AN ANALYSIS OF FACTORS DRIVING THE INCREASES IN TRAFFIC FATALITIES IN THE UNITED STATES

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ABSTRACT

According to the U.S. Department of Transportation's National Highway Traffic Safety Administration (NHTSA), 37,461 people died in the United States in traffic crashes in 2016, a 5.6% increase in fatalities from 2015. It was the second consecutive year of increasing fatalities following an 8.4% increase from 2014 to 2015. This study applies random-effects generalized linear mixed modeling techniques to examine the association of changes in traffic fatality counts with changes in explanatory factors, by state, between 2005 and 2016. Three regressions modeled different outcomes: 1) passenger vehicle occupant fatalities, 2) pedestrian fatalities, and 3) motorcycle fatalities

Motor vehicle-related traffic fatalities were collected by year and by state using NHTSA's Fatality Analysis Reporting System (FARS). A variety of sources provided measures on explanatory factors. The Fatality counts (outcome) and explanatory factors were then combined as panel data by year (2005-2016) and state (51 states including the District of Columbia). The models tested the association between fatalities and more than seventy explanatory factors including economic, exposure, behavioral and vehicle factors.

The study found that the increases in passenger vehicle fatality counts were associated with increases in vehicle miles traveled (exposure) and an improving economy. In addition, the increase in the population age 65 and older and an increase in the percent of this population in the workforce also was associated with increasing fatality counts. Several behavioral factors were associated with changes in fatality counts, including non-belt use and increased drunk driving. Conversely, improved vehicle safety design was associated with a decline in occupant fatalities. A rise in motorcycle fatalities was associated with increased exposure (motorcycle registrations and overall vehicle miles travelled) and an improving economy. Among pedestrian and motorcycle fatalities, there is some evidence that driver distraction plays a role.

While the quasi-experimental study design does not allow for inferences of causality, the models can be applied to forecast future fatality counts based on expected or observed environmental, behavioral and vehicle factors or to evaluate the potential impact of prospective interventions.

Increased exposure, the improving economy, and behavioral factors drove increases in fatality counts between 2005 and 2016. However, improved vehicle safety design substantially countered these effects, mitigating the increases.

INTRODUCTION

According to the U.S. Department of Transportation's National Highway Traffic Safety Administration (NHTSA), 37,461 people died in the United States in traffic crashes in 2016, a 5.6% increase in fatalities from 2015 the second consecutive year of increasing fatalities following a 8.4% increase from 2014 to 2015 [1]. The data further showed traffic deaths rising across nearly every segment of the population. The last single-year increase of this magnitude was in 1966, when fatalities rose 8.1 percent from the previous year.

These figures come after a decade of progress. Eleven years ago, the number of traffic deaths was nearly 25 percent higher, with 42,708 fatalities reported nationwide in 2005 [2]. In the past two decades, behavioral safety and enforcement programs have helped lower the number of deaths by increasing seat belt use and reducing impaired driving [3][4]. Vehicle improvements, including air bags and electronic stability control, have made substantial contributions to reducing traffic fatalities [5].

Increased exposure in terms of vehicle miles travelled (VMT) does not account for all of the increases. In 2014 there were 1.08 traffic-related deaths per 100 million VMT. This increased to 1.12/ 100 million VMT in 2015 and 1.18/100 million VMT in 2016, a 6.5% and 2.5% change, respectively [1][2]. Changes in fatality counts varied by person type, with non-occupants contributing more to the increases than occupants[2]. The toll was particularly high among and older drivers (age 65+) in 2015 and 2016.

Risk factors for traffic crashes and deaths are fairly well understood. One tool for analyzing an injury event and ways to either prevent the injury or reduce the harm done is the Haddon Matrix. In 1970, William Haddon Jr. proposed a matrix that allows simultaneous consideration of the stages over time of an injury event (pre-, during, and post-event) with all the possible host, agent/carrier, and environment factors involved in the event. Table 1 presents a Haddon Matrix that identifies factors relevant to traffic fatalities. Important person-level factors include restraint use, driver impairment, and driver distraction, age and gender. Important vehicle factors include speed, vehicle size, age and safety design. Environment factors are differentiated as either physical (i.e. road conditions, weather, proximity to emergency medical services) or social (i.e. existing safety laws and economic conditions).

Table 1. Haddon Matrix of factors relevant to traffic deaths

	Person Factors	Vehicle/Equipment Factors	Environment	
			Physical	**Social/Economic**
Pre-Crash	Driver Experience Impairment Gender Driver condition Risk-taking behavior	Vehicle condition Driving Speed Load characteristics Safety package	Road quality Road characteristics Weather Conditions	Existing laws Enforcement of laws Safety culture Economy Congestion Travel time/Exposure
Crash	Helmet use Restraint use Injury Propensity Health Age	Speed Crashworthiness/safety design of vehicle Vehicle size/Body Type Vehicle condition Type of crash	Road features Type and size of object struck	Laws relevant to human/ vehicle/ physical factors
Post-Crash	Health Age Impairment	Integrity of fuel and battery systems Availability of automated crash notification and GPS locator	EMS response speed and quality Distance to trauma care Availability of rehabilitation programs Accessibility to crash victims	EMS protocols Public support for trauma care and rehab

Changes in these factors will influence the number of crashes or reduce the severity of crashes resulting in fewer fatalities. Depending on the factor or the combination of factors, small changes can have large impacts and vice versa. State or local level policies, laws, enforcement, and education can influence many of these factors.

Engineering approaches (e.g. traffic calming, rumble strips, advanced driving systems in vehicles, vehicle safety design) may also counter some factors.

The growth in the population of motor vehicles and the increase in VMT that accompanies economic growth is associated with an increase in road traffic crashes. According to NHTSA, job growth and low fuel prices were two factors that led to increased driving, including increased leisure driving and driving by young people [2].

Weather and regional demographic distributions are other examples of high-level factors shown to play a role in crash rates. Consistently, studies have shown that increases in temperature are associated with an increase in fatal traffic crashes due to an increase in VMT and exposure for pedestrians, bicyclists, and motorcyclists [6][7].

Nevertheless, even when state characteristics are similar, considerable variability in traffic deaths exists. For example, states with similar populations and seat belt laws have substantially different outcomes with respect to vehicle occupant deaths, seat-belt-use rates, and unbelted vehicle occupant fatalities.

This paper examines the association of these factors with the number of traffic deaths in the United States to identify key factors driving the changes in deaths over the past twelve years. This study quantifies the contribution of high-level factors like the economy and VMT to distinguish the role of key factors relevant to intervention by state and local governments and vehicle manufacturers.

METHODS

This study analyzes changes in traffic death counts in U.S. states from 2005 to 2016 using generalized linear mixed modeling. These regressions model the association of changes in measurable factors (explanatory variables) with changes in traffic death counts by state (outcome variable). Three regressions modeled different outcomes: 1) passenger vehicle occupant fatalities, 2) pedestrian fatalities, and 3) motorcycle fatalities.

Explanatory Variable Selection

The Haddon matrix (Table 1) was used as a guide in selecting explanatory variables to test in the model. To be included in the model, the variable had to be available by state and year. Over seventy variables were tested. These are listed in Appendix A.

Data Sources

Table 2, Table 3, and Table 4 detail the data sources for the outcome, exposure and explanatory variables included in the final models.

Table 2. Data Sources for the Outcome Measure

Measure of Outcome	Data Source and Description
Fatality Counts	Fatal Analysis Reporting System (FARS)

Table 3. Data Sources for Exposure Measures

Measures of Exposure	Data Source and Description
Vehicle Miles Travelled	Highway Statistics, Federal Highway Administration
Population	United States Census Bureau
Number of Vehicles	National Vehicle Population Profile, R.L. Polk
Motorcycle Registrations	Motorcycle Sales Report, 2000-2016, Motorcycle Industry Council

Table 4. Data Sources for Explanatory Measures

Measure of Key Factors	Data Source and Description
U.S. Population Counts, demographic	United States Census Bureau

distributions	
Gross Domestic Product	United States Bureau of Economic Analyses
Employment percentages by age	United States Census Bureau
Average Annual Temperature	National Oceanic and Atmospheric Administration
Motorcycle Registrations	Motorcycle Sales Report, 2000-2016, Motorcycle Industry Council
Alcohol Consumption	National Institute of Alcohol Abuse and Alcoholism
Self-Reported Belt Use	Behavioral Risk Factor Surveillance System, Centers for Disease Control
Self-Reported Drunk Driving	Behavioral Risk Factor Surveillance System, Centers for Disease Control
Observed Driver Handheld Use while Driving	National Occupant Protection Use Survey, National Highway Traffic Safety Administration
Average IIHS crash test rating of vehicle fleet	Insurance Institute for Highway Safety crash test ratings
Average NCAP Score of vehicle fleet	National Highway Traffic Safety Administration, New Car Assessment Program
Percent of vehicle fleet ESC-equipped	Safercar.gov, National Highway Traffic Safety Administration
Average, Median, Vehicle Mass and Mass distribution of state vehicle fleet	National Vehicle Population Profile, R.L. Polk

State motor vehicle traffic deaths counts were tabulated using the NHTSA-administered Fatality Analysis Reporting System (FARS). VMT was tabulated by state using annual data from the Federal Highway Administration. Gross Domestic Product (GDP), based on data from the U.S. Bureau of Economic Analysis, was the primary economic measure included in the final model. United States Census Bureau data provided information on state demographic distributions over time, means of transportation to work, and population employment characteristics.

