarios requiring drivers to brake (e.g., brake, brake and steer left, and brake and steer right), suggesting that braking is most drivers' intuitive reaction. On the other hand, during events that required acceleration or no braking, most drivers made unsafe maneuvers. When considering event outcomes (Figure 39), drivers made safe evasive maneuvers in 73% of near-crashes but only 44% of crash events. Note that for Level 1 crashes, drivers only made safe evasive maneuvers in 18% of the events. Level 4 crashes are low-risk tire strikes, and it was possible that many drivers made no evasive maneuvers during such events. When looking at struck object types (Figure 40), events involving animals and roadway debris had the highest percentage of drivers making safe maneuvers, while events involving medians and curbs had the lowest percentage.

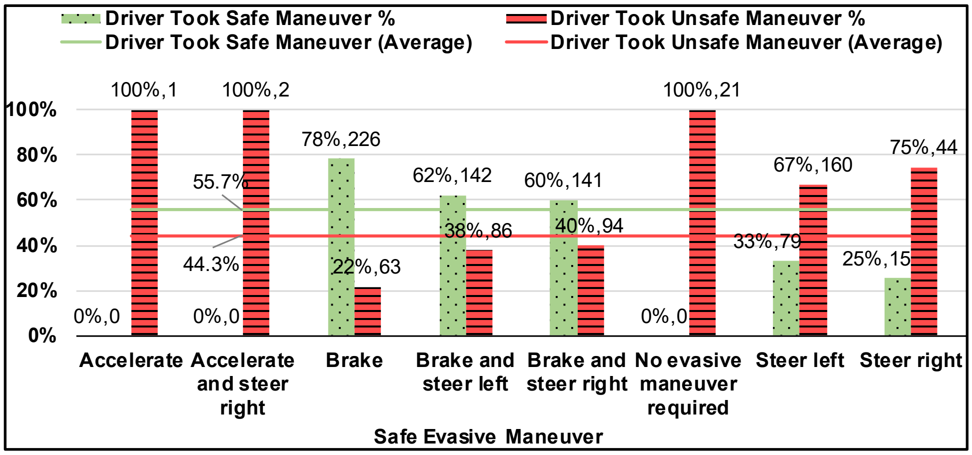


Figure 38. Bar graph. Percentage of events in which drivers made safe evasive maneuvers by safe evasive maneuver type.

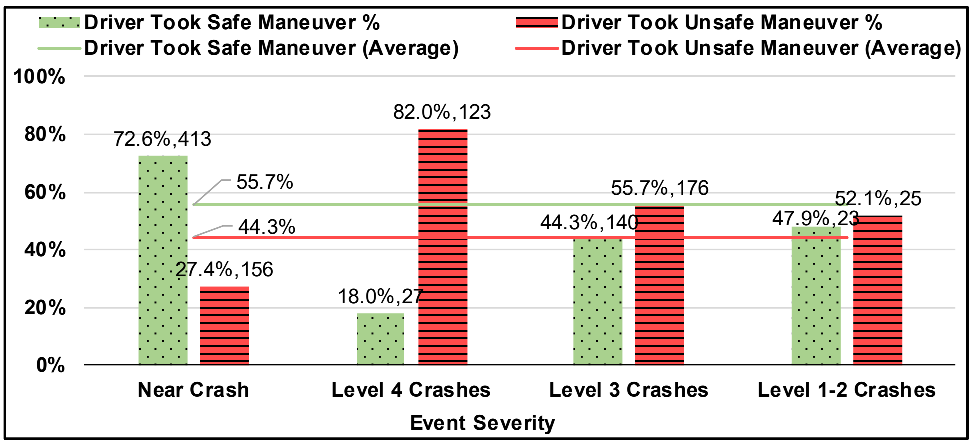


Figure 39. Bar graph. Percentage of events in which drivers made safe evasive maneuvers by event severity.

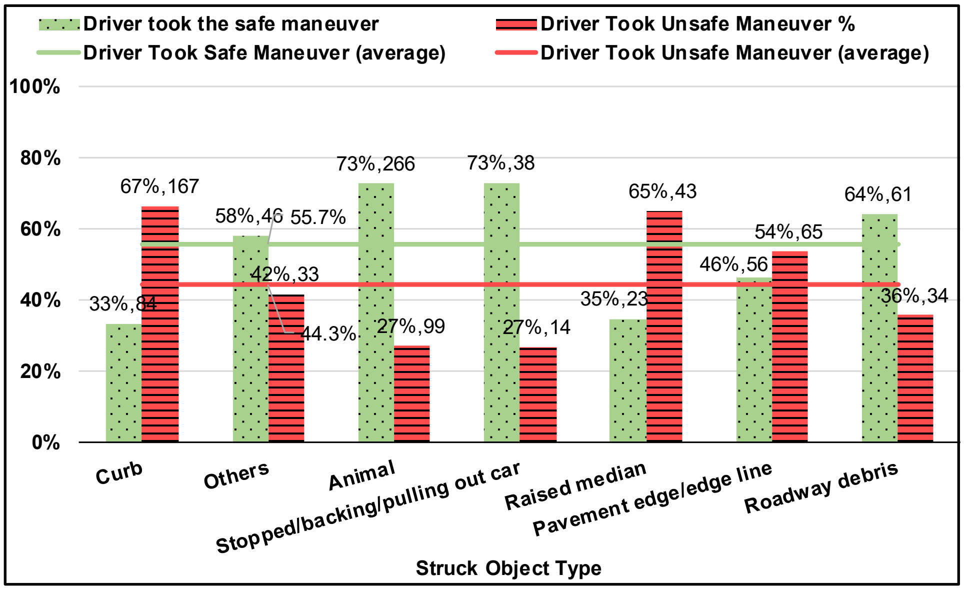


Figure 40. Bar graph. Percentage of events in which drivers made safe evasive maneuvers by struck object type.

Driver Reactions for Events Involving Animals and Roadway Debris

Figure 41 shows the percentage of events in which drivers made a safe evasive maneuver by safe evasive maneuver type. When compared to Figure 38, results show that drivers were more likely to make a safe evasive maneuver when conflicting with animals and roadway debris, representing an overall percentage of 71.9% and 55.7%, respectively. Among all the maneuver types, drivers were more likely to make safe evasive maneuvers at crash scenarios requiring drivers to brake. In contrast, drivers were less likely to make the correct maneuver in scenarios requiring steering left or accelerating.

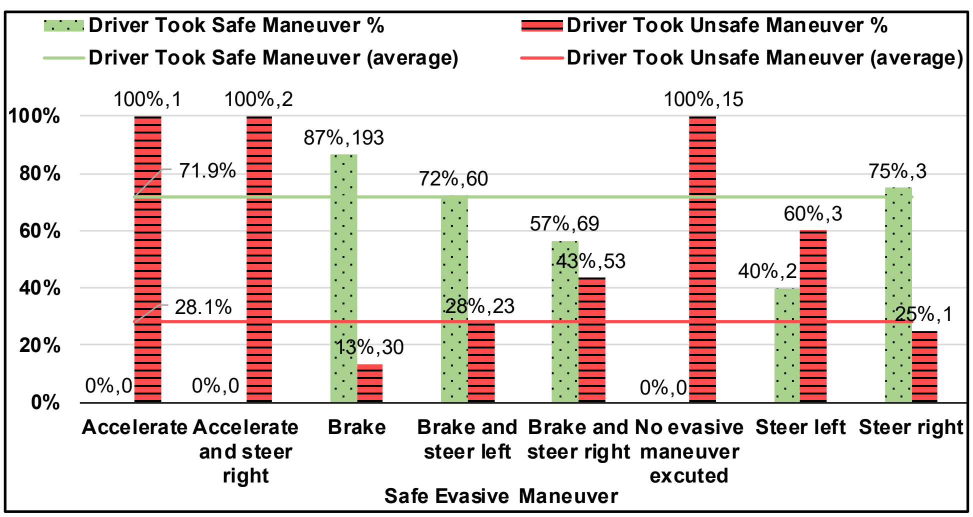


Figure 41. Bar graph. Percentage of events in which drivers made safe evasive maneuvers by safe evasive maneuver type (for animal and roadway debris).

Figure 42 shows the percentage of events in which drivers made safe maneuvers by event severity. Drivers made safe maneuvers in 78% of near-crash scenarios and in 49% of Level 1 crashes. Levels 1–2 and 4 crashes are not shown in the figure due to limited sample sizes.

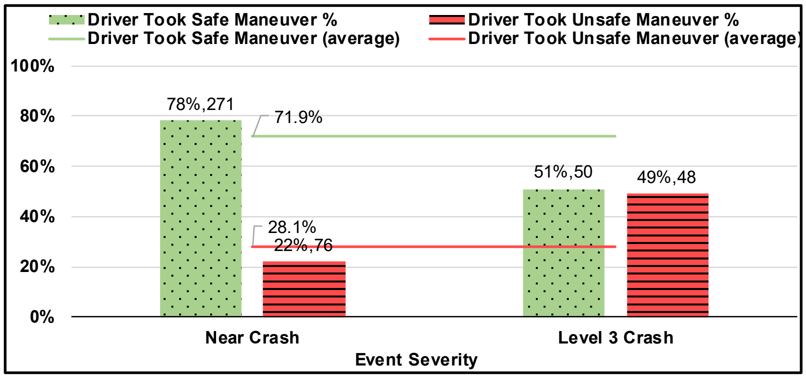


Figure 42. Bar graph. Percentage of events in which drivers made safe evasive maneuvers by event severity (for animal and roadway debris).

SUMMARY OF FINDINGS

In this chapter, the research team conducted a mixture of statistical and descriptive analyses of the objects involved in the analyzed SHRP 2 events and the correlations between their characteristics and machine vision performance during different environmental and lighting conditions. The research team also compared the driver reactions during the analyzed events, and safe reactions were determined by the research team. The analyses provide valuable insights into the potential challenges machine vision systems must conquer to perform reliably. Note that the machine vision performance measures in this study were based on the cameras used in the SHRP 2 NDS, which was conducted in the early 2010s, and as such they may be considered relatively outdated by modern machine vision system standards.

The analysis results showed that:

- The average detection distance based on the analyzed SHRP 2 events was approximately 20 m. The average time available for machine vision reaction was 1.5 seconds for all events but 1.1 seconds for animals and roadway objects/debris.
- Machine vision reaction time was found to be shorter than human reaction time in many cases, indicating that camera-based machine vision detection range was generally shorter than for humans.
- Machine vision detection distance was found to be significantly correlated with gray value and color contrasts. The results showed that an increase of 10 in gray value contrast for the object would result in an increase of approximately 0.8 m (or 30 in) in detection distance. The color contrast model had a lower *p*-value than the gray value contrast model, suggesting that the inclusion of color in object detection algorithms could improve object detection performance.

- The level of reaction time provided by machine vision was generally equal to driver reaction time but was less than driver reaction time for events involving animals, debris, and other objects on roadways. There also appeared to be a positive correlation between lighting conditions and longer machine vision reaction time, although the Tukey test did not show statistical significance.

- Drivers were able to make safe maneuvers in most cases, especially in cases involving on-road objects, such as animals and roadway debris. Among the evasive maneuver types, drivers were more likely to make safe maneuvers in the scenarios requiring braking. In cases where reactions such as no evasive maneuvers, steering left, and acceleration were considered safe, drivers frequently made the wrong maneuver. Typical examples of such cases are events involving small animals or traversable roadway debris. Drivers frequently braked and/or steered right when encountering such objects, increasing secondary crash risks.