The Center for Disease Control's Behavioral Risk Factor Surveillance System (BRFSS) provided data on risk behaviors. The BRFSS is a national random digit dial telephone survey. Data are collected at the state level among a representative sample of the population over 18 years of age. Regarding belt use, the survey asks the question: "How often do you use seatbelts in your car?" The possible responses are: always, nearly always, sometimes, seldom, and never. For this study we defined "rarely belted" as those responding "sometimes", "seldom", or "never". Regarding drunk driving, the survey asks the question: "In the past 30 days, have you driven after drinking too much?" with a yes or no response. The BRFSS also includes a question on binge drinking (5 or more drinks for men and 4 or more drinks for women in one drinking session).

Observed belt use data are available by state from the annual National Occupant Protection Use Survey (NOPUS), coordinated by NHTSA. This probability-based survey collects observations on driver and right-front passenger seat belt use. Observations of driver hand held use are also included in the NOPUS and used in this study.

Weather data (precipitation and temperature) were obtained from the National Oceanic and Atmospheric Administration (NOAA). The NOAA maintains and collects data from automated weather stations distributed across all 50 states.

Changes in state laws (in particular alcohol, motorcycle, and graduated drivers licensing) were assessed using information available from the IIHS and the Governors Highway Safety Association.

This study includes a detailed focus on the role of vehicle fleet characteristics (age, safety design, mass disparity). To compute measures of these characteristics, we compiled, by state and year, counts of the vehicle population by vehicle make, model and model year using data published by R.L Polk and Co. Vehicle mass (from NHTSA) and crash testing data (from the Insurance Institute for Highway Safety and from NHTSA's New Car Assessment Program) are available by make, model and model year. IIHS ratings were converted to numeric scores: poor=1, marginal=2, acceptable=3 and good=4. Using these data merged with R.L. Polk vehicle population data (by make, model and model year), the study computed safety-related measures of the vehicle fleet for each state over time. Therefore, changes in these measures represent the improved safety design of new vehicles as they penetrate the fleet. including average IIHS rating, average NCAP rating, average vehicle mass, and fleet age. In addition, we computed several measures of mass disparity to characterize any changing distribution of passenger vehicles by mass.

Other measures tested in the regression models but not included in the final models were obtained from an additional number of data sources: Gasoline prices (from the U.S. Energy Information Administration), driving and walking time per day (from the American Time Use Survey, Bureau of Labor Statistics), drug- and opioid-related fatalities (Multiple Cause of Death File, CDC), number of mobile phone subscribers (Voice Telephone Services Report, Federal Communications Commission).

A full list of measures and data sources is compiled in Appendix A.

Data Preparation
Outcome and explanatory variables were compiled as panel data by year (2005-2016) and state, resulting in 612 observations (12 years x 51 states/DC). Because the scales of the explanatory variables varied dramatically, all variables were standardized and centered. For some data sources the data were missing in one year. In this case, the variable was imputed as the mid-way between the previous year and the following year. No 2016 estimates (last values) were missing in the final analysis.

Statistical Modeling
Generalized linear mixed models (GLMM) were created modeling the relationship between changes in the explanatory variables with fatality counts by year and state. GLMM is an extension of linear mixed models that combines the characteristics of generalized linear models and mixed models. The mixed model includes variables on two levels, time and state. This type of regression is appropriate for panel data with repeated measures over time.

While the outcome variables are count data (count of traffic fatalities), the assumptions for Poisson regression (equality of mean and variance of the outcome variable given the explanatory variables) were not met. Therefore, we used the negative binomial log link function.

Model Specification
GLMMs were fitted at two levels (state and time) using the panel data. The model allows for independent random effects for the intercept and slope for each subject (i.e. state). The model allows for an independent state-level random effect to incorporate the data structure of years nested in a state.

Measures to be included as explanatory variables were collected from multiple sources. Often there was more than one way to measure a key factor; either in different ways by different sources or by defining one source in different ways. For example, we developed three measures of belt use: 1) percent reporting rarely belted, 2) percent reporting always belted in the BRFSS, and 3) the percent observed daytime belted rate reported in the NOPUS. Different measures of the same key factor were tested separately for inclusion in the model. In determining which variable to use in the final model we considered measure's significance in the model and its contribution to model fit (measured by Bayesian Information Criterion, BIC).

Criteria for inclusion in the final model included testing for significance, collinearity, interaction effects, examining the impact on the coefficients of other explanatory variables, and the variable's contribution to model fit. The number of explanatory variables included in the final model was limited to between eight and ten due to the model degrees of freedom. Highly correlated variables (Pearson correlation coefficient>0.8) were not included simultaneously in specifying or in the final model.

This study further estimates the individual contribution of each key factor in the change in fatalities from 2015 to 2016 by applying the model to the known change in that key factor from 2015 to 2016 holding the other variables at 2015 values. For example, the contribution of the change in percent of adults reporting driving drunk is determined by predicting the number of fatalities in 2016 based on the change in this variable where all other explanatory variables remain at 2015 levels. The individual factor contributions by this method are not additive as their effects interact.

RESULTS

Figure 1 presents the counts of traffic-related fatalities over time, by person type. Changes in fatality counts varied by person type, with non-occupants contributing more to the increases than occupants. Fatalities decreased monotonically until 2012. In 2015 and 2016 traffic-related deaths increased again. Increases among non-occupant fatalities were greater than vehicle occupant fatalities. Fatality counts increased by 11.9% and 9.0% among pedestrians in 2015 and 2016, respectively, and 13.7% and 1.3%, respectively, among pedalcyclists. Motorcyclist deaths increased 9.5% and 5.1% in 2015 and 2016, respectively. Passenger vehicle occupant deaths increased 7.5% and 4.7%, respectively.

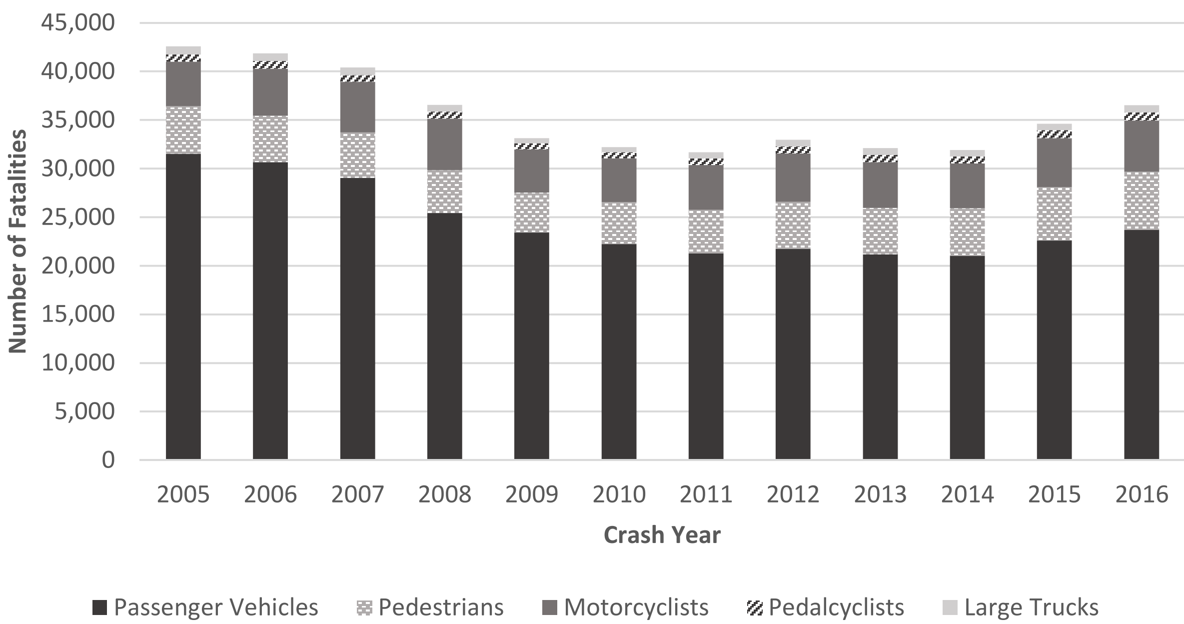

Figure 1. Number of Fatalities by Crash Year and Person Type (Source: Fatality Analysis Reporting System, National Highway Traffic Safety Administration)

Figure 2 plots state VMT versus the count of traffic-related fatalities for the 50 states and Washington D.C. for each of the years between 2005 and 2016. The trendline shows that fatality counts are highly correlated with exposure. However, the points do not cluster tightly around the line indicating that state- and time-related variability in risk exists that is not fully explained by changes in VMT alone.