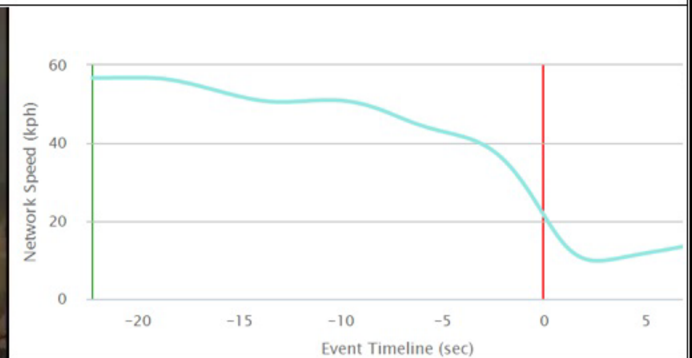
CHAPTER 6. ROADWAY OBJECT CRASH CASE STUDIES

The logistic regression and SVM analyses revealed a variety of factors with potential impacts on the risks of roadway object crash occurrences and higher severity outcomes. In this section, the research team further provides a number of case studies representing typical roadway object scenarios based on a careful study of the SHRP 2 event videos. These case studies provide additional information on the sequence of events and exact causes for the SHRP 2 roadway object crashes and near-crashes.

For each case study, the research team included a number of key data elements to convey the causes, contributing factors, environmental conditions, and insights into potential countermeasures.

ROADWAY OBJECT CRASH CASE STUDIES

Example 1: a crash involving a vehicle running over raised median when turning left



Event ID	29750780	**Lighting**	Darkness with light
Weather	No adverse weather	**Location Type**	Signalized Intersection
Maneuver	Turning left	**Crash severity**	Level 3
Roadway	Divided multilane	**Travel Speed**	Medium (~30 mph)
Reaction time	No reaction	**Detection Challenge**	None
Description	Subject driver approached a 4-leg signalized intersection in the dedicated left-turn lane. There was a raised median dividing the road. As the traffic light was green, the driver steered left to complete a turning maneuver. The driver apparently misjudged the turn and ran over the median. The intersection was lighted, but lighting seemed to be not sufficient to allow clear identification of the appropriate turning path.		
Observation	The subject driver failed to identify the proper turning path and made the left turn too early. Pavement markings clearly delineating the left turn path could potentially prevent such events.		

Figure 43 through

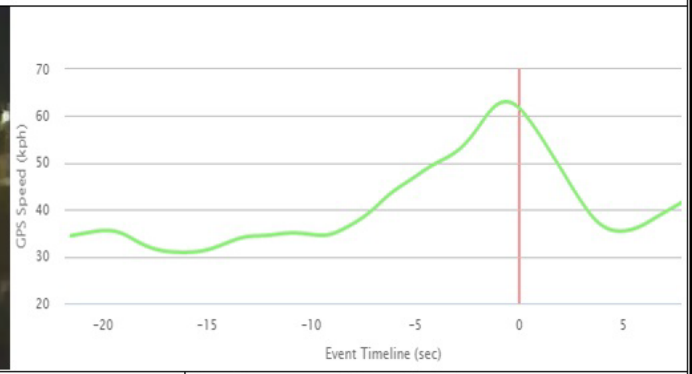
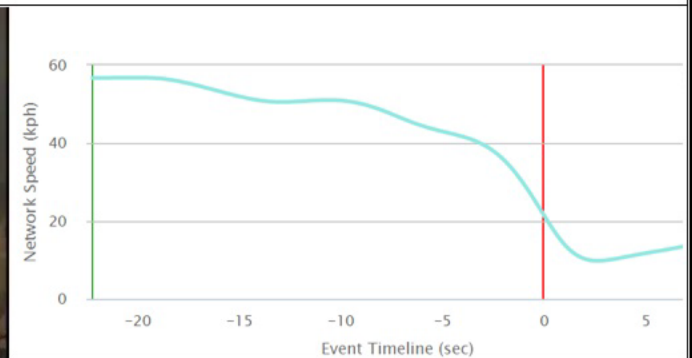
Example 3: Vehicle running over raised gore at a lighted entrance ramp junction			
			
Event ID	129878680	**Lighting**	Darkness with light
Weather	Light rain	**Location Type**	Entrance ramp
Maneuver	Going straight	**Crash severity**	Level 3
Roadway	C-D road	**Travel Speed**	Medium (~35 mph)
Reaction time	0.989 s	**Detection Challenge**	None. Median separated by lane markings.
Description	Subject vehicle was attempting to enter a freeway via a lighted two-lane C-D road. At the end of the C-D road, the lanes separated into two single-lane ramps with the right ramp curving to the right with a relatively sharp radius. The driver was supposed to merge to the left lane to enter the freeway main lanes. However, the driver appeared to be confused by the ramp configuration and went straight onto the raised gore area. Both ramp lanes were illuminated, but neither luminaire provided sufficient light to the gore point. The driver was a senior driver and appeared to be looking intently throughout the entire event. Notice that the roadway was wet, which might have contributed to the event as well.		
Observation	At this location, the right lane on the C-D road diverts from the entrance ramp via a relatively sharp curve towards the right. The trajectory of the subject vehicle appeared to be aiming straight to the correct entrance ramp. The senior driver appeared to have thought both lanes were part of the entrance ramp. While lighting was provided upstream of the ramp junction on both lanes, the gore was not sufficiently illuminated.		

Figure 45 show three sample roadway object crashes that involved medians or channelization devices. These events were attributable to a combination of weather conditions, roadway design issues, lighting conditions, and/or driver errors.

Example 1: a crash involving a vehicle running over raised median when turning left



Event ID	29750780	**Lighting**	Darkness with light
Weather	No adverse weather	**Location Type**	Signalized Intersection
Maneuver	Turning left	**Crash severity**	Level 3
Roadway	Divided multilane	**Travel Speed**	Medium (~30 mph)
Reaction time	No reaction	**Detection Challenge**	None
Description	Subject driver approached a 4-leg signalized intersection in the dedicated left-turn lane. There was a raised median dividing the road. As the traffic light was green, the driver steered left to complete a turning maneuver. The driver apparently misjudged the turn and ran over the median. The intersection was lighted, but lighting seemed to be not sufficient to allow clear identification of the appropriate turning path.		
Observation	The subject driver failed to identify the proper turning path and made the left turn too early. Pavement markings clearly delineating the left turn path could potentially prevent such events.		

Figure 43. Annotated event screenshot. Case Study 1: Crash with raised median at intersection approach.

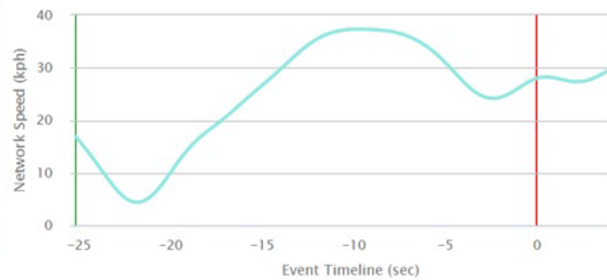
Example 2: Vehicle struck a raised median after making a left turn			
			
Event ID	60632630	**Lighting**	Daylight
Weather	Light rain	**Location Type**	Signalized Intersection
Maneuver	Turning left	**Crash severity**	Level 3
Roadway	Divided multilane	**Travel Speed**	Medium (~20 mph)
Reaction time	0.469 s	**Vision Challenge**	None during daytime. Median not delineated.
Description	The subject vehicle proceeded into a 4-leg signalized intersection from the dedicated left-turn lane. The subject vehicle driver turned too early and sharply and struck the raised median on the exit approach.		
Observation	Based on the vehicle turning trajectory, the driver did not identify the raised median, possibly because the A pillar on the driver side blocked their view. Pavement markings clearly delineating the left turn path can potentially prevent such events.		

Figure 44. Annotated event screenshot. Case Study 2: Crash with raised median at intersection exit.

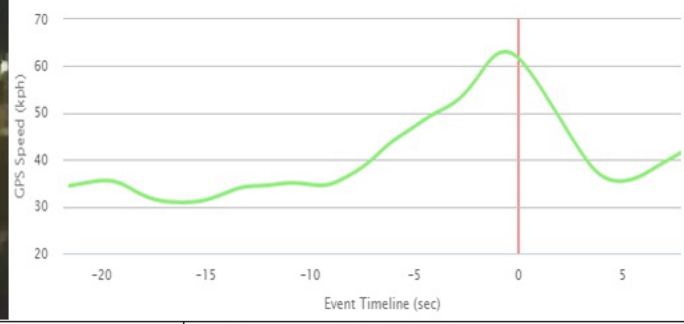
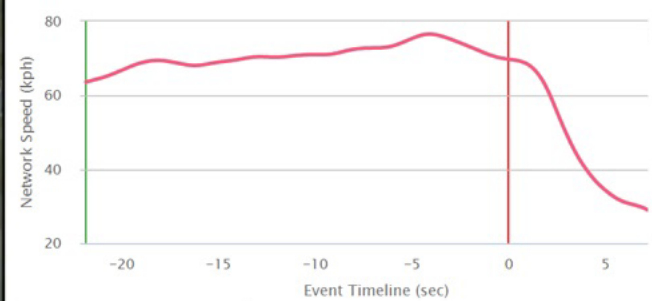
Example 3: Vehicle running over raised gore at a lighted entrance ramp junction			
			
Event ID	129878680	**Lighting**	Darkness with light
Weather	Light rain	**Location Type**	Entrance ramp
Maneuver	Going straight	**Crash severity**	Level 3
Roadway	C-D road	**Travel Speed**	Medium (~35 mph)
Reaction time	0.989 s	**Detection Challenge**	None. Median separated by lane markings.
Description	Subject vehicle was attempting to enter a freeway via a lighted two-lane C-D road. At the end of the C-D road, the lanes separated into two single-lane ramps with the right ramp curving to the right with a relatively sharp radius. The driver was supposed to merge to the left lane to enter the freeway main lanes. However, the driver appeared to be confused by the ramp configuration and went straight onto the raised gore area. Both ramp lanes were illuminated, but neither luminaire provided sufficient light to the gore point. The driver was a senior driver and appeared to be looking intently throughout the entire event. Notice that the roadway was wet, which might have contributed to the event as well.		
Observation	At this location, the right lane on the C-D road diverts from the entrance ramp via a relatively sharp curve towards the right. The trajectory of the subject vehicle appeared to be aiming straight to the correct entrance ramp. The senior driver appeared to have thought both lanes were part of the entrance ramp. While lighting was provided upstream of the ramp junction on both lanes, the gore was not sufficiently illuminated.		

Figure 45. Annotated event screenshot. Case Study 3: Crash with raised median at entrance ramp separation.

Figures

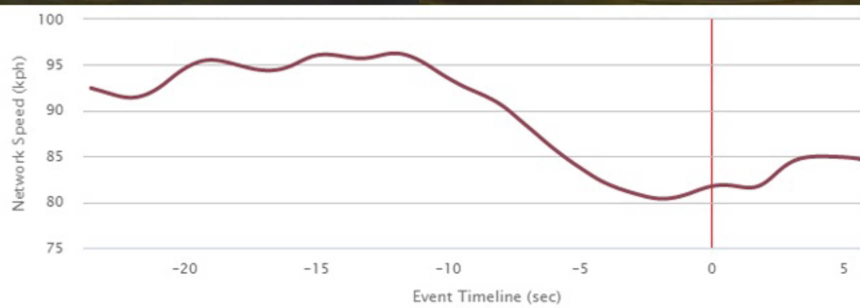
Example 4: Vehicle hitting curb on the right while driver texted



Event ID	24517596	**Lighting**	Daylight
Weather	No adverse weather	**Location Type**	Bridge
Maneuver	Going straight	**Crash severity**	Level 2
Roadway	Undivided local road	**Travel Speed**	Medium (~45 mph)
Reaction time	0.07 s	**Detection Challenge**	None
Description	Subject vehicle drifted unintentionally to the right, striking the curb on the bridge at a speed of about 44 mph. Subject vehicle driver was clearly distracted while texting on a phone. After the impact, subject driver steered left immediately to get vehicle back on the road, traveled shortly and pulled the car over to check vehicle damage.		
Observation	Driver was distracted.		