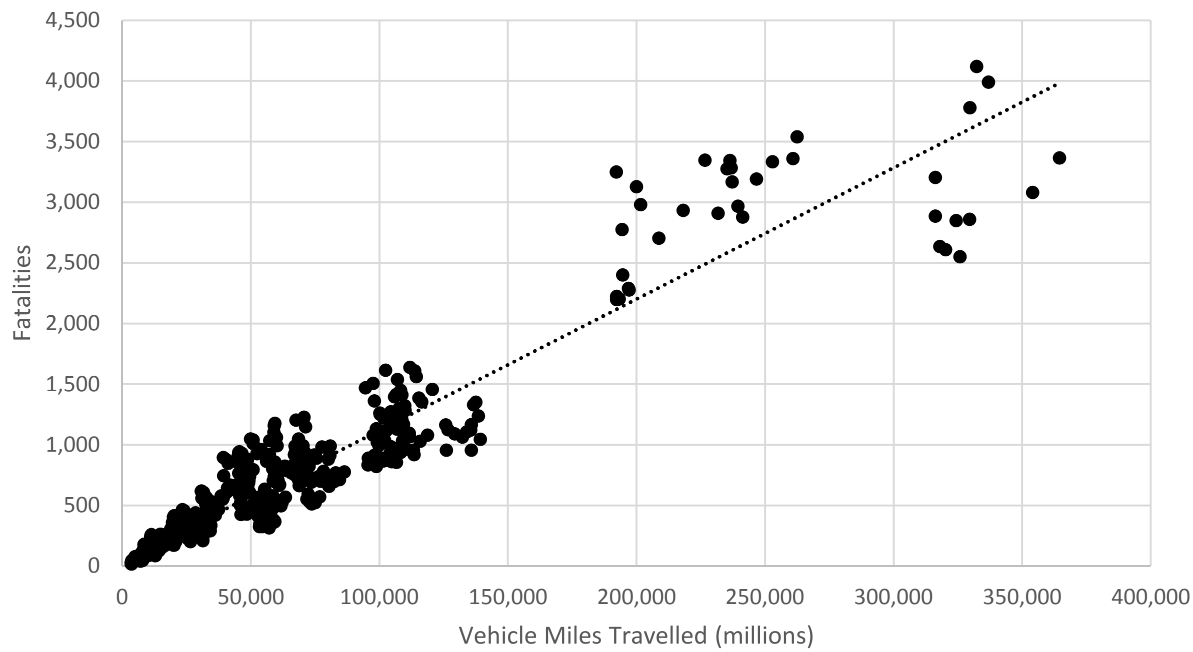

Figure 2. Count of Fatalities Versus Vehicle Miles Travelled, for 50 states and the District of Columbia between 2005 and 2016.

Table 5, Table 6, and Table 7 present the modeled fixed effects parameter estimates of the explanatory variables and the direction of this relationship for passenger vehicle occupant fatalities (Table 5), pedestrian fatalities (Table 6), and motorcycle fatalities (Table 7). "Positive" indicates that as the explanatory variable changes, fatalities change in the same direction; i.e. an increase in the explanatory variable is associated with increasing fatalities, and vice versa. "Negative" indicates that as the explanatory variable changes, fatalities change in the opposite direction; i.e. an increase in the explanatory variable is associated with decreasing fatalities, and vice versa.

Passenger Vehicle Occupant Fatalities

Eight explanatory variables were included in the final model predicting passenger vehicle occupant fatalities (Table 5). The final model controlled for high-level factors related to exposure (VMT per capita), the economy (GDP) and temperature. With the exception of average IIHS rating, all explanatory variables showed a positive association with fatality counts, i.e. an increase in the explanatory variable was associated with an increase in fatality counts. The models found that an increase in the average IIHS rating was associated with a decrease in fatality counts.

Table 5. Fixed Effects Parameter Estimates of Explanatory Variables Included in the Final Model of Passenger Vehicle Occupant Fatalities

Explanatory Variable	Estimate	p-value	Association with Fatalities
Average fleet IIHS Rating	-0.204	< 0.001	Negative
Employment Rate for the Population Age 65+ (%)	0.211	< 0.001	Positive
Population Age 65+ (% of total population)	0.167	< 0.001	Positive
Adults Reporting Rarely Belted (% reporting sometimes, seldom or never wear seatbelt)	0.116	< 0.001	Positive
Adults Reporting Drunk Driving in the past 30 days (%)	0.012	0.016	Positive
Average Temperature (degrees F)	0.137	< 0.001	Positive
VMT per Capita (millions)	0.196	< 0.001	Positive

GDP (Billions)	0.004	0.292	Positive

Pedestrian Fatalities
Nine explanatory variables were included in the final model predicting pedestrian fatalities (Table 6). The final model controlled for high-level factors related to exposure (VMT per capita), the economy (GDP) and temperature. With the exception of percent of workers who walk to work and GDP, all explanatory variables showed a significant positive association with fatality counts. The models found that an increase in the percent of workers who walk to work was associated with a decrease in fatality counts. GDP, however, was included in the model because it significantly modified the effect of VMT in urban areas: increasing urban VMT with a concurrent increase in GDP was associated with a decrease in pedestrian fatalities.

Table 6. Fixed Effects Parameter Estimates of Explanatory Variables Included in the Final Model of Pedestrian Fatalities

Explanatory Variables (Key Factors)	Estimate	p-value	Association with Fatalities
Walk to Work (% of workers)	-0.122	0.012	Negative
% Vehicles with Mass above the U.S. 90^{th} %ile	0.121	0.002	Positive
Observed Using Hand-Held Device (% of drivers)	0.016	0.027	Positive
Population Age 65+ (% of total population)	0.151	< 0.001	Positive
VMT in Urban Areas (% of overall VMT)	0.089	0.140	Positive
Average Temperature (degrees F)	0.175	< 0.001	Positive
VMT per Capita (millions)	0.060	0.060	Positive
GDP (Billions)	0.453	< 0.001	Positive
Police per Million	-0.044	0.005	Negative
Interaction effect: VMT in Urban Areas x GDP	-0.116	0.003	Negative

Motorcycle Fatalities
Eight variables were included in the final model predicting motorcycle fatalities (Table 7). The final model controlled for high-level exposure-related factors (Total VMT and registered motorcycles), economic changes (GDP), motorcycle registrations, and temperature. With the exception of implementing a universal helmet law and population density, all explanatory variables showed a significant positive association with fatality counts. The presence of a universal helmet law was included in the model because it significantly modified the effect of total VMT: the presence of a universal helmet law where there was a concurrent increase in total VMT was associated with decreased fatalities.

Table 7. Fixed Effects Parameter Estimates of Explanatory Variables Included in the Final Model of Motorcycle Fatalities

Variables (Key Factors)	Estimate	p-value	Association with Fatalities
Statewide Universal Helmet Law (1=Yes/0=no)	-0.048	0.513	Negative
Beer Consumption (gallons of ETOH/capita)	0.083	0.002	Positive
Observed Using Hand-Held Device (% of drivers)	0.021	0.008	Positive
Population Density (Population/square mile)	-0.361	< 0.001	Negative
Registered Motorcycles (#)	0.111	0.001	Positive
Average Temperature (degrees F)	0.239	< 0.001	Positive
Total VMT (millions of miles)	0.437	< 0.001	Positive
GDP (Billions)	0.225	0.041	Positive

Interaction effect: Universal Helmet Law x Total VMT	-0.208	0.030	Negative

The models were applied to estimate the contribution of each key factor to changes in fatality counts. Table 8, Table 9, and Table 10 present the estimated change in the number of fatalities between 2015 and 2016 for the observed changed in each individual key factor between 2015 and 2016, holding the other factors constant. (Note: The factor-related contributions by this method are not additive as their effects interact)

In general, high-level factors (i.e. VMT, GDP, Temperature) are related to the highest corresponding changes in fatalities (Table 8, Table 9, Table 10). Increases in non-belt use (reporting rarely belted) and drunk driving (in the past 30 days) were substantial and corresponded to an estimated increase of 220 and 371 occupant fatalities, respectively (Table 8, Table 9). The 2.6% increase in the over-65 population corresponded to an increase in 647 occupant fatalities (Table 8) and 162 pedestrian fatalities (Table 9). The proportion of this population working has increased in the past decade, by 2.3% from 2015 to 2016, and corresponded to an increased 352 occupant fatalities (Table 8). Distracted driving, measured with the NOPUS of observed driver cell phone use, decreased and corresponded with a decline in vulnerable road user fatalities (49 fewer pedestrian fatalities and 60 fewer motorcycle fatalities).

Improved vehicle safety design, as measured by the average IIHS score of the vehicle fleet, was the one factor that corresponded with a substantial decrease in fatalities; 1,325 fewer occupant fatalities. Mass discrepancy, measured by the percent of vehicles in the fleet whose mass is above that of the 90th U.S. percentile declined and corresponded with a decrease of 42 in pedestrian fatalities.

No change, or an insignificant change, in a key factor will not play a role in driving the number of traffic deaths (e.g. no states changed their motorcycle helmet laws between 2015 and 2016).

Table 8. Estimated Individual Contribution of each Key Factor in the Change in Passenger Vehicle Occupant Fatalities from 2015 to 2016

Key Factor	Change 2015 to 2016	Corresponding change in Fatalities
Average IIHS Score	+7.0%	-1,325
Employment Rate for Age 65+ (%)	+2.3%	+352
Population Age 65+ (%)	+2.6%	+647
Adults Reporting Rarely Belted (%)	+6.9%	+220
Adults Reporting Drunk Driving (%)	+14.7%	+371
Average Temperature (degrees F)	+1.5%	+223
Total VMT (millions of miles) per Capita	+1.2%	+293
GDP (Billions)	+1.5%	+417

Table 9. Estimated Individual Contribution of each Key Factor in the Change in Pedestrian Fatalities from 2015 to 2016

Key Factor	Change 2015 to 2016	Corresponding change in Fatalities
Workers who Walk to Work (%)	-1.9%	+18
% Vehicles with Mass above the U.S. 90th %ile	-3.2%	-42
Drivers Observed Using Hand-Held Device (%)	-11.5%	-49
Population Age 65+ (%)	+2.6%	+162
VMT in Urban Areas (%)	+0.9%	+55
Average Temperature (degrees F)	+1.5%	+53

Total VMT (millions of miles) per Capita	+1.2%	+27
GDP	+1.5%	+74

Table 10. Estimated Individual Contribution of each Key Factor in Motorcycle Fatalities from 2015 to 2016

Key Factor	Change 2015 to 2016	Corresponding change in Fatalities
Universal Helmet Law	No change	0
Beer Consumption (gallons/capita)	+0.2%	+9
Drivers Observed Using Hand-Held Device (%)	-11.5%	-60
Population Density (Population/square mile)	+0.8%	-2
Motorcycle Registrations (#)	+2.2%	+2
Average Temperature (degrees F)	+1.5%	+81
Total VMT (millions of miles)	+1.2%	+99
GDP	+1.5%	+45

To gauge the accuracy of the models, we compared the modeled predicted 2016 fatality counts using data from 2005 to 2015 to actual fatality counts (Table 11).