Figure 46 through

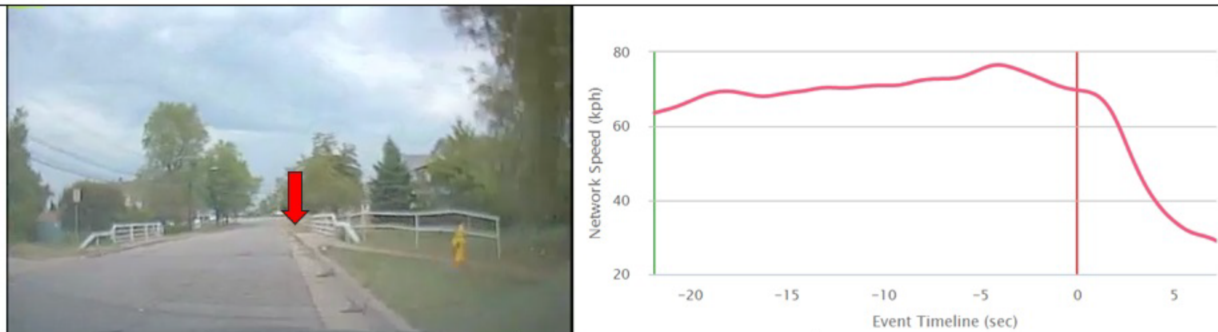
Example 6: Vehicle hitting curbs and left wall in an over-lighted underground ramp



Event ID	134947926	**Lighting**	Darkness with light
Weather	Light rain	**Location Type**	Freeway underground ramp
Maneuver	Turning left	**Crash Severity**	Level 3
Roadway	One-lane tunnel	**Travel Speed**	High (~60 mph)
Reaction time	1.073 s	**Detection Challenge**	Sharp lighting contract entering over-lighted tunnel.
Description	Shortly after entering a lighted tunnel at a freeway interchange, the subject vehicle failed to correctly follow the curved roadway and crashed into the left curb and then the tunnel wall on the left, causing the vehicle to lose control and then crash onto the curve on the right side. The tunnel had a much higher lighting level compared to the roadway prior to it and the driver appeared to be adapting to the sudden brightness while negotiating the curve. The driver was not distracted and there were no other vehicles in the close vicinity.		
Observation	In this scenario, the lighting level in the tunnel appeared to be too bright. The subject driver could not adapt to the condition quickly enough while negotiating the curved roadway. A transition should be provided at the tunnel entrance to improve the lighting condition.		

Figure 48 are three representative cases of roadway object crashes involving curbs. These cases illustrate how driver errors, lighting, and roadway design/traffic control issues contributed to roadway object crashes.

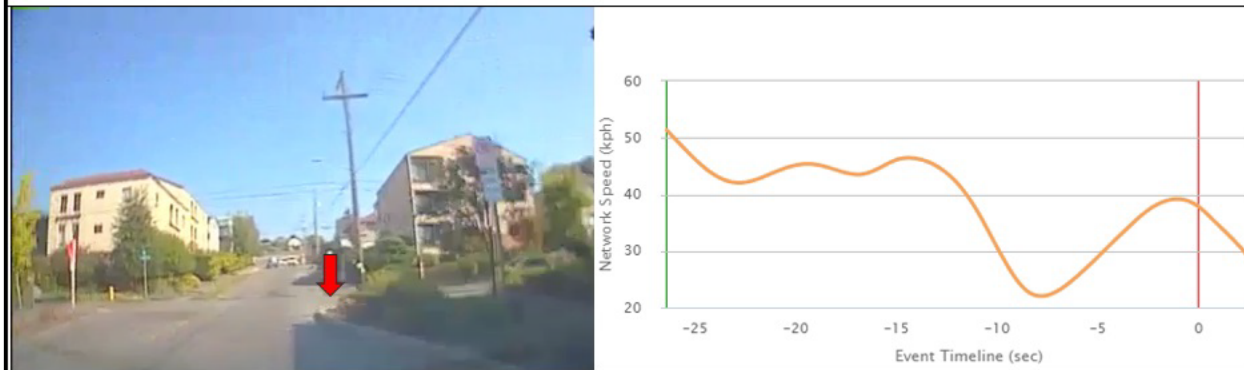
Example 4: Vehicle hitting curb on the right while driver texted



Event ID	24517596	**Lighting**	Daylight
Weather	No adverse weather	**Location Type**	Bridge
Maneuver	Going straight	**Crash severity**	Level 2
Roadway	Undivided local road	**Travel Speed**	Medium (~45 mph)
Reaction time	0.07 s	**Detection Challenge**	None
Description	Subject vehicle drifted unintentionally to the right, striking the curb on the bridge at a speed of about 44 mph. Subject vehicle driver was clearly distracted while texting on a phone. After the impact, subject driver steered left immediately to get vehicle back on the road, traveled shortly and pulled the car over to check vehicle damage.		
Observation	Driver was distracted.		

Figure 46. Annotated event screenshot. Case Study 4: Distracted driver crashing with curb on the right.

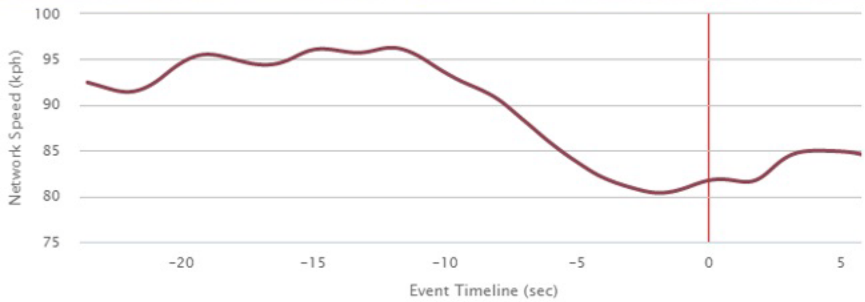
Example 5: Vehicle running over curb on the right



Event ID	23771192	**Lighting**	Daylight
Weather	No adverse weather	**Location Type**	Straight local road
Maneuver	Going straight	**Crash severity**	Level 3
Roadway	Undivided two-lane road	**Travel Speed**	Low (~25 mph)
Reaction time	No reaction	**Detection Challenge**	Undelineated curb in shadow during bright daylight.
Description	The subject driver traveled on an undivided local two-lane road. The road reduces width ahead, but the curb was not conspicuous due to the shadow of the adjacent building. The subject driver was on the phone intermittently.		
Observation	In this crash, there was an unexpected curb narrowing the street, which was covered by shadows during bright daylight, making it difficult for drivers to identify. Delineating the curb using retroreflective materials would increase its visibility.		

Figure 47. Annotated event screenshot. Case Study 5: Driver crashing with undelineated curb on the right.

Example 6: Vehicle hitting curbs and left wall in an over-lighted underground ramp



Event ID	134947926	**Lighting**	Darkness with light
Weather	Light rain	**Location Type**	Freeway underground ramp
Maneuver	Turning left	**Crash Severity**	Level 3
Roadway	One-lane tunnel	**Travel Speed**	High (~60 mph)
Reaction time	1.073 s	**Detection Challenge**	Sharp lighting contract entering over-lighted tunnel.
Description	Shortly after entering a lighted tunnel at a freeway interchange, the subject vehicle failed to correctly follow the curved roadway and crashed into the left curb and then the tunnel wall on the left, causing the vehicle to lose control and then crash onto the curve on the right side. The tunnel had a much higher lighting level compared to the roadway prior to it and the driver appeared to be adapting to the sudden brightness while negotiating the curve. The driver was not distracted and there were no other vehicles in the close vicinity.		
Observation	In this scenario, the lighting level in the tunnel appeared to be too bright. The subject driver could not adapt to the condition quickly enough while negotiating the curved roadway. A transition should be provided at the tunnel entrance to improve the lighting condition.		

Figure 48. Annotated event screenshot. Case Study 6: Vehicle crashing with curb and wall in lighted tunnel.

Example 7: Vehicle striking a utility pole at a Y intersection			
			
Event ID	142053520	**Lighting**	Darkness with light
Weather	Light rain	**Location Type**	Signalized Y-intersection
Maneuver	Going straight	**Crash severity**	Level 2
Roadway	Undivided two-lane	**Travel Speed**	Medium (~35 mph)
Reaction time	2.622 s	**Detection Challenge**	Off-road light pole in darkness
Description	Subject driver approached a signalized intersection with a yellow light. There was streetlight, but it appeared to be very dim, maybe partially due to the rainy weather. The subject driver followed the pavement marking and crossed the intersection at a relatively high speed. The driver soon realized that the intersection curved sharply to the left when they approached the middle of the intersection. The driver braked hard to avoid colliding with the utility pole ahead but was unsuccessful.		
Observation	In this scenario, the intersection alignment was unconventional, and there were no sign warning drivers about this irregular alignment ahead. The dim streetlight, rainy weather, wet road surface and darkness all added to the driver's difficulty in distinguishing the road alignment earlier. Potential countermeasures include clearly delineating the travel lanes, providing advanced warning of the unconventional intersection layout, and redesigning lighting to illuminate the entire intersection.		

Figure 49 is an example of a roadway object crash involving a light pole at a Y intersection. The unconventional layout of the intersection combined with low-visibility conditions during nighttime contributed to this event.

Example 7: Vehicle striking a utility pole at a Y intersection			
 			
Event ID	142053520	**Lighting**	Darkness with light
Weather	Light rain	**Location Type**	Signalized Y-intersection
Maneuver	Going straight	**Crash severity**	Level 2
Roadway	Undivided two-lane	**Travel Speed**	Medium (~35 mph)
Reaction time	2.622 s	**Detection Challenge**	Off-road light pole in darkness
Description	Subject driver approached a signalized intersection with a yellow light. There was streetlight, but it appeared to be very dim, maybe partially due to the rainy weather. The subject driver followed the pavement marking and crossed the intersection at a relatively high speed. The driver soon realized that the intersection curved sharply to the left when they approached the middle of the intersection. The driver braked hard to avoid colliding with the utility pole ahead but was unsuccessful.		
Observation	In this scenario, the intersection alignment was unconventional, and there were no sign warning drivers about this irregular alignment ahead. The dim streetlight, rainy weather, wet road surface and darkness all added to the driver's difficulty in distinguishing the road alignment earlier. Potential countermeasures include clearly delineating the travel lanes, providing advanced warning of the unconventional intersection layout, and redesigning lighting to illuminate the entire intersection.		

Figure 49. Annotated event screenshot. Case Study 7: Vehicle crashing into utility pole at Y intersection.

Figures

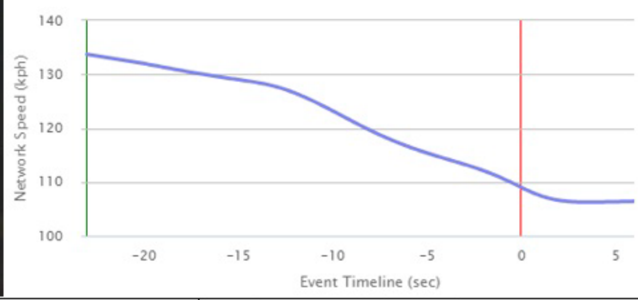
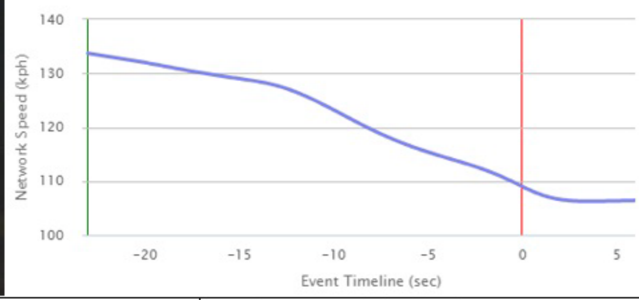
Example 8: Vehicle struck guardrail when the driver was impaired by drowsiness.			
			
Event ID	9886402	**Lighting**	Darkness with light
Weather	No adverse weather	**Location Type**	Freeway
Maneuver	Going straight	**Crash severity**	Level 1
Roadway	Divided freeway	**Travel Speed**	High (~80 mph)
Reaction time	0.186 s	**Detection Challenge**	Off-road light pole in darkness
Description	Subject vehicle is about to exit a freeway while traveling in a deceleration lane. Subject driver appeared to be tired and drowsy. While decelerating, the vehicle drifted towards the right, hitting the guardrail on the right side.		
Observation	The subject driver was impaired by drowsiness.		

Figure 50 to

Example 10: Vehicle striking guardrail terminal at the entrance of a split ramp.			
			
Event ID	61033664	**Lighting**	Daylight
Weather	No adverse weather	**Location Type**	Ramp gore
Maneuver	Going straight	**Crash severity**	Level 2
Roadway	Freeway exit ramp	**Travel Speed**	High (~60 mph)
Reaction time	0.467 s	**Detection Challenge**	None
Description	The subject driver decelerated in the exit lane of an interstate highway. The exit ramp split into two exits to different destinations identified by overhead signs. The subject driver drove on towards the left exit initially. When the signs came into view, the subject driver tried to switch to the right lane. However, due to a conflicting vehicle occupying the lane, the subject vehicle could not successfully make the lane change and ran into the guardrail terminal dividing the two ramps while braking.		
Observation	The driver was not familiar with the roadway condition. The guardrail was provided to shield the signpost, resulting in additional risks for roadway object crashes. In this scenario, the sign may be better located on the side, eliminating the need for the guardrail.		

Figure 52 show examples of roadway object crashes involving guardrails. For the first two cases, driver errors appeared to be the major contributing factor. The third case illustrates potential roadway and traffic design issues that might have contributed to the event.

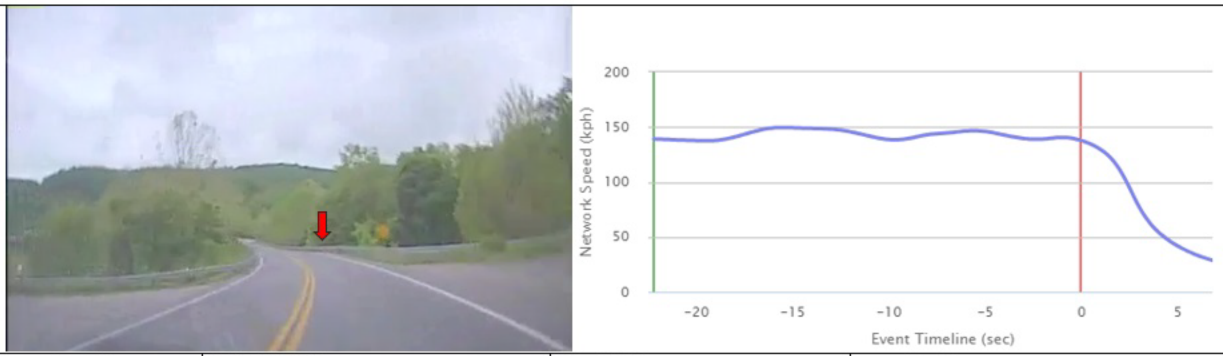
Example 8: Vehicle struck guardrail when the driver was impaired by drowsiness.



Event ID	9886402	**Lighting**	Darkness with light
Weather	No adverse weather	**Location Type**	Freeway
Maneuver	Going straight	**Crash severity**	Level 1
Roadway	Divided freeway	**Travel Speed**	High (~80 mph)
Reaction time	0.186 s	**Detection Challenge**	Off-road light pole in darkness
Description	Subject vehicle is about to exit a freeway while traveling in a deceleration lane. Subject driver appeared to be tired and drowsy. While decelerating, the vehicle drifted towards the right, hitting the guardrail on the right side.		
Observation	The subject driver was impaired by drowsiness.		

Figure 50. Annotated event screenshot. Case Study 8: Drowsy driver colliding with guardrail on freeway.

Example 9: Vehicle striking guardrail at high speed after running off road.



Event ID	29730844	**Lighting**	Daylight
Weather	No adverse weather	**Location Type**	Curvy local road
Maneuver	Going straight with unintentional drifting	**Crash severity**	Level 1
Roadway	Undivided two-lane road	**Travel Speed**	High (~85 mph)
Reaction time	1.815 s	**Detection Challenge**	None
Description	Subject driver was driving down a curvy, undivided, 2-lane road with no leading traffic. The speed limit was 40 mph, but the subject driver drove at 80 mph. After disregarding two yellow caution signs that warned drivers of the curvy road, the driver lost control on a curve, striking the guardrail on the right, spinning 720 degrees counterclockwise into the opposing lane.		
Observation	Speeding was the major cause of the event.		

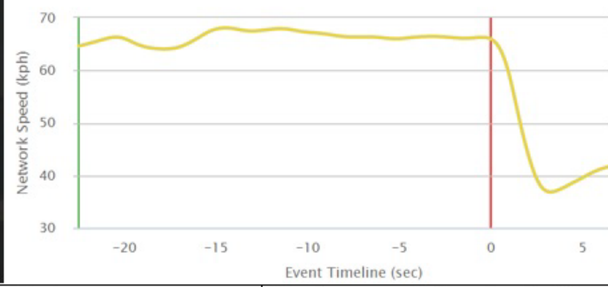
Figure 51. Annotated event screenshot. Case Study 9: Speeding driver colliding with guardrail.

Example 10: Vehicle striking guardrail terminal at the entrance of a split ramp.

Event ID	61033664	**Lighting**	Daylight
Weather	No adverse weather	**Location Type**	Ramp gore
Maneuver	Going straight	**Crash severity**	Level 2
Roadway	Freeway exit ramp	**Travel Speed**	High (~60 mph)
Reaction time	0.467 s	**Detection Challenge**	None
Description	The subject driver decelerated in the exit lane of an interstate highway. The exit ramp split into two exits to different destinations identified by overhead signs. The subject driver drove on towards the left exit initially. When the signs came into view, the subject driver tried to switch to the right lane. However, due to a conflicting vehicle occupying the lane, the subject vehicle could not successfully make the lane change and ran into the guardrail terminal dividing the two ramps while braking.		
Observation	The driver was not familiar with the roadway condition. The guardrail was provided to shield the signpost, resulting in additional risks for roadway object crashes. In this scenario, the sign may be better located on the side, eliminating the need for the guardrail.		

Figure 52. Annotated event screenshot. Case Study 10: Vehicle colliding with guardrail terminal at ramp split.

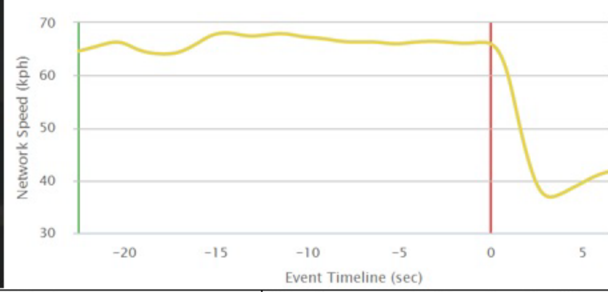
Example 11: Vehicle striking a deer during nighttime.



Event ID	30880858	**Lighting**	Darkness without light
Weather	Mist/Light Rain	**Location Type**	Straight local road
Maneuver	Going straight	**Crash severity**	Level 2
Roadway	Undivided two-lane road	**Travel Speed**	Medium (~40 mph)
Reaction time	1.026 s	**Detection Challenge**	Nighttime moving animal in rainy condition
Description	The subject driver traveled on a straight two-lane road at nighttime, hitting a deer that was walking across the road from the left. There was light rain, and the road surface was wet. The road was unlighted and no leading traffic was present. Prior to the event, the driver was interacting with a passenger as well.		
Observation	It was dark and the vehicle had its headlamps on low beam. After identifying the deer, the driver did not have enough time to react to avoid the crash.		

Figure 53 is an example of a nighttime roadway object crash involving a crossing deer. The roadway was not lighted, and it was difficult to identify the deer well in advance.

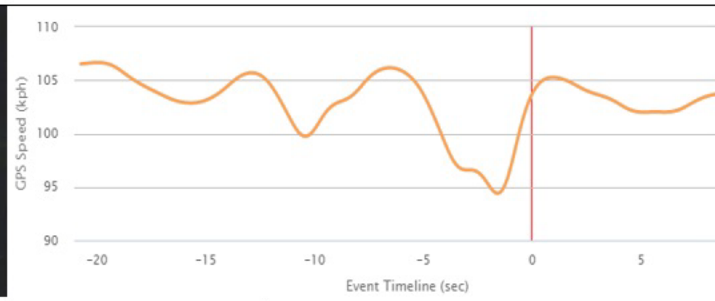
Example 11: Vehicle striking a deer during nighttime.



Event ID	30880858	**Lighting**	Darkness without light
Weather	Mist/Light Rain	**Location Type**	Straight local road
Maneuver	Going straight	**Crash severity**	Level 2
Roadway	Undivided two-lane road	**Travel Speed**	Medium (~40 mph)
Reaction time	1.026 s	**Detection Challenge**	Nighttime moving animal in rainy condition
Description	The subject driver traveled on a straight two-lane road at nighttime, hitting a deer that was walking across the road from the left. There was light rain, and the road surface was wet. The road was unlighted and no leading traffic was present. Prior to the event, the driver was interacting with a passenger as well.		
Observation	It was dark and the vehicle had its headlamps on low beam. After identifying the deer, the driver did not have enough time to react to avoid the crash.		

Figure 53. Annotated event screenshot. Case Study 11: Vehicle colliding with deer during nighttime.

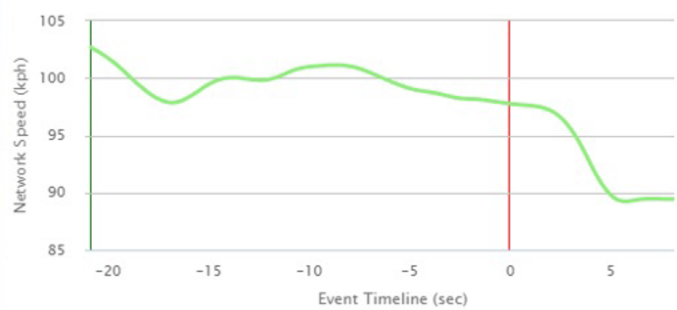
Example 12: A vehicle running over a large piece of debris on a lighted freeway.



Event ID	61216654	**Lighting**	Darkness without light
Weather	None	**Location Type**	Freeway interchange
Maneuver	Going straight	**Crash severity**	Level 3
Roadway	Multilane freeway	**Travel Speed**	High (~65 mph)
Reaction time	0.206 s	**Detection Challenge**	Nighttime, low contrast, high speed
Description	Subject vehicle was traveling straight on freeway main lanes at an interchange area. The driver failed to identify a large piece of debris (which appeared to be a blown truck tire) in the travel lane and ran over it, almost losing control of the vehicle. The lane changing activities associated with the exiting traffic seemingly caused some speed fluctuation of the subject vehicle prior to the event.		
Observation	The roadway was not lighted. The subject vehicle was traveling at a relatively high speed and did not identify the debris on the road. The driver was a senior citizen and was not distracted throughout the entire event.		