Table 11. Modeled Predicted 2016 Fatality Counts versus Actual 2016 Fatality Counts

Model	Forecasted 2016	Actual 2016	% difference (Forecasted versus Actual)
Passenger Vehicles	23,102 (2.5%)	23,714	-2.5%
Pedestrians	5,671 (5.2%)	5,987	-5.2%
Motorcycles	5,271 (0.2%)	5,286	-0.2%

CONCLUSION

The models presented in this study suggest that observed increases in passenger vehicle fatality counts in 2015 and again in 2016 were driven by measurable changes in vehicle miles of travel (exposure) and an improving economy. Beyond these high-level factors, changes in the elderly population age 65 and older, the percent of this population employed, non-belt use, and drunk driving were associated with increasing fatality counts. However, improved vehicle safety design that accompanied the new vehicles as they entered the fleet substantially countered these effects, thereby tempering fatality increases.

Increases in motorcycle fatalities were associated with increased motorcycle registration, overall VMT (exposure), and an improving economy. Among pedestrian and motorcycle fatalities, there is some evidence that other factors like driver distraction plays a role but could not be easily measured.

DISCUSSION

Newer vehicles, for the most part, receive higher IIHS ratings and NCAP scores. Therefore, IIHS average rating is a surrogate measure of new vehicles penetrating the fleet and the accompanying improving overall safety design. However, it is important to note that the attrition from the fleet of older vehicles without airbags and other safety features is also contributing. The other measure of average safety design, average NCAP score, had the same effect in the models and was collinear with the measure of average IIHS rating. Because both could not be included at the same time, the average IIHS rating was chosen because model fit was slightly better.

The method presented in this paper provides a resource to study the impact of year-to-year changes in factors known to impact fatalities. For vehicle manufacturers the models can be used to examine how vehicle fleet changes are influencing fatality counts in the context of other factors. For example, the models can be applied to estimate fatalities prevented if fleet turnover is accelerated given expected economic changes. This method can be further applied to study how fleet changes influence fatality counts in different crash segments (for example, intersection crashes, rural crashes) to identify opportunities for vehicle safety advancements or detailed follow-up studies.

The models are useful to policy- and decision-makers to identify opportunities for intervention. The resulting models can be applied to forecast future fatality counts, given that a known set of input parameters exists, on at a national level or by state. For example, the model can be applied to predict the number of deaths prevented if seat belt use increased to 95%.

An insignificant change, in a key factor will not contribute to a change in the number of traffic deaths. For example, because there were no changes in universal helmet laws between 2015 and 2016, there was no estimated contribution of this key factor to fatality counts.

Even proven effective countermeasures will not appear to have an impact on fatality counts unless their year to year change is significant. For example, one might expect that the belt use rate should have a large effect on the number of deaths occurring. While safety belts are proven effective in preventing fatalities, no significant change in the belt use rate has been observed in recent years (Enriquez and Pickrell, 2019). However, if safety belt use rates were to increase dramatically to, for example, 95% from their national average of 90%, the impact would be measurable.

The quality of these forecasting models relies on a number of critical factors. First, the data must be available and consistently collected per state for the full study period. A smaller number of training data points would degrade model performance. In many cases data have become available only recently (i.e. self-reported drunk driving), however no historical record exists in earlier years. Next, the homogeneity of each state becomes important for each factor sampled. Since a single value represents each parameter for each state and input year, we assume that this value appropriately represents that condition for the entire state. While this assumption is true in many ways, there are exceptions. For example, average precipitation may provide a useful metric for smaller states while large states may have widely varying conditions depending on the specific region. Depending on the population distribution, these region-specific disparities can be important. A third factor that impacts the quality of models is the representativeness of the data. For example, the model uses observed driver handheld device use as a surrogate for driver distraction. While the use of a handheld device certainly plays a role, it is not the only factor impacting the likelihood of distraction while operating a vehicle.

Finding a suitable measure for some factors was challenging and sometimes not available. In particular, measures of distracted driving, motorcycle helmet use, and speeding were difficult to obtain in a consistent way.

The models generated by this study provide a resource to study the impact of year to year changes in factors known to impact fatalities among passenger vehicle occupants, motorcycle riders and pedestrians.

Limitations

An important limitation of the current study is availability of direct measures to characterize important known risk factors including motorcycle helmet use, distraction, drunk driving and speeding.

In addition, in order to understand any relationship, the measure or a proxy must exist for each state and year. Forecasting the impact of factors that are not yet measurable is also not possible. For example, forecasting the impact of the newest emerging technologies is challenging because limited data exist.

The model examines the relationship of changes in factors with changes in fatality counts. Due to the quasi-experimental design, cause and effect cannot be inferred from the modeled relationships.

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APPENDIX A: MEASURED KEY FACTORS TESTED AS EXPLANATORY VARIABLES IN THE MODELS

CATEGORY	VARIABLE	SOURCE
Weather	Annual Precipitation	National Oceanic and Atmospheric Administration
	Annual Average Temperature	National Oceanic and Atmospheric Administration
Urban/Rural	Urban VMT (million) per Capita	Federal Highway Administration (FHWA)
	VMT in Urban Areas	FHWA
	Urban VMT/Total VMT	FHWA
	VMT in Rural Areas	FHWA
	Rural VMT per Capita	FHWA
Social	Education Level: High School and Higher	United States Census (US Census)
	Police per Capita	US Census
Policies/Laws	Alcohol Policy	Governors Highway Safety Association
	GDL - strength of policy	Insurance Institute for Highway Safety (IIHS); strength based on [9]
	Universal Motorcycle Helmet Law	IIHS
Regulations	FMUSS 214 (side impact protection) implemented	NHTSA
	% of registered vehicles with ESC	R.L. Polk U.S. Vehicle registrations
Economy	Mean Travel Time to Work	US Census
	Gross Domestic Product	Bureau of Economic Analyses

CATEGORY	VARIABLE	SOURCE
	Gas Price per Gallon	Energy Information Administration (EIA)
	Poverty	US Census
	Employment Rate for People 65	US Census
	Population without Health Insurance (%)	US Census
	Average Gas Price per BTU	EIA
	Household Income	US Census
	Employment Rate	US Census
	No Health Insurance	US Census
Exposure	VMT	FHWA (Highway Statistics: 5.4.1. Vehicle-miles of travel, by functional system)
	Total Population	US Census
	Average Driving Minute per Capita per Day	American Time Use Survey
	Number of vehicles	R.L. Polk U.S. Vehicle registrations
	% Who Use Vehicle to Work (Alone)	US Census
	% Who Walk to Work	US Census
	Average Walking Minute per Capita per Day	American Time Use Survey
	Population Density	US Census
	Average Cycling Minute per Capita per Day	American Time Use Survey
	Average Driving Minute per Day for Driver 65	American Time Use Survey
	Total VMT (million) per Capita	FHWA (Highway Statistics: 5.4.1. Vehicle-miles of travel, by functional system)
Demographics	Population age 65 and over	US Census
	Race White%	US Census
	Male Ratio	US Census
	Median age of population	US Census
Car Safety	ESC % of Vehicles on Road	R.L. Polk U.S. Vehicle registrations
	Average IIHS Score	R.L. Polk U.S. Vehicle registrations/IIHS crashworthiness testing
	% of Vehicles with Electronic Stability Control	R.L. Polk U.S. Vehicle registrations
	Vehicle Age 90 Percentile	R.L. Polk U.S. Vehicle registrations
	Average NCAP Score	R.L. Polk U.S. Vehicle registrations/New Car Assessment Program
	Percent of Old Vehicles on Road	R.L. Polk U.S. Vehicle registrations
	Percent of New Vehicles on Road	R.L. Polk U.S. Vehicle registrations
	Average Vehicle Age	R.L. Polk U.S. Vehicle registrations
	Vehicle Age 50 Percentile	R.L. Polk U.S. Vehicle registrations
	Vehicle Age 10 Percentile	R.L. Polk U.S. Vehicle registrations
	Vehicle Age 25 Percentile	R.L. Polk U.S. Vehicle registrations
	Vehicle Age 75 Percentile	R.L. Polk U.S. Vehicle registrations
Vehicle Mass Disparity	Difference of 10th percentile and 90th percentile of Mass	R.L. Polk U.S. Vehicle registrations/NHTSA Safecar.com
	% of Vehicles Below the Bottom 10%	R.L. Polk U.S. Vehicle registrations/NHTSA Safecar.com