Figure 54 and

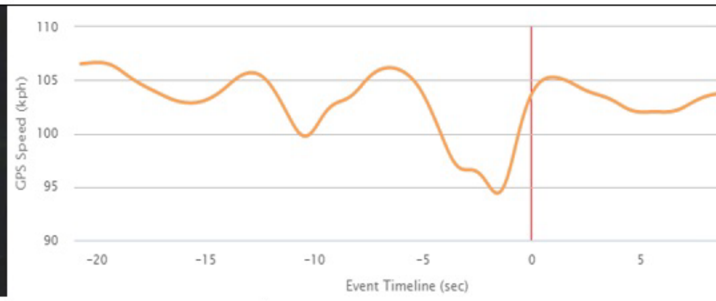
Example 13: A vehicle running over a piece of wood when following another vehicle.



Event ID	60631677	**Lighting**	Daylight
Weather	None	**Location Type**	Freeway
Maneuver	Going straight	**Crash severity**	Level 3
Roadway	Multilane freeway	**Travel Speed**	High (~65 mph)
Reaction time	No reaction	**Detection Challenge**	None
Description	The subject driver was following a lead vehicle on a freeway. There was a large piece of wood in the travel lane of the subject vehicle that was not visible due to the lead vehicle. Both the lead vehicle and the subject vehicle ran over the wood, causing a noticeable vibration to the subject vehicle.		
Observation	The subject driver followed the leading vehicle closely, and there was not enough time for the subject driver to take action to avoid hitting the wood after it became visible to the driver.		

Figure 55 illustrate two cases of crashes involving on-road debris. As the cases illustrate, large pieces of debris may be difficult to identify, particularly during nighttime and on high-speed roadways. For the first case, the reaction time was 0.206 seconds. In the second case, the driver did not react before the collision.

Example 12: A vehicle running over a large piece of debris on a lighted freeway.



Event ID	61216654	**Lighting**	Darkness without light
Weather	None	**Location Type**	Freeway interchange
Maneuver	Going straight	**Crash severity**	Level 3
Roadway	Multilane freeway	**Travel Speed**	High (~65 mph)
Reaction time	0.206 s	**Detection Challenge**	Nighttime, low contrast, high speed
Description	Subject vehicle was traveling straight on freeway main lanes at an interchange area. The driver failed to identify a large piece of debris (which appeared to be a blown truck tire) in the travel lane and ran over it, almost losing control of the vehicle. The lane changing activities associated with the exiting traffic seemingly caused some speed fluctuation of the subject vehicle prior to the event.		
Observation	The roadway was not lighted. The subject vehicle was traveling at a relatively high speed and did not identify the debris on the road. The driver was a senior citizen and was not distracted throughout the entire event.		

Figure 54. Annotated event screenshot. Case Study 12: Vehicle colliding with roadway debris on freeway.

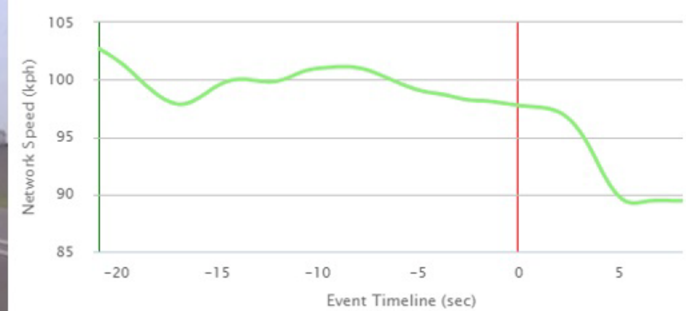
Example 13: A vehicle running over a piece of wood when following another vehicle.			
		 	
Event ID	60631677	**Lighting**	Daylight
Weather	None	**Location Type**	Freeway
Maneuver	Going straight	**Crash severity**	Level 3
Roadway	Multilane freeway	**Travel Speed**	High (~65 mph)
Reaction time	No reaction	**Detection Challenge**	None
Description	The subject driver was following a lead vehicle on a freeway. There was a large piece of wood in the travel lane of the subject vehicle that was not visible due to the lead vehicle. Both the lead vehicle and the subject vehicle ran over the wood, causing a noticeable vibration to the subject vehicle.		
Observation	The subject driver followed the leading vehicle closely, and there was not enough time for the subject driver to take action to avoid hitting the wood after it became visible to the driver.		

Figure 55. Annotated event screenshot. Case Study 13: Vehicle colliding with wood piece when following another vehicle.

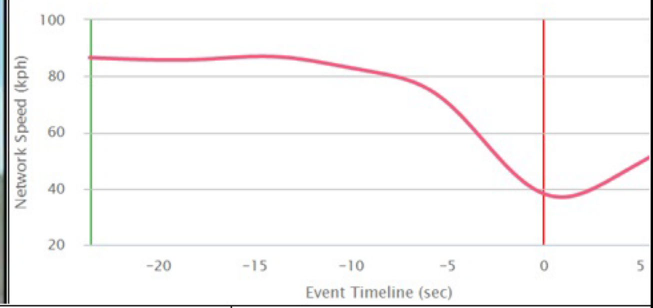
Example 14: Vehicle ran off the road when making left turn			
		 	
Event ID	61216945	**Lighting**	Daylight
Weather	No adverse weather	**Location Type**	Unsignalized Y-intersection
Maneuver	Turning left	**Crash severity**	Level 3
Roadway	Undivided two-lane road	**Travel Speed**	High (~50 mph)
Reaction time	No reaction	**Detection Challenge**	None. Median separated by lane markings.
Description	The subject driver negotiated a curve to the left and approached a Y-intersection. The destination road was the left leg. However, the driver did not turn left sufficiently following the appropriate path, running off the road between the two legs and narrowly missing a sign.		
Observation	In this scenario, the intersection layout was uncommon. The centerline markings were not present at the intersection, leaving a wide paved area unmarked. The median area separating the two approaches was lower than the pavement, leaving the roadway edge of the left leg un-delineated. Potential countermeasures would be better delineating the turning paths using centerline/edge line markings.		

Figure 56 is a case when a vehicle ran off the roadway at an intersection on a curved roadway segment.

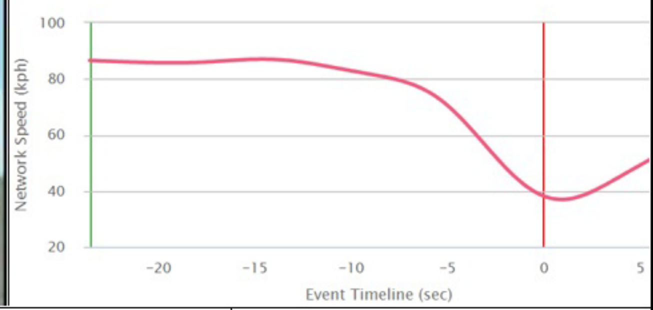
Example 14: Vehicle ran off the road when making left turn			
			
Event ID	61216945	**Lighting**	Daylight
Weather	No adverse weather	**Location Type**	Unsignalized Y-intersection
Maneuver	Turning left	**Crash severity**	Level 3
Roadway	Undivided two-lane road	**Travel Speed**	High (~50 mph)
Reaction time	No reaction	**Detection Challenge**	None. Median separated by lane markings.
Description	The subject driver negotiated a curve to the left and approached a Y-intersection. The destination road was the left leg. However, the driver did not turn left sufficiently following the appropriate path, running off the road between the two legs and narrowly missing a sign.		
Observation	In this scenario, the intersection layout was uncommon. The centerline markings were not present at the intersection, leaving a wide paved area unmarked. The median area separating the two approaches was lower than the pavement, leaving the roadway edge of the left leg un-delineated. Potential countermeasures would be better delineating the turning paths using centerline/edge line markings.		

Figure 56. Annotated event screenshot. Case Study 14: Vehicle running off road at an unconventional Y intersection.

SUMMARY AND DISCUSSION

The scenarios illustrated by the case studies and other SHRP 2 fixed object event videos pointed at a number of contributing factors and potential countermeasures:

- Driver errors. Driver errors were a major contributing factor for many SHRP 2 roadway object crashes. Among the various driver errors, the following were examples of common contributors:
    - Improper turns were present for many roadway object crashes at intersections or curved roadways involving raised medians and curbs. About one fourth (26.05%) of events relevant to fixed objects involved improper turning. Previous logistic regression analysis results indicated that drivers were about 10 times more likely to be involved in roadway object SCEs during or after making a turn than when traveling straight.
    - Driver distraction contributed to many roadway object crashes. Distractions involving cell phones and other passengers were found in a number of SHRP 2 roadway object crashes.

  - Driver impairments, such as drowsy driving, were found in a number of events. Drowsy driving tends to occur particularly at nighttime. Combined with limited visibility, drowsy driving can frequently lead to roadway object crashes.

  - Speeding or driving too fast for conditions can contribute to roadway departures and therefore lead to roadway object crashes involving roadside objects. Speeding is particularly risky for roadway object crashes at intersections or on curved roadway sections.

- Roadway and traffic control issues. The case studies and video data analysis showed that many roadway object crashes involved raised medians at intersections. In many cases, these medians were not marked with retroreflective materials or not well lighted at nighttime. Many roadway object crashes occurring during left turns may be prevented by properly delineating the left-turn paths at intersections (particularly intersections with unconventional layouts) with pavement markings. In some cases, the use of traffic control devices introduced additional objects that created risks for roadway object crashes.

- Lighting and visibility. Many roadway object crashes occurred during nighttime. Some cases were on roadways without lighting; others occurred on roadways with lighting. However, a study of fixed object cases on roadways with lighting also unveiled that improperly designed lighting could not prevent and, in some cases, contributed to roadway object crashes.

- Adverse weather conditions. Adverse weather conditions can be a contributing factor for roadway object crashes, since such weather conditions frequently result in limited visibility and slippery roadways.

CHAPTER 7. CONCLUSION AND RECOMMENDATIONS

Roadway object crashes can cause severe injuries and are a major concern for the traveling public, state transportation agencies, and the automotive industry. Many previous studies addressed roadway object crashes in the context of roadway departures. Such studies tended to focus on how to prevent roadway departures, sometimes without fully addressing why and how roadway object crashes occur. Traditional safety studies also rely on police-reported crash data, leaving out potentially important information available through unreported roadway object crashes. The analyses based on traditional crash data are also limited to post-crash information, which means that they are missing some critical information about real-time driver behavior and reaction before and during the crashes.

Recognizing the significance of the safety concern and the potential of the SHPR 2 NDS data, this research was funded to identify cost-effective strategies to reduce roadway object crashes nationwide. The project used SHRP 2 NDS data as an alternate data source to police-reported crash data to better understand such crashes.

The specific objectives of this project were to:

- Analyze roadway object crashes and near-crashes in the SHRP 2 NDS database to understand exactly how and why roadway object crashes took place.
- Recommend strategies relevant to traffic control and roadway design to prevent roadway object crashes.
- Understand and document implications of roadway object crashes relevant to the emerging vehicle vision technologies used by HAVs.

The research team addressed these objectives using a three-pronged approach. The research team first conducted a detailed engineering study of the roadway object events to identify and quantify the effects of a large number of relevant variables. A machine-vision-oriented study was then performed to document the implications of the roadway object events on machine vision performance. To develop a complete understanding of roadway object crashes, the research team also conducted detailed case study analyses of representative roadway object events. The case studies provided further qualitative results on how and why roadway object crashes occur and what potential actions can be effectively taken to prevent such events.

CONCLUSIONS

The results of the analysis showed the following:

- Significant increases in the crash ORs for driver behaviors, with pre-incident maneuvers such as turning or drifting on the roadway and secondary task performance having the most significant impact.

- Fewer significant factors in terms of the roadway and traffic, with only the free flow traffic (LOS A1) and local roads being significant; however, fewer of these categories of crashes were analyzed, and further research should be considered.

- In terms of the roadway environment, the time of day (nighttime versus daytime) had a significant impact on the occurrence of fixed object crashes, while roadway surface conditions and adverse weather increased the severity but not the occurrence of crashes.

- Drivers were able to make safe maneuvers in most cases, especially in cases involving on-road objects, such as animals and roadway debris. Among the evasive maneuver types, drivers were more likely to make safe maneuvers when the scenarios required braking, with drivers reacting incorrectly more frequently when steering left or when acceleration was considered safe.

- The sensitivity analysis of the three SVM classifiers confirmed that driver behavior/errors, critical speed, struck object type, and reaction time were major factors affecting roadway object event occurrence and severity outcomes. The SVM models also indicated the potential for machine-learning algorithms to identify the risks of roadway object crashes.

- In terms of machine vision systems, this analysis found that, for fixed object crashes, the machine vision reaction time was shorter than human reaction time in many cases, indicating that camera-based machine vision detection range was generally shorter than the range for humans. The exception was incidents with animals, where the machine vision reaction time was equal to or longer than that of the human. Note that this analysis is limited to the technology used for the SHRP 2 study, and advances in camera technology could influence this result.

RECOMMENDATIONS

The results based on the statistical, machine learning, and case study analyses pointed at the following recommendations to mitigate roadway object crash risks effectively:

- **Roadway improvements.** Several findings suggested the importance of improving roadways to mitigate roadway object crash risks. Transportation agencies should avoid sharp curves whenever possible to reduce roadway departures. At curved segments where pavement edges may not be clearly visible due to certain terrains or roadside ditches, retroreflective edge lines should be added to aid driver navigation. At rural intersections, particularly those intersections with unconventional layouts, retroreflective edge and lane markings should also be considered to delineate the travel paths clearly (see Case Study 14).

- **Traffic control and signage**. The findings of this study demonstrated the risks caused by insufficient and/or improperly designed traffic control devices and the potential methods for mitigating roadway object crashes. Based on the results, the researchers recommend the following:

- **Delineate raised channelizing islands at intersections**. Raised medians and curbs (including curbs for roadway debris) were frequently involved in the analyzed roadway object crashes, particularly during low-visibility conditions. Running over such devices may cause vehicles to temporarily lose control and therefore increase the risks of secondary, and sometimes severe, crashes. Channelization devices and curbs with a high risk of being struck should be sufficiently delineated with retroreflective materials to improve their visibility and conspicuity, particularly during low light conditions.

- **Remove or relocate unnecessary on-road or roadside structures.** The location of signs and other traffic control devices should be designed appropriately, possibly considering factors such as alignments (e.g., direction and characteristics of horizontal and vertical curves) and sight distance. Case Study 10, for example, illustrates a scenario where the sign pole may be better installed on the side instead of the middle of the diverging ramp lanes. In addition to adding the signpost in the middle of the two ramp lanes, the sign placement also required the addition of the longitudinal guardrail that further added to the risks of roadway object crashes.

- **Provide pavement markings at intersections to guide turning vehicles**. Several roadway object crashes involved improper turning movements, as illustrated by the case studies. To reduce improper turning, a potentially effective measure is to add adequate pavement markings to clearly guide left-turning vehicles through the intersection. This measure is particularly beneficial for intersections with unconventional layouts, large paved areas, and on major roadways with unlevel pavement surface due to terrain or drainage requirements.

- **Provide sufficient, proper lighting when necessary**. Lighting, when used properly, is an effective method to improve visibility during nighttime. The case studies demonstrated a few issues related to the use and design of lighting. The current lighting design standards use minimum lighting levels as the primary design control. Designers frequently design lighting to meet this requirement without carefully examining the risk locations of a design area. At intersections, for example, the focus areas of the luminaires should be on high-risk features, such as the raised medians and/or curbs at intersections, and gore points where lanes divide. In addition, at intersections with unconventional layouts, lighting should be provided to clearly illuminate the paths and layout of the intersection approaches.

  The case studies also illustrated the needs for better designed lighting transitions at locations where lighting levels change. Sufficient lighting transitions allow drivers to visually adapt to the new lighting level and therefore avoid temporary blindness during driving.

- **Consider driver education and enforcement whenever possible**. Several findings showed the significant role of driver errors in the occurrence and severity outcome of roadway object crashes. Engineering solutions alone can hardly eliminate crashes. It is important to conduct driver education and enforcement activities when possible to raise safety awareness and ensure safety driver behavior. Risky driver behaviors identified during this study included, for example, speeding, distraction, and drowsiness/fatigue.

- **Implement advanced vehicle technologies and features**. Vehicle vision-based advanced technologies offer the possibility of identifying and avoiding risks for roadway object crashes. However, for such technologies to maximally function in all scenarios, vehicle vision technologies and associated algorithms should be further improved. Some case studies showed several potential challenges for certain vehicle vision technologies, particularly those based on cameras, such as low-visibility conditions and low contrasts between fixed objects and the surroundings. In addition, algorithms should be able to identify the safest actions for vehicles and/or drivers to avoid crash risks. Such actions should not only consider avoiding objects, but also weigh risks and different severity outcomes if such actions are taken. Case Studies 12 and 13, for example, illustrated scenarios where simple braking or lane changes could result in more severe secondary crashes.

LIMITATIONS

As previously noted, the SHRP 2 crashes and near-crashes included a large proportion of minor crashes. To completely understand roadway object crash risks, it is necessary to further compare the findings of this study with those of similar studies that used police-reported crashes.

This study was based on the technology used in the SHRP 2 NDS; as such, camera technologies and the machine vision analysis results are based on the technology used at that time. Significant technological advances in camera performance and algorithm development could change the final outcomes regarding detection distance and performance.

APPENDIX A. DETAILED TABLE OF EXPLANATORY VARIABLES

Variable	Definition	Values	SVM Vector	Baseline	SCE
Age Group	The age group of the participant driver.	16-19	1	192	343
		20-29	2	360	511
		30-39	3	75	112
		40-49	4	71	112
		50-59	5	86	122
		60-69	6	91	151
		70-79	7	97	146
		80-89	8	62	121
		90-99	9	2	3
Annual Miles	The estimated average annual mileage over the past 5 years of the participant driver.	0-5000 miles	1	100	192
		5000-10000	2	211	330
		10000-15000	3	344	503
		15000-20000	4	159	262
		20000-25000	5	94	131
		25000-30000	6	52	86
		30000 and more	7	64	96
Number of Violation	The number of violations that the participant driver has in last 3 years.	0	0	658	1058
		1	1	241	344
		2 or 2+	2	141	218
State	The state where the event happened.	FL	[1 0 0 0 0 0]	259	444
		IN	[0 1 0 0 0 0]	89	156
		NC	[0 0 1 0 0 0]	169	259
		NY	[0 0 0 1 0 0]	251	366
		PA	[0 0 0 0 1 0]	63	95
		WA	[0 0 0 0 0 1]	219	319
Years of Driving	The number of years since the driver got his/her license.	≤ 1	1	68	142
		(1,2]	2	86	130
		(2,5]	3	182	275
		(5,10]	4	185	258
		(10,20]	5	105	138
		≥ 20	6	415	687
Pre-incident Maneuver	The last driving maneuver that the driver engaged in prior to or at the time of event.	Changing lanes	[1 0 0 0 0 0]	30	63
		Going straight	[0 1 0 0 0 0]	863	607
		Going straight but with unintentional drifting	[0 0 1 0 0 0]	8	71
		Making a turn	[0 0 0 1 0 0]	8	621
		Negotiating a curve	[0 0 0 0 1 0]	131	240
		Other	[0 0 0 0 0 1]	10	37
Maneuver Judgement	Judgement of the safety and legality of pre-incident maneuver.	Safe and legal	[1 0 0 0]	993	1118
		Safe but illegal	[0 1 0 0]	5	65
		Unsafe and illegal	[0 0 1 0]	44	239
		Unsafe but legal	[0 0 0 0]	8	217
Driver Behavior	Driver behaviors that occurred within seconds	Apparent unfamiliar with roadway	[1 0 0 0 0 0 0 0 0]	0	36

Variable	Definition	Values	SVM Vector	Baseline	SCE
	prior to the event, or those contribute to the event occurrence.	Avoiding animal, or other vehicle	[0 1 0 0 0 0 0 0 0]	2	21
		Distracted	[0 0 1 0 0 0 0 0 0]	0	313
		Drowsy, sleepy, asleep, fatigued	[0 0 0 1 0 0 0 0 0]	24	30
		Exceeded safe speed, or speed limit	[0 0 0 0 1 0 0 0 0]	43	201
		Failed to signal, improper signal	[0 0 0 0 0 1 0 0 0]	4	34
		Improper turn	[0 0 0 0 0 0 1 0 0]	1	430
		None	[0 0 0 0 0 0 0 0 0]	958	481
		Sign, signal violation	[0 0 0 0 0 0 0 1 0]	2	37
		Other	[0 0 0 0 0 0 0 0 1]	16	56
Driver Impairments	Physical impairments (drowsiness, fatigue) or police-reported impairments (alcohol, drug) that possibly result in the event.	None apparent	0	1024	1562
		With apparent impairments	1	26	77
Passenger Existence	Whether other passengers exist in the vehicle.	No	0	689	1219
		Yes	1	361	420
Secondary Task	Any observable driver engagement in tasks irrelevant to driving prior to or at the time of event.	Adjusting/monitoring vehicle devices	[1 0 0 0 0 0 0 0 0 0]	21	56
		Cell phone usage	[0 1 0 0 0 0 0 0 0 0]	89	167
		Drinking/Eating/Smoking	[0 0 1 0 0 0 0 0 0 0]	24	44
		External distraction (objects, animal, pedestrian, etc.)	[0 0 0 1 0 0 0 0 0 0]	59	141
		Interaction with passenger	[0 0 0 0 1 0 0 0 0 0]	162	209
		Internal distraction (object, pet, etc.)	[0 0 0 0 0 1 0 0 0 0]	33	51
		Other	[0 0 0 0 0 0 1 0 0 0]	27	38
		Personal hygiene	[0 0 0 0 0 0 0 1 0 0]	29	52
		Reaching, moving object in vehicle	[0 0 0 0 0 0 0 0 1 0]	6	106
		Talking/singing, audience unknown	[0 0 0 0 0 0 0 0 0 1]	75	121
		No secondary tasks	[0 0 0 0 0 0 0 0 0 0]	525	654
Hands on Wheel	How many hands the driver had on the steering wheels at the start of the event.	Both hands	[1 0 0]	420	737
		None or at least one hand off	[0 1 0]	26	36
		Only one hand or at least one hand on	[0 0 1]	604	866