CATEGORY	VARIABLE	SOURCE
	National Mass	
	% of Vehicles Above the Top 10% National Mass	R.L. Polk U.S. Vehicle registrations/NHTSA Safecar.com
	Average Mass	R.L. Polk U.S. Vehicle registrations/NHTSA Safecar.com
	Standard Deviation of the Mass of Vehicles on Road	R.L. Polk U.S. Vehicle registrations/NHTSA Safecar.com
	Total % of Vehicles above and below the top 10% and bottom 10% National Mass	R.L. Polk U.S. Vehicle registrations/NHTSA Safecar.com
Belt Use	Self Report Rarely Belted %	Behavioral Risk Factor Surveillance System (BRFSS)
	Self Report NOT Always Belted %	BRFSS
	Self Report Always Belted % for Age 65	BRFSS
	Self Report Always Belted %	BRFSS
	Self Report Rarely Belted % for Age 20-	BRFSS
	Self Report Always Belted % for Age 20-	BRFSS
	Self Report Rarely Belted % for Age 65	BRFSS
	Observed Belted Rate	NOPUS
Alcohol/Drugs	Opioid Related Fatalities	Multiple Cause of Death File, Centers for Disease Control
	Beer Consumption (gallons of ethanol/capita)	National Institute of Alcohol Abuse and Addiction (NIAAA)
	All Beverage Consumption(gallons of ethanol/capita)	NIAAA
	Spirit Consumption(gallons of ethanol/capita)	NIAAA
	Wine Consumption(gallons of ethanol/capita)	NIAAA
	% who Report Binge drinking	BRFSS
	% Self Report Never Drunk Driving	BRFSS
	% Self Report Drunk Driving in Past 30 Days	BRFSS
	Self Report Binge Drinking in Past 30 Days % for Age 65	BRFSS
	Self Report Binge Drinking in Past 30 Days % for Age 20-	BRFSS
Distraction	Phone Subscribers per Capita	FCC (Voice Telephone Services Report) Additional Data
	Phone Subscribers	FCC (Voice Telephone Services Report) Additional Data
	Observed Driver Hand-held Device Use while driving	NOPUS

ANALYSIS OF SERIOUS INJURY IN CAR TO CAR ACCIDENTS TO IMPROVE OF CRASH TEST PROTOCOLS IN KNCAP

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ABSTRACT
All over the world, there are many institutional programs used to enhance the safety of vehicles. The NCAP is a program that assesses the safety of vehicles sold by manufacturers in order to provide consumers with information on vehicle safety and to induce them to produce vehicles with enough safety. In Korea, the KNCAP has been carried out continuously since 1999. However, the fatal rate from traffic accidents per 100,000 population in 2017 is 8.1, which is above the OECD average. Therefore, it is necessary to improve various systems, but it is also necessary to improve the crash assessment protocols reflecting the actual accident. The purpose of this paper is to improve the crash test protocols of KNCAP by analyzing the status of the serious injury in case of an accident in Korea. Accident data were used for the latest three years(2015-2017) in car to car accident of domestic insurers. Raw data shows that 9,399 cases occurred due to accidents involving more than MAIS3 + of occupants' injuries. Of these, 279 cases were analyzed. In the collision type, the full width impact was the largest at 68.5%, and the small overlap and moderate at 28.3%. The low severity with 0 failure depth was 2% and the center impact was 2%. Impact angle was 51.1% for co-linear, 33.3% for left oblique angle and 15.6% for right oblique angle. In case of overlap, moderate overlap was about 47.9% and small overlap was about 17.5%. In the case of full width, crash extent3 + was 80.6%, while moderate overlap and small overlap were 36.8% and 24.3%, respectively. The collision type and impact angle compared to other country.

1. Introduction

There are many systems used to enhance the safety of motor vehicles around the world. Among them, the new car assessment program which is not legally binding is the most effective system under which the safety of motor vehicles is improved voluntarily by the vehicle manufacturers. This system is being employed in countries such as USA, Europe, Japan, China, and Korea. Recently, it has been introduced in India, ASEAN and countries in South America. The motor vehicle safety assessment system tests and evaluates the safety of motor vehicles sold by manufacturers. The system also makes the information on the motor vehicle safety public to encourage manufacturers to make safer motor vehicles. Korea has implemented the KNCAP since 1999. However, the fatalities from traffic accidents in every 100,000 people in 2017 years is 8.1, which is still higher than that of OECD average. The safety of motor vehicles has been improved, but more effective measures to reduce casualties shall be devised. For example, some safety devices may not function as intended under the accident conditions other than the test conditions. It is necessary to reflect the accident conditions in real world on the test methods. Internationally the traffic accidents pattern has been reflected on the test methods.
Euro-NCAP will replace the existing offset deformable barrier frontal impact method (40% Overlap) with a ca-to-car test method(a moving barrier, 50% overlap) for moderate overlap assessment under Roadmap 2020. In NCAP US NHTSA also announced the introduction of a car-to-car frontal oblique test using OMDB (Oblique Moving Deformable Barrier) based on NHTSA's 2015 RFC (Request for

Comments). However, in the Korean NCAP unlike those in Europe and the United States researches for the specific assessment details, protocols, and timeline have not been carried out yet for car-to-car collisions. The current domestic vehicle safety assessment is carried out under the test conditions simulating vehicle-to-fixed objects collisions and vehicle-to-pedestrian collisions among real world accidents.

Since the introduction of KNCAP the safety of vehicles in the domestic market has been continuously improved so that vehicles with high safety ratings have the effect of reducing the injury severities and fatalities. However, it is suspected that the safety performance may not be not fully realized due to the failure of some safety devices in the real accident conditions other than the assessment conditions, These discrepancies between assessment ratings and real world performances are posing a potential threat to the credibility of the safety ratings.

Therefore, it is necessary to take a careful consideration and improvement measures for vehicle safety in case of car-to-car accidents with high frequency in addition to car-to-pedestrians accidents and single vehicle accidents among real world vehicle accidents. In particular, considering the fact that car-to-car accidents are more frequent than single vehicle accidents from casualties' point of view among the victims of traffic accidents, it is necessary to investigate that the occupant protection in car-to-car accidents is equivalent to that in single vehicle accidents through the current assessment program. In this study, based on the analysis of the main accident type and injury characteristics of fatalities and severe injuries excerpted from vehicle accidents database, the improvement of motor vehicle assessment program will be proposed through feasibility study on car-to-car crash tests.

2. Contents and Methods of Investigation

For the in-depth analysis of the injury characteristics of severely injured occupants from car-to-car accidents, the injury characteristics were analyzed based on accident data from insurance companies database between from 2015 and 2017(3 years) met the following conditions. Among frontal collisions and side impacts involving only two vehicles were selected and the ones with more than two vehicles involved were excluded. In the cases investigated, the accidents resulted in fatal or injured occupants with AIS 3 or higher, who had fastened their safety belts at the time of accidents. In addition, damage on vehicles due to collision has to be identifiable in the accidents involving only passenger vehicles. Analysis data were in the following Table 1.

Table 1. Overview of Analysis Data

Category	Item	Explanatory Note
Scope	·Collision Type	·Frontal collision
	·Occupant	·Severely Injured Occupants with AIS 3 or higher
	·Vehicle Classification	·Passenger vehicle-to-Passenger vehicle
Period	·Reported Period	·1. 1. 2015 ~ 31. 12. 2017
Contents	·Analysis of Frequent Accident Types → Vehicle Deformation → Collision Angle and Degree of Overlap	· 279 cases in Frontal collision
	·Characteristics of Severely Injured Occupants → Distribution of Severe Injury Areas → Injury Types in Severe Injury Areas	· 311 severely injured occupants in frontal collision

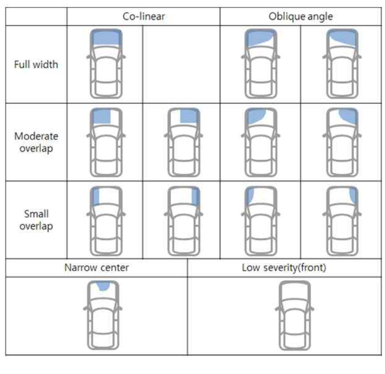

Figure 1. Collision Deformation Classification

The types of damage and the angles of collisions were classified by the Collision Deformation Classification (CDC) as the Figure 1, and the types of collisions and the angles of collisions were categorized based on detailed damaged areas and extent of damage.

The types of damage from frontal collision were classified into 5 types as Figure 2. A full frontal collision case is the case when both left and right side member structures, including the center, of a vehicle were destroyed. A moderate overlap frontal collision case is the case when either left or right

side member of a vehicle was damaged and also the center of a vehicle was damaged. A small overlap frontal collision case is the case when only either left or right side member of a vehicle was damaged, but the center of a vehicle was not damaged. A narrow center frontal collision case is the case when both left and right side member structures of a vehicle were not destroyed, but the center of a vehicle was destroyed. A frontal collision case with low severity is the case where the extent of damage is zero regardless of the location of damage.
The degree of overlap in a partial frontal collision was defined by the step of 20% overlap after the front part of a damaged vehicle was divided into 5 parts vertically and laterally. The degree of overlap in the partial frontal collision was set as follows according to the point of the damaged part.

20% Overlap : point 2~3 or 4~5 damaged
40% Overlap : point 1~3, 2~4, 3~5 or 4~6 damaged
60% Overlap : point 1~4 or 3~6 damaged

the degree of small overlap was defined as follows.
10% Overlap: only point 1 or 6 damaged
20% Overlap: only point 1~2 or 5~6 damaged

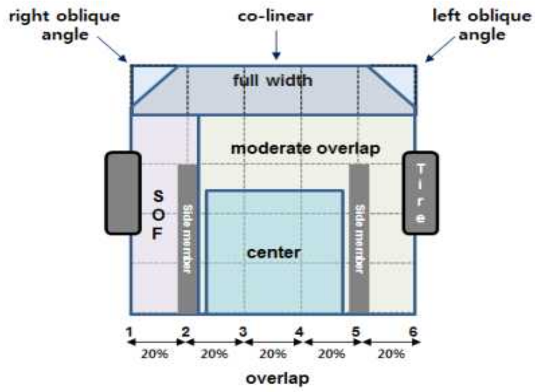

Figure 2. Types of Frontal Collision and Definition of Overlap

The injury characteristics analysis of severely injured occupants was carried out by the gender and occupied seat of an occupant according to the type of deformation, collision angle and degree of overlap of an accident vehicle as follows. The type of deformation, collision angle and degree of overlap was examined according to the criteria described previously. During the analysis, severely injured occupants resulted from a narrow center frontal collision and a frontal collision case with low severity were excluded from the analysis. For injury area analysis, multiple injuries in various areas of single severely injured occupant were repeatedly counted in consideration of multiple compound injuries. For example, if one severely injured occupant sustained two injuries in the head, two injuries were counted as two.

3. Results of Analysis

3-1. Analysis of Deformation Characteristics of Accident Vehicles with High Frequency and Severely Injured Occupants

The type of full frontal damage(Full width) accounted for 68.5% and the type of partial frontal damage(Moderate overlap + Small overlap) accounted for 28.3% as Table 2. In the type of partial frontal damage, a similar share was observed between two sub categories.

Table 2. Types of Deformation in case of Frontal Collisions with High Frequency (unit: No. of vehicles, %)

Types of Deformation		Frequency(%)
Full Frontal (Full width)		191 (68.5)
Partial Frontal	Moderate overlap	38 (13.6)
	Small overlap	41 (14.7)
Narrow Center Frontal Collision		4 (1.4)
Frontal Collision with Low Severity		5 (1.8)
Total		279 (100.0)

In terms of collision angles, as Table 3, the type of frontal collision in the perpendicular direction accounted for 51%, the type of frontal collisions in the left oblique direction accounted for 33% and the type of frontal collisions in the right oblique direction accounted for 16%.

Out of frontal collisions in the perpendicular direction, the type of full frontal collisions accounted for 64.5%, the type of partial frontal collisions accounted for 15.2%, and the type of small overlap frontal collisions accounted for 20.2%. For the type of frontal collisions in the left oblique direction, the type of full frontal collisions accounted for 78.9%, the type of partial frontal collisions accounted for 12.2%, and the type of small overlap frontal collisions accounted for 8.9%. For the type of frontal collisions in the right oblique direction, the type of full frontal collisions accounted for 73.8%, the type of partial frontal collisions accounted for 14.3%, and the type of small overlap frontal collisions accounted for 11.9%.

Table 3. Collision Angles in case of Frontal Collisions with High Frequency (unit: No. of vehicles, %)

Collision Angle	Deformation Type	Damage Area	Frequency(%)	Total
Co-liner Direction	Full width	Full with	89(64.5)	138 (51.1)
	Moderate	Left side	14(10.1)	
		Right side	7(5.1)	
	Small overlap	Left side	14(10.1)	
		Right side	14(10.1)	
Sum			138(100.0)	
Left oblique Direction	Full width	Left side	71(78.9)	90 (33.3)
	Moderate	Left side	11(12.2)	
	Small overlap	Left side	8(8.9)	
Sum			90(100.0)	
Right oblique Direction	Full width	Right side	31(73.8)	42 (15.6)
	Moderate	Right side	6(14.3)	
	Small overlap	Right side	5(11.9)	
Sum			42(100.0)	
Total				270(100.0)

Note) Total No. is not included the Narrow center and Low severity cases

As comparison of the degrees of overlap in partial frontal collisions shown in the Table 4, the average degree of overlap in the partial frontal collisions(moderate overlap) was 47.9%, and the portions of 40% overlap and 60% overlap were similar to each other. The average degree of in the partial frontal collisions(small overlap) was 17.5%, and 20% overlap accounted for the largest portion of 75.6%.

Table 4. Degree of Overlap in case of Partial Frontal Collisions with High Frequency (unit: No. of vehicles, %)

Degree of Overlap		Frequency(%)	Average Degree of Overlap
Moderate overlap	20% overlap	3(7.9)	47.9%
	40% overlap	17(44.7)	
	60% overlap	18(47.4)	
	Sum	38(100.0)	
Small overlap	10% overlap	10(24.4)	17.5%
	20% overlap	31(75.6)	
	Sum	41(100.0)	

Table 5. shows the results of comparison and analysis of the extent of damage according to the types of damage. Most full frontal collisions resulted in Extent of Damage 3 or higher, and most partial frontal collisions resulted in Extent of Damage 3 or less. In case of full frontal collisions, Extent of Damage 3 or higher accounted for 80.6%, while in case of partial frontal collisions Extent of Damage 3 or less accounted for the majority.

Table 5. Types of Deformation in case of Frontal Collisions with High Frequency(units : No. of vehicles, %)

Types of Deformation		Extent of Damage					Total
		1	2	3	4	5	
Full width		7 (3.7)	30 (15.7)	82 (42.9)	66 (34.6)	6 (3.1)	191 (100)
Partial	Moderate overlap	12 (31.6)	12 (31.6)	10 (26.3)	3 (7.9)	1 (2.6)	38 (100)
	Small overlap	20 (48.8)	11 (26.8)	5 (12.2)	5 (12.2)	0 (0)	41 (100)
Narrow center		0 (0)	3 (75.0)	1 (25.0)	0 (0)	0 (0)	4 (100)

Note) frontal collision with low severity : EXTENT 0 = 5 units

3-2 Injury Analysis of Severely Injured Occupants

The analysis of distribution of severely injured occupants according to the gender and seat of occupant showed that the majority of male were drivers and the majority of female were passengers. In the case of severely injured male occupants, 74% of occupants in the driver's seat and 14% in the passenger seats account for 91.7% of the occupants in the first row seats (driver's seat + passenger's seat). In the case of severely injured female occupants, 78.2% of severely injured female occupants were seated in the first row seat (driver's seat + passenger's seat), but the occupancy rate of severely injured female occupants in the second row seat (18.3%) was higher than that of the male. (See the Table 6.)

Table 6. Distribution of Severely Injured Occupants according to the Seat/Gender in case of Frontal Collisions with High Frequency(units : No. of injuries, %)

Gender	1st row Seat		2nd row Seat			Total
	Driver'	Passenger'	behind Driver	Center	behind Passenger	
Male	125 (74.0)	30 (17.8)	1 (0.6)	1 (0.6)	10 (5.9)	169 (100.0)
Female	63 (44.4)	48 (33.8)	10 (7.0)	1 (0.7)	15 (10.6)	142 (100.0)
Total	188 (60.5)	78 (25.1)	11 (3.5)	2 (0.6)	25 (8.0)	311 (100.0)

Table 7. shows the analysis of distribution of severely injured occupants according to the age of occupant. Severely injured adult occupants were drivers who accounted for 76.9%. Severely injured

adult female drivers accounted for 50.9%, while severely injured adult female passengers accounted for 46.6%. There is little difference. For elderly people, the majority of injured occupants were male drivers, while the majority of old female occupants were seated in the passenger seat in the 1st and 2nd rows. For elderly female occupants, passengers next to the driver accounted for 31.8%. Female occupants in the passenger seat in the 1st and 2nd rows accounted for 40.9%.

Table 7. Distribution of Severely Injured Occupants according to the Seat/Age of Occupant in case of Frontal Collisions with High Frequency(units : No. of injuries, %)

Age		1st row Seat		2nd row Seat			Total
		Driver'	Passenger'	behind Driver	Center	behind Passenger‘	
Male	Child	0 (0.0)	1 (33.3)	0 (0.0)	0 (0.0)	2 (66.7)	3 (100.0)
	Adult	110 (76.9)	22 (15.4)	1 (0.7)	1 (0.7)	7 (4.9)	143 (100.0)
	Elderly	15 (65.2)	7 (30.4)	0 (0.0)	0 (0.0)	1 (4.3)	23 (100.0)
Fema le	Child	0 (0.0)	1 (25.0)	1 (25.0)	1 (25.0)	1 (25.0)	4 (100.0)
	Adult	59 (50.9)	40 (34.5)	5 (4.3)	0 (0.0)	9 (7.8)	116 (100.0)
	Elderly	4 (18.2)	7 (31.8)	4 (18.2)	0 (0.0)	5 (22.7)	22 (100.0)
Total		188 (60.5)	78 (25.1)	11 (3.5)	2 (0.6)	25 (8.0)	311 (100.0)

Table 8. shows the analysis of distribution of severely injured occupants according to types of deformation in frontal collisions. In case of a full frontal collision, chest injuries were most frequent, followed by low extremity injuries and head injuries. In case of a moderate frontal collision, low extremity injuries were most frequent, followed by chest injuries and upper extremity injuries. In case of a small overlap frontal collision, upper extremity injuries were most frequent, follwed by low extremity injuries and chest injuries. As the area of the damaged part if an accident vehicle changes, the behavior of occupants may also change. Due to the different behavior frequently injured areas in occupants shows different tendency. The chest injuries became less and less frequent from full frontal collision to partial frontal collision, which is considered to be correlated with the reduction in damaged area. In case of upper/lower extremities, the rate of injury increased in a full frontal collision compared with a partial frontal collision because the safety belt could not effectively restrain an occupant due to yawing in a frontal collision.