Variable	Definition	Values	SVM Vector	Baseline	SCE
Driver Seatbelt Use	The use of the driver's seatbelt at the time of the event.	Lap/shoulder belt not properly worn or not used	0	44	135
		Lap/shoulder belt properly worn	1	1006	1504
Lighting	Lighting condition at the time of event.	Daylight	[1 0 0 0]	790	1072
		Dawn, dusk	[0 1 0 0]	50	81
		Darkness, not lighted	[0 0 1 0]	95	143
		Darkness, lighted	[0 0 0 1]	115	343
Weather	Weather condition at the time of event.	Adverse weather	1	82	209
		No adverse weather	0	968	1430
Road Surface Condition	The type of roadway surface condition that would influence vehicle coefficient of friction at the time of event.	Dry	0	910	1258
		Icy/snowy/wet	1	140	381
Traffic Flow	Roadway design regarding to the presence of median or barrier. If the event occurs in intersection, it indicates the roadway design prior to that intersection.	Divided (median strip or barrier)	[1 0 0 0]	598	398
		No lanes	[0 1 0 0]	0	41
		Not divided	[0 0 1 0]	424	1119
		One-way traffic	[0 0 0 1]	28	81
Traffic Density	The level of service at the time of the event. Based on number of vehicles present in subject's travel direction and the ability of the subject driver to maneuver between lanes and select driving speed.	LOS A1: Free flow, no lead traffic	[1 0 0 0 0]	293	910
		LOS A2: Free flow, leading traffic present	[0 1 0 0 0]	366	366
		LOS B: Flow with some restrictions	[0 0 1 0 0]	305	312
		LOS C: Stable flow, maneuverability and speed are more restricted	[0 0 0 1 0]	56	44
		LOS D/E/F	[0 0 0 0 1]	30	7
Contiguous Travel Lane	The total number of contiguous travel lanes at the time of event that vehicles could easily maneuver into, including any turn lanes.	0	0	0	41
		1	1	22	96
		2	2	458	974
		3	3	253	228
		4	4	164	151
		5 and 5+	5	153	149
Traffic Control	Type of traffic control applicable to the subject's travel direction at the time of event.	No traffic control	[0 0 0 0]	931	1150
		Sign control	[1 0 0 0]	63	212
		Traffic lanes marked	[0 1 0 0]	13	40
		Traffic signal	[0 0 1 0]	40	175
		Other	[0 0 0 1]	3	62
Relation to Junction	The spatial relation of the roadway that the	Driveway, alley access, etc.	[1 0 0 0 0 0]	59	156
		Entrance/Exit ramp	[0 1 0 0 0 0]	26	33
		Interchange area	[0 0 1 0 0 0]	144	67

Variable	Definition	Values	SVM Vector	Baseline	SCE
	vehicle was traveling to the junction.	Intersection, intersection-related	[0 0 0 1 0 0]	135	500
		Parking lot entrance/exit	[0 0 0 0 1 0]	49	269
		Other	[0 0 0 0 0 1]	0	11
		Non-junction	[0 0 0 0 0 0]	637	603
Alignment	The roadway curvature in the subject vehicle's travel direction at the time of event.	Curve	1	155	327
		Straight	0	895	1312
Grade	The roadway profile in the subject vehicle's travel direction at the time of event.	Dip/Hillcrest	[1 0 0]	6	20
		Grade down	[0 1 0]	64	116
		Grade up	[0 0 1]	99	184
		Level	[0 0 0]	881	1319
Locality	Description of the surroundings that influence or might influence the flow of traffic at the time of event.	Business/Industrial	[1 0 0 0 0 0 0]	252	612
		Bypass/Divided highway with traffic signal	[0 1 0 0 0 0 0]	52	27
		Interstate/Bypass/Divided Highway with no traffic signal	[0 0 1 0 0 0 0]	451	173
		Open country	[0 0 0 1 0 0 0]	19	23
		Residential area	[0 0 0 0 1 0 0]	199	591
		School/Church/Playground	[0 0 0 0 0 1 0]	60	159
		Urban	[0 0 0 0 0 0 1]	15	54
		Other	[0 0 0 0 0 0 0]	2	0
Construction Zone	Description of whether the event occurs in or in relation to construction zone.	Construction zone, or related	1	49	74
		No construction zone influence	0	1001	1565
AADT	Annual average daily traffic, an indicator of traffic volume.	≤ 5000	1	92	99
		5000-10000	2	109	102
		10000-15000	3	94	78
		15000-20000	4	76	56
		20000-30000	5	97	93
		30000-50000	6	106	79
		50000-100000	7	79	34
		≥ 100000	8	58	39
Speed Limit	The posted speed limit of the subject's traveling roadway at the time of event.	20		1	1
		25		0	2
		30		5	11
		35		12	22
		40		11	10
		45		40	16
		50		15	6
		55		63	22
		60		10	10
		65		31	11
		70		24	6
IRI		≤ 20		20	57

Variable	Definition	Values	SVM Vector	Baseline	SCE
	International roughness index, an indicator of road surface roughness.	20-50		41	19
		50-100		307	103
		100-150		109	69
		150-200		28	43
		> 200		10	41
Radius	The radius of roadway curvature.	0-500		11	25
		500-1000		18	36
		1000-2000		26	27
		2000-5000		60	31
		> 5000		58	32
		Straight		397	434
Curve Direction	The curve direction of roadway in vehicle's travel direction.	-1		85	69
		0		397	434
		1		88	82
Struck Object Type	The type of object that involved in the event.	Others	[1 0 0 0 0 0 0 0 0 0 0 0 0]		94
		Raised median	[0 1 0 0 0 0 0 0 0 0 0 0 0]		121
		Animal	[0 0 1 0 0 0 0 0 0 0 0 0 0]		366
		Concrete barrier	[0 0 0 1 0 0 0 0 0 0 0 0 0]		7
		Curb	[0 0 0 0 1 0 0 0 0 0 0 0 0]		640
		Ditch	[0 0 0 0 0 1 0 0 0 0 0 0 0]		15
		Pavement edge/edge line	[0 0 0 0 0 0 1 0 0 0 0 0 0]		201
		Roadway debris	[0 0 0 0 0 0 0 1 0 0 0 0 0]		96
		Signpost	[0 0 0 0 0 0 0 0 1 0 0 0 0]		10
		Stopped car	[0 0 0 0 0 0 0 0 0 1 0 0 0]		58
		Tree/shrub	[0 0 0 0 0 0 0 0 0 0 1 0 0]		7
		Utility/light pole	[0 0 0 0 0 0 0 0 0 0 0 1 0]		6
		W-beam barrier	[0 0 0 0 0 0 0 0 0 0 0 0 1]		18
Critical speed	The speed representing general traveling speed.	Continuous			
Reaction time	The time it took for the driver to make an evasive maneuver.	Continuous			

REFERENCES

1. National Highway Traffic Safety Administration. (n.d.). Fatality Analysis Reporting System. U.S. Department of Transportation. http://www-fars.nhtsa.dot.gov

2. Insurance Institute for Highway Safety, Highway Loss Data Institute. (n.d.). *Collisions with fixed objects and animals*. http://www.iihs.org/iihs/topics/t/roadway-and-environment/fatalityfacts/fixed-object-crashes Accessed Dec. 7, 2017.

3. National Highway Traffic Safety Administration. (2015). *Traffic safety facts 2015* (DOT HS 812 384). U.S. Department of Transportation. https://crashstats.nhtsa.dot.gov/Api/Public/Publication/812384

4. Bambach, M. R., Mitchell, R. J., & Mattos, G. A. (2015). Mean injury costs of run-off-road collisions with fixed objects: Passenger vehicles and motorcycles. *Journal of Transportation Safety and Security, 7*(3), 228-242.

5. Tefft, B. C. (2016). *The prevalence of motor vehicle crashes involving road debris, United States, 2011-2014*. AAA Foundation for Traffic Safety. http://mail.thenewspaper.com/rlc/docs/2016/aaadebris.pdf

6. Blincoe, L., Miller, T. R., Zaloshnja, E., & Lawrence, B. A. (2015). T*he economic and societal impact of motor vehicle crashes, 2010 (Revised)* (DOT HS 812 013). National Center for Statistics and Analysis, National Highway Traffic Safety Administration.

7. Liu, C., & Subramanian, R. (2009). *Factors related to fatal single-vehicle run-off-road crashes* (No. HS-811 232). National Highway Traffic Safety Administration. http://www-nrd.nhtsa.dot.gov/Pubs/811232.pdf

8. Neyens, D. M., & Boyle, L. N. (2007). The effect of distractions on the crash types of teenage drivers. *Accident Analysis & Prevention, 39*(1), 206-212.

9. Takemoto, A., Hirasawa, M., & Kasai, S. (2011). Causes of and countermeasures for fixed object crashes. In *Proceedings of the Eastern Asia Society for Transportation Studies Vol. 8 (The 9th International Conference of Eastern Asia Society for Transportation Studies, 2011*) (p. 357-357). Eastern Asia Society for Transportation Studies.

10. Dissanayake, S., & Lu, J. J. (2002). Factors influential in making an injury severity difference to older drivers involved in fixed object–passenger car crashes. *Accident Analysis & Prevention, 34*(5), 609-618.

11. Souleyrette, R., Kamyab, A., Hans, Z., Knapp, K. K., Khattak, A., Basavaraju, R., & Storm, B. (2001). *Systematic identification of high crash locations* (Publication Iowa DOT TR-442, CTRE 0059, Final Report). Iowa State University Center for Transportation Research and Education. http://www.ctre.iastate.edu/reports/hcl.pdf

12. Holdridge, J. M., Shankar, V. N., & Ulfarsson, G. F. (2005). The crash severity impacts of fixed roadside objects. *Journal of Safety Research, 36*(2), 139-147.

13. Dissanayake, S., & Roy, U. (2014). Crash severity analysis of single vehicle run-off-road crashes. *Journal of Transportation Technologies, 4*(01), 1.

14. Dingus, T. A., Hankey, J. M., Antin, J. F., Lee, S. E., Eichelberger, L., Stulce, K., McGraw, D., Perez, M., & Stowe, L. (2015). *Naturalistic driving study: Technical coordination and quality control* (SHRP 2 Report S2-S06-RW-1). Transportation Research Board. http://onlinepubs.trb.org/onlinepubs/shrp2/SHRP2_S06Report.pdf

15. Hankey, J. M., Perez, M. A., & McClafferty, J. A. (2016). *Description of the SHRP 2 naturalistic database and the crash, near-crash, and baseline data sets.* Virginia Tech Transportation Institute.

16 Campbell, K. (2012). The SHRP 2 Naturalistic Driving Study: Addressing driver performance and behavior in traffic safety. *TR News, 282*, 30-35.

17. Transportation Research Board of the National Academy of Sciences. (2013). The Second Strategic Highway Research Program Naturalistic Driving Study Dataset. Available from the SHRP 2 NDS InSight Data Dissemination website: https://insight.shrp2nds.us

18. McLaughlin, S., & Hankey, J. (2015). *Naturalistic Driving Study: Linking the study data to the Roadway Information Database* (SHRP 2 Report S2-S31-RW-3). Virginia Tech Transportation Institute.

19. American Association of State Highway and Transportation Officials. (2011). *Roadside design guide* (4th ed.).

20. Neuman, T. R., Pfefer, R., Slack, K. L., Hardy, K. K., Lacy, K., & Zegeer, C. (2003). *Guidance for implementation of the AASHTO strategic highway safety plan. Volume 3: A guide for addressing collisions with trees in hazardous locations* (No. Project G17-18 (3) FY'00). Transportation Research Board of the National Academy of Sciences.

21. Federal Highway Administration. (2009). *Manual on uniform traffic control devices for streets and highways*.

22. McGee, H. W. (2010). *Maintenance of signs and sign supports: A guide for local roads maintenance personnel* (No. FHWA-SA-09-025). Federal Highway Administration.

23. Lacy, K., Srinivasan, R., Zegeer, C. V., Pfefer, R., Neuman, T. R., Slack, K. L., & Hardy, K. K. (2004). *Guidance for implementation of the AASHTO strategic highway safety plan. Volume 8: A guide for reducing collisions involving utility poles* (No. Project G17-18 (3) FY'00). Transportation Research Board of the National Academy of Sciences.

24. Gabler, H. C., Gabauer, D. J., & Riddell, W. T. (2007). *Breakaway utility poles: Feasibility of energy absorbing utility pole installations in New Jersey* (No. FHWA-NJ-2007-018). Federal Highway Administration.