Table 8. Severely Injured Area according to Types of Deformation in case of Frontal Collisions with High Frequency(units : No. of injuries, %)

Deformation Type	head	neck	back-spine	chest	abdomin al	upper extremit y	lower extremit y	full body	Total
Full width	43 (14.4)	39 (13.1)	5 (1.7)	115 (38.6)	2 (0.7)	30 (10.1)	63 (21.1)	1 (0.3)	298 (100.0)
Moderate overlap	6 (8.8)	8 (11.8)	0 (0.0)	19 (27.9)	0 (0.0)	11 (16.2)	22 (32.4)	2 (2.9)	68 (100.0)
Small overlap	4 (7.0)	10 (17.5)	2 (3.5)	11 (19.3)	0 (0.0)	17 (29.8)	13 (22.8)	0 (0.0)	57 (100.0)

The analysis of distribution of severely injured area of occupants according to the collision angle in frontal collisions shows that in case of a full frontal collision, the differences among the shares of

injured areas were little regardless of collision angles, while the shares of injured areas tend to differ greatly depending on collision angles in case of a partial frontal collision as Table 9.
In case of a moderate overlap frontal collision, lower extremity injuries in frontal collisions in the left oblique direction decreased by 12% compared with that in frontal collisions in the perpendicular direction; chest injuries increased by 13%; head injuries increased by 8%.
In case of a small overlap frontal collision, lower extremity injuries in frontal collisions in the left oblique direction decreased by 11% compared with that in frontal collisions in the perpendicular direction; chest injuries increased by 10%; head injuries increased by 5%.

Table 9. Distribution of Severely Injured Area of Occupants according to the Collision Angle in case of Frontal Collisions with High Frequency(units : No. of injuries, %)

Collision Angle		head	neck	back-spine	chest	abdominal	upper extremity	lower extremity	full body	Total
Full width	perpendicular	22 (15.9)	17 (12.3)	1 (0.7)	49 (35.5)	0 (0.0)	15 (10.9)	33 (23.9)	1 (0.7)	138 (100.0)
	oblique	21 (13.1)	22 (13.8)	4 (2.5)	66 (41.3)	2 (1.3)	15 (9.4)	30 (18.8)	0 (0.0)	160 (100.0)
Moderate overlap	perpendicular	2 (5.4)	5 (13.5)	0 (0.0)	8 (21.6)	0 (0.0)	6 (16.2)	14 (37.8)	2 (5.4)	37 (100.0)
	oblique	4 (12.9)	3 (9.7)	0 (0.0)	11 (35.5)	0 (0.0)	5 (16.1)	8 (25.8)	0 (0.0)	31 (100.0)
Small overlap	perpendicular	2 (5.3)	7 (18.4)	1 (2.6)	6 (15.8)	0 (0.0)	11 (28.9)	11 (28.9)	0 (0.0)	38 (100.0)
	oblique	2 (10.5)	3 (15.8)	1 (5.3)	5 (26.3)	0 (0.0)	6 (31.6)	2 (10.5)	0 (0.0)	19 (100.0)

The analysis of distribution of severely injured area of occupants according to the degree of overlap in frontal collisions shows that upper/lower extremity injuries increased as the degree of overlap decreased.(See the Table 10) In case of a moderate overlap frontal collision, neck injuries decreased and upper extremity injuries increased from 6.3% to 29.0% as the degree of overlap decreased. In case of a small overlap frontal collision, neck injuries decreased from 22% to 6% and lower extremity injuries increased from 12% to 50% as the degree of overlap decreased.

Table 10. Distribution of severely Injured Area of Occupants according to the Degree of Overlap in case of Frontal Collisions with High Frequency(units : No. of injuries, %)

Degree of Overlap		head	neck	back-spine	chest	abdominal	upper extremity	lower extremity	full body	Total
Moderate overlap	20%	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	5 (100.0)	0 (0.0)	5 (100.0)
	40%	4 (12.9)	1 (3.2)	0 (0.0)	9 (29.0)	0 (0.0)	9 (29.0)	8 (25.8)	0 (0.0)	31 (100.0)
	60%	2 (6.3)	7 (21.9)	0 (0.0)	10 (31.3)	0 (0.0)	2 (6.3)	9 (28.1)	2 (6.3)	32 (100.0)
Small overlap	10%	1 (6.3)	1 (6.3)	0 (0.0)	2 (12.5)	0 (0.0)	4 (25.0)	8 (50.0)	0 (0.0)	16 (100.0)
	20%	3 (7.3)	9 (22.0)	2 (4.9)	9 (22.0)	0 (0.0)	13 (31.7)	5 (12.2)	0 (0.0)	41 (100.0)

As Table 11, the analysis of distribution of severely injured area of occupants according to the seat/gender in frontal collisions shows that chest injuries were most frequent in the occupants in the 1st row seats while head injuries were most frequent in the occupants in the 2nd row seats. In case of drivers, the distribution of severely injured areas in male and female drivers were similar to each other. Chest injuries were most frequent, followed by lower extremity injuries and neck injuries. Head injuries were least frequent. For male drivers, chest injuries(37.4%) were most frequent, followed by lower extremity injuries(23.6%) and neck injuries(17.1%). Head injuries(13.0%) were least frequent. For female drivers, chest injuries(39.3%) were most frequent, followed by lower extremity injuries(19.6%) and neck injuries(14.3%). Head injuries(12.5%) were least frequent. In case of passengers next to drivers, chest injuries were most frequent in male and female passengers. For male passengers, head injuries were the next most frequent, while for female passengers, lower extremity injuries were the next most frequent. For male passengers, chest injuries(46.5%) were most frequent, followed by head injuries(18.2%) and upper/lower extremity injuries(15.2). For female passengers, chest injuries(45%) were most frequent, followed by lower extremity injuries(24%), upper extremity injuries(21%) and head injuries(4%). Head injuries were least frequent. In case of occupants in the 2nd row, head injuries were most frequent in male and female passengers. Chest injuries for male passengers and lower extremity injuries for female passengers were next highest. For male passengers, head(35.7%) and chest injuries(35.7%) were most frequent, followed by neck injuries(21.4%). For female passengers, head injuries(31.8%) and lower extremity injuries(31.8%) were most frequent, followed by chest injuries(22.7%).

Table 11. Distribution of Severely Injured Area of Occupants according to the Occupied Seat in case of Full Frontal Collisions(Full Width) with High Frequency(units : No. of injuries, %)

Occupied Seat		head	neck	back-spine	chest	abdominal	upper extremity	lower extremity	full body	Total
Male	Driver's	16 (13.0)	21 (17.1)	2 (1.6)	46 (37.4)	1 (0.8)	8 (6.5)	29 (23.6)	0 (0.0)	123 (100.0)
	Passenger's	6 (18.2)	2 (6.1)	0 (0.0)	15 (45.5)	0 (0.0)	5 (15.2)	5 (15.2)	0 (0.0)	33 (100.0)
	2nd Row	5 (35.7)	3 (21.4)	1 (7.1)	5 (35.7)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	14 (100.0)
Female	Driver's	7 (12.5)	8 (14.3)	1 (1.8)	22 (39.3)	0 (0.0)	6 (10.7)	11 (19.6)	1 (1.8)	56 (100.0)
	Passenger's	2 (4.3)	3 (6.4)	0 (0.0)	21 (44.7)	0 (0.0)	10 (21.3)	11 (23.4)	0 (0.0)	47 (100.0)
	2nd Row	7 (31.8)	2 (9.1)	0 (0.0)	5 (22.7)	1 (4.5)	0 (0.0)	7 (31.8)	0 (0.0)	22 (100.0)

Table 12. Distribution of Severely Injured Area of Occupants according to the Occupied Seat in case of Moderate Frontal Collisions with High Frequency (units : No. of injuries, %)

Occupied Seat		head	neck	back-spine	chest	abdominal	upper extremity	lower extremity	full body	Total
Male	Driver's	1 (3.6)	3 (10.7)	0 (0.0)	8 (28.6)	0 (0.0)	3 (10.7)	11 (39.3)	2 (7.1)	28 (100.0)
	Passenger's	1 (25.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	3 (75.0)	0 (0.0)	4 (100.0)
	2nd Row	0 (0.0)	0 (0.0)	0 (0.0)	1 (100.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	1 (100.0)
Female	Driver's	1 (9.1)	1 (9.1)	0 (0.0)	3 (27.3)	0 (0.0)	3 (27.3)	3 (27.3)	0 (0.0)	11 (100.0)
	Passenger's	1 (12.5)	2 (25.0)	0 (0.0)	2 (25.0)	0 (0.0)	2 (25.0)	1 (12.5)	0 (0.0)	8 (100.0)
	2nd Row	1 (8.3)	1 (8.3)	0 (0.0)	4 (33.3)	0 (0.0)	2 (16.7)	4 (33.3)	0 (0.0)	12 (100.0)

The distribution of severely injured area of occupants according to the seat/gender in moderate overlap frontal collisions was analyzed. For the occupants in the 1st row seats, lower extremity injuries for male passengers

and chest and upper extremity injuries for female passengers were most frequent. For female occupants in the 2nd row seats, chest injuries and lower extremity injuries were most frequent. (See the Table 12)
Lower extremity injuries were most frequent for both male and female drivers. For passengers next to drivers, lower extremity injuries were most frequent for male passengers and chest injuries, neck injuries and upper extremity injuries for female passengers were most frequent.
Table 13 shows that the analysis of distribution of severely injured area of occupants according to the seat/gender in small overlap frontal collisions were that upper extremity injuries for male passengers and lower extremity injuries for female passengers were most frequent among the occupants in the 1st row seats.
In case of male drivers, upper extremity injuries were most frequent, followed by lower extremity injuries and chest injuries. In case of female drivers, neck injuries were most frequent, followed by lower extremity injuries and chest injuries.