25. Jones, J. G. (2016). *Noteworthy practices: Roadside tree and utility pole management* (No. FHWA-SA-16-043). Federal Highway Administration.

26. American Association of State Highway and Transportation Officials. (2001). *A policy on geometric design of highways and streets*.

27. Eccles, K., Council, F., McGee, H., Tiso, P., & Orengo, F., Weir, J. A., Ray, M. H., & Plaxico, C. A. *Recommended guidelines for curb and curb-barrier installations* (NCHRP Report, No. 537). Transportation Research Board of the National Academy of Sciences.

28. Ross, H. E., Jr., Sicking, D. L., Zimmer, R. A., & Michie, J. D. (1993). *Recommended procedures for the safety performance evaluation of highway features* (No. 350). Transportation Research Board of the National Academy of Sciences.

29. Stephens, L. B., Jr. (2005). *Barrier guide for low volume and low speed roads* (No. FHWA-CFL/TD-05-009). Federal Highway Administration.

30. Kissinger, D. (2012). Radar fundamentals. In *Millimeter-wave receiver concepts for 77 GHz automotive radar in silicon-germanium technology.* SpringerBriefs in Electrical and Computer Engineering. Springer Science & Business Media (pp. 9-19).

31. Iwasaki, Y., & Itoyama, H. (2007). Real-time vehicle detection using information of shadows underneath vehicles. In *Advances in Computer, Information, and Systems Sciences, and Engineering* (pp. 94-98). Springer, Dordrecht.

32. Satzoda, R. K., Lee, S., Lu, F., & Trivedi, M. M. (2016). Vision-based front and rear surround understanding using embedded processors. *IEEE Transactions on Intelligent Vehicles, 1*(4), 335-345.

33. Santos, D., & Correia, P. L. (2009, May). Car recognition based on back lights and rear view features. In *2009 10th Workshop on Image Analysis for Multimedia Interactive Services* (pp. 137-140). IEEE.

34. Iwasaki, Y., Kawata, S., & Nakamiya, T. (2011). Robust vehicle detection even in poor visibility conditions using infrared thermal images and its application to road traffic flow monitoring. *Measurement Science and Technology, 22*(8).

35. Iwasaki, Y., Kawata, S., & Nakamiya, T. (2013). Vehicle detection even in poor visibility conditions using infrared thermal images and its application to road traffic flow monitoring. In *Emerging Trends in Computing, Informatics, Systems Sciences, and Engineering* (pp. 997-1009). Springer: New York, NY.

36. Viola, P., & Jones, M. (2001, December). Rapid object detection using a boosted cascade of simple features. In *Proceedings of the 2001 IEEE Computer Society Conference on Computer Vision and Pattern Recognition* (p. 511). IEEE.

37. Elkerdawi, S. M., Sayed, R., & ElHelw, M. (2014). Real-time vehicle detection and tracking using Haar-like features and compressive tracking. In *ROBOT2013: First Iberian Robotics Conference* (pp. 381-390). Springer, Cham.

38. Dalal, N., & Triggs, B. (2005, June). Histograms of oriented gradients for human detection. In *International Conference on Computer Vision & Pattern Recognition* (CVPR'05) (Vol. 1, pp. 886-893). IEEE Computer Society.

39. Zhang, G., Gao, F., Liu, C., Liu, W., & Yuan, H. (2010, August). A pedestrian detection method based on SVM classifier and optimized Histograms of Oriented Gradients feature. In *2010 Sixth International Conference on Natural Computation* (Vol. 6, pp. 3257-3260). IEEE.

40. Chen, Z., Chen, K., & Chen, J. (2013, December). Vehicle and pedestrian detection using support vector machine and histogram of oriented gradients features. In *2013 International Conference on Computer Sciences and Applications* (pp. 365-368). IEEE.

41. Shustanov, A., & Yakimov, P. (2017). CNN design for real-time traffic sign recognition. *Procedia Engineering, 201*, 718-725.

42. Mobileye. (n.d.). *How it works*. https://www.mobileye.com/en-us/technology/how-it-works/

43. Tarko, A. P., Ariyur, K. B., Romero, M., Bandaru, V. K., & Jimenez, C. L. (2016). *Guaranteed LiDAR-aided multi-object tracking at road intersections: USDOT Region V Regional University Transportation Center final report*. Purdue University.

44. Wijesoma, W. S., Kodagoda, K. S., & Balasuriya, A. P. (2004). Road-boundary detection and tracking using LiDar sensing. *IEEE Transactions on Robotics and Automation, 20*(3), 456-464.

45. Lee, U., Jung, J., Jung, S., & Shim, D. H. (2018). Development of a self-driving car that can handle the adverse weather. *International Journal of Automotive Technology, 19*(1), 191-197.

46. Gargoum, S. A., Koch, J. C., & El-Basyouny, K. (2018). A voxel-based method for automated detection and mapping of light poles on rural highways using LiDAR data. *Transportation Research Record*, *2672*(45), 274–283. https://doi.org/10.1177/0361198118787657

47. LiDARUSA. (n.d.). *We are LiDAR*. https://www.lidarusa.com/sample-data.html

48. Yamada, N., Tanaka, Y., & Nishikawa, K. (2005, October). Radar cross section for pedestrian in 76GHz band. In *2005 European Microwave Conference* (Vol. 2, p. 4-p). IEEE.

49. Palubinskas, G., Runge, H., & Reinartz, P. (2004, September). Radar signatures of road vehicles. In *IGARSS 2004: 2004 IEEE International Geoscience and Remote Sensing Symposium.* https://doi.org/10.1109/IGARSS.2004.1368705

50. Digi-Key Electronics. (2016, November). Radar sensing for driverless vehicles. https://www.digikey.com/en/articles/techzone/2016/nov/radar-sensing-for-driverless-vehicles

51. Bartsch, A., Fitzek, F., & Rasshofer, R. H. (2012). Pedestrian recognition using automotive radar sensors. *Advances in Radio Science, 10*(B. 2), 45-55.

52. Hasirlioglu, S., Doric, I., Kamann, A., & Riener, A. (2017, June). Reproducible fog simulation for testing automotive surround sensors. In *2017 IEEE 85th Vehicular Technology Conference (VTC Spring)* (pp. 1-7). IEEE.

53. Filgueira, A., González-Jorge, H., Lagüela, S., Díaz-Vilariño, L., & Arias, P. (2017). Quantifying the influence of rain in LiDAR performance. *Measurement, 95*, 143-148.

54. Nelson, R. (2016). Technologists, officials boost autonomous vehicles. *EE-Evaluation Engineering, 55*(3), 2-3.

55. *Thermal network cameras--performance considerations for intelligent video.* (2016). Lund, Sweden. https://www.axis.com/files/whitepaper/wp_thermal_cams_67679_en_1605_hi.pdf

56. Chen, C. C. (1975). *Attenuation of electromagnetic radiation by haze, fog, clouds, and rain, 1694*(PR). Rand Corporation.

57. Barnard, M. (2017). Tesla & Google disagree about LIDAR—which is right. *Clean Technica*. https://cleantechnica.com/2016/07/29/tesla-google-disagree-lidar-right/

58. Lambert, F. (2016). Understanding the fatal Tesla accident on autopilot and the NHTSA probe. *Electrek*. https://electrek.co/2016/07/01/understanding-fatal-tesla-accident-autopilot-nhtsa-probe/

59. ABC Action News. (2018, March 21). Uber self-driving car dash camera video released in deadly crash. [Video file]. Youtube.com. https://www.youtube.com/watch?v=8IqpUK5teGM

60. Favarò, F. M., Nader, N., Eurich, S. O., Tripp, M., & Varadaraju, N. (2017). Examining accident reports involving autonomous vehicles in California. *PLoS One, 12*(9), e0184952.

61. Favarò, F., Eurich, S., & Nader, N. (2018). Autonomous vehicles' disengagements: Trends, triggers, and regulatory limitations. *Accident Analysis & Prevention, 110*, 136-148.

62. Tuohy, S., O'Cualain, D., Jones, E., & Glavin, M. (2010). Distance determination for an automobile environment using inverse perspective mapping in OpenCV. In *IET Irish Signals and Systems Conference (ISSC 2010)*. Cork, Ireland.

63. Rezaei, M., Terauchi, M., & Klette, R. (2015). Robust vehicle detection and distance estimation under challenging lighting conditions. *IEEE Transactions on Intelligent Transportation Systems, 16*(5), 2723-2743.

64. Hallmark, S. L., Tyner, S., Oneyear, N., Carney, C., & McGehee, D. (2015). Evaluation of driving behavior on rural 2-lane curves using the SHRP 2 naturalistic driving study data. *Journal of Safety Research, 54*, 17-e1.

65. Li, Z., Liu, P., Wang, W., & Xu, C. (2012). Using support vector machine models for crash injury severity analysis. *Accident Analysis & Prevention, 45*, 478-486.

66. Li, X., Lord, D., Zhang, Y., & Xie, Y. (2008). Predicting motor vehicle crashes using support vector machine models. *Accident Analysis & Prevention, 40*(4), 1611-1618.

67. Jones, A., & Huddleston, E. (2008). *SAS/STAT 9.2 user's guide* (2nd ed.). SAS Institute Inc. https://support.sas.com/documentation/cdl/en/statug/63033/HTML/default/viewer.htm#statug_reg_sect038.htm

68. Hosmer, D. W., Jr., Lemeshow, S., & Sturdivant, R. X. (2013). *Applied logistic regression* (3rd ed.). John Wiley & Sons.

69. Cortes, C., & Vapnik, V. (1995). Support-vector networks. *Machine Learning, 20*(3), 273-297.

70. Hsu, C. W., & Lin, C. J. (2002). A comparison of methods for multiclass support vector machines. *IEEE Transactions on Neural Networks, 13*(2), 415-425.

71. Support-vector machine. (2019, February 11). In *Wikipedia*. https://en.wikipedia.org/w/index.php?title=Support-vector_machine&oldid=882751641

72. Hsu, C. W., Chang C. C., Lin, C. J. (2003). *A practical guide to support vector classification.* Department of Computer Science, National Taiwan University. http://www.csie.ntu.edu.tw/cjlin/papers.html

73. Cross-validation (statistics). (2019, February 19). In *Wikipedia*. https://en.wikipedia.org/w/index.php?title=Cross-validation_(statistics)&oldid=884077007

74. MathWorks. (n.d.). *Train models to classify data using supervised machine learning - MATLAB*. https://www.mathworks.com/help/stats/classificationlearner-app.html

75. Fish, K. E., & Blodgett, J. G. (2003). A visual method for determining variable importance in an artificial neural network model: An empirical benchmark study. *Journal of Targeting, Measurement and Analysis for Marketing, 11*(3), 244-254.

76. Delen, D., Tomak, L., Topuz, K., & Eryarsoy, E. (2017). Investigating injury severity risk factors in automobile crashes with predictive analytics and sensitivity analysis methods. *Journal of Transport & Health, 4*, 118-131.

77. Delen, D., Sharda, R., & Bessonov, M. (2006). Identifying significant predictors of injury severity in traffic accidents using a series of artificial neural networks. *Accident Analysis & Prevention, 38*(3), 434-444.

78 Gibbons, R., Guo, F., Medina, A., Terry, T., Du, J., Lutkevich, P., & Li, Q. (2014). *Design criteria for adaptive roadway lighting*. Federal Highway Administration.

79. Xu-hui, W., Ping, S., Li, C., & Ye, W. (2009, December). A ROC curve method for performance evaluation of support vector machine with optimization strategy. In *2009 International Forum on Computer Science-Technology and Applications,* 2 (pp. 117-120). IEEE.

80. World Wide Web Consortium. (2008). 2008 Web Accessibility Initiative, Web Content Accessibility Guidelines 2.0. http://www.w3.org/TR/WCAG20/