Table 13. Distribution of Severely Injured Area of Occupants according to the Occupied Seat in case of Small Overlap Frontal Collisions(Full Width) with High Frequency(units : No. of injuries, %)

Occupied Seat		head	neck	back-spine	chest	abdominal	upper extremity	lower extremity	full body	Total
Male	Driver's	2 (8.3)	3 (12.5)	1 (4.2)	4 (16.7)	0 (0.0)	9 (37.5)	5 (20.8)	0 (0.0)	24 (100.0)
	Passenger's	0 (0.0)	1 (25.0)	0 (0.0)	1 (25.0)	0 (0.0)	2 (50.0)	0 (0.0)	0 (0.0)	4 (100.0)
	2nd Row	0 (0.0)	0 (0.0)	0 (0.0)	2 (100.0)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	2 (100.0)
Female	Driver's	1 (6.3)	5 (31.3)	1 (6.3)	3 (18.8)	0 (0.0)	2 (12.5)	4 (25.0)	0 (0.0)	16 (100.0)
	Passenger's	0 (0.0)	1 (14.3)	0 (0.0)	1 (14.3)	0 (0.0)	1 (14.3)	4 (57.1)	0 (0.0)	7 (100.0)
	2nd Row	1 (33.3)	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	2 (66.7)	0 (0.0)	0 (0.0)	3 (100.0)

4. Discussion

It is time for a new car assessment program on which multiple vehicle accidents patterns are reflected to encourage manufacturer to improve vehicle safety through assessing vehicle safety in the car-to-car accidents which account for the majority among traffic accidents. It is expected that vehicle safety will be assessed in the event of car-to-car collisions under both Euro-NCAP and US NCAP. It is required to develop measures to strengthen the competitiveness of domestic automobile industry, in addition to enhance the domestic traffic safety index.
In consideration of the high fatality and severe injury rate in partial frontal collisions, the damage area/collision angle/speed of an assessed vehicle should be reviewed when developing a scenario for a new car assessment program on which the characteristics of real world vehicle accidents in Korea will be reflected. Specially the high severe injury rate in partial frontal collisions should be noted even though the extent of damage in a partial frontal collisions is lower than that of a full frontal collision. Because fatalities and severely injured occupants in the same occupied seat are quite different in the genders, various type of test dummies and occupied seats may be considered in a new car assessment program on which the characteristics of real world vehicle accidents in Korea will be reflected.
In addition, in consideration of major injured areas and injury types of severely injured occupants resulted from car-to-car accidents were chest fractures and upper/lower extremity fractures, It is deem to be necessary to establish the evaluation criteria to reduce these kinds of injuries in assessing impacts to the parts of a test dummy corresponding to the frequently injured areas of occupants. It is possible to minimize the discrepancy between the assessment and the actual accident injury reduction

effect by supplementing the additional parts in addition to the parts of a test dummy used in the current new car assessment program in consideration of the injury characteristics of severely injured occupants resulted from real world car-to-car accidents.

5. Conclusion

The following conclusions were drawn from the analysis of characteristics of the severely injured occupants based on the database of domestic insurance companies.
Partial frontal collisions and side impacts resulted in severely injured occupants even though the extent of damage was low. For partial frontal collisions, the type of 60% off-set collision co-linearly on the left(driver side) was most frequent. In this type of collisions male drivers and female passengers were severely injured with high frequency regardless of age. Chest injuries were most frequent in the severely injured occupants.
Based on the results of the analysis of the car-to-car accidents in Korea, it is necessary to further study the standardization of the collision assessment technology which the real world accidents patterns can be reflected in order to secure the collision safety additionally in the new car assessment program.

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AUTOMATIC IDENTIFICATION OF CRITICAL SCENARIOS IN A

PUBLIC DATASET OF 6000 KM OF PUBLIC-ROAD DRIVING

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ABSTRACT

An increasing number of driving tasks in vehicles is being taken over by automation as automated driving technology is developed. An important aspect in this development is the safety assessment of new functions and systems. Scenario-based assessment is a promising tool, but it relies heavily on the availability of realistic scenarios for generating test cases.

Traditional methods take analyses from in-depth accident databases as a starting point to describe accident scenarios. In TNO's StreetWise methodology, the list of critical scenarios resulting from accidentology is expanded with scenarios that are identified from normal every day driving dat. In this paper we describe a machine learning approach of automatic scenario identification in a dataset of public-road driving. The dataset together with the results will be made public to serve as a benchmark.

TNO will publish a dataset containing 6000 kilometers of driving on the public road, containing information on the ego vehicle CAN; the GPS position; information on the objects around the ego vehicle from radar and camera; and road lanes and lines. Furthermore, we propose a framework for automatic scenario extraction from real-world microscopic driving data, including measures of safety criticality.

Scenarios that are similar form a scenario class, currently we distinguish approximately 60 of such classes. Each instance of a scenario is described by a set of parameters that is specific for the scenario class. By analyzing large amounts of driving data, not only scenarios to fit in different classes are identified, but also the parameter values for each scenario instance are determined. This results in the frequency of occurrence of scenarios and the probability density function (PDF) for each of the scenario parameters. Metrics for safety criticality are defined based on time-to-collision, time-headway, post-encroachment time, etc. For each case, the safety criticality is evaluated based on the proposed metrics.

We have automatically identified two scenarios in the data: 1. Gap closing; 2. Cut-in of a vehicle in front of the ego vehicle. From the identified PDFs the nominal scenarios are identified as well as corner cases with parameter values

in the tail of the PDF. By changing parameter values within a realistic range around the corner cases, a check is made regarding their criticality.

The two scenarios that are identified describe only a small part of the total number of kilometers driven. However, the bottom up approach to scenario mining described here can be extended to more scenarios in a relatively straightforward way, with the goal of describing the entire dataset with scenarios.

Automatic scenario mining from driving data is an essential step towards safety validation of AD functionalities. TNO publishes a dataset with 6000 kilometers of public-road driving, for which we show that it is possible to identify critical scenarios, in addition to nominal scenarios, even if in these kind of studies critical situations are rare.

INTRODUCTION

Automated driving (AD) functions are considered an important tool for increasing road safety and comfort, reducing emissions and improving traffic flow. The increase in automation requires a different protocol for quality and performance assessment of vehicles than traditionally done [1][2][3]. For this, a scenario-based approach has been proposed [4][5]. The collection of scenarios used for defining test cases should represent and cover the entire range of real-world traffic situations that might be encountered by the AD system under test. In the TNO StreetWise methodology, scenarios are extracted from real-world microscopic traffic data, and are used to build a database suitable for testing and validation of automated driving functions [6]. The use of real-world scenarios for testing purposes requires accurate scenario extraction methods from driving data, to ensure representativeness of the scenario database. In order to facilitate a comparison between different scenario-mining methods, a public benchmark dataset would be a valuable tool.

Several public public-road driving datasets already exist. The Oxford robotcar dataset contains data of 100 repetitions of the same route in Oxford, UK [7]. The sensors that were used on the recording vehicle include multiple cameras, LIDAR and GPS, but no sensor fusion has been performed on the raw data. Hence, no object level data is available from this dataset. For the Next Generation Simulation (NGSIM) program[1], data was collected at several US highways with a network of synchronized digital video cameras, from which vehicle trajectory data was extracted. This provides a bird's eye view of specific portions of road. The Apollo obstacle trajectory prediction dataset[2] contains data collected with LIDAR, cameras and GPS. The data has been turned into features that can be used to train a Machine Learning algorithm on the provided labels on the intention of the other road users.

In this work we present a dataset of public-road driving for benchmarking scenario-mining algorithms. This dataset is available at www.tno.nl/streetwise. Unlike the previously mentioned public datasets, this dataset contains object-level data from an in-car perspective that can be directly used to identify scenarios in the data. As a first benchmark, we present the results of a scalable approach to scenario mining, based on fundamental building blocks describing the trajectories of all road users. Two scenarios are shown as example, 'gap closing' and 'cut in'. As scenario-mining algorithms are continuously improved, progress can be measured on this public dataset. Finally, we show how a scenario database of driving data can be used to assess the safety criticality of the scenarios found in the data.

METHOD

Real-world data logging

TNO recorded data from 20 different drivers between 25-60 years old, all of whom had their driving license for more than 5 years and are driving more than 5000 km per year. They drove together about 6000 km in mixed traffic, of which approximately half in manual mode and half in ACC mode. All driving was performed during the day time (from 8:30 to 17:00) under dry weather conditions.

A dedicated specially prepared vehicle (Toyota Prius) was used for the tests. The vehicle records information from the following sensors:

[1] https://data.transportation.gov/
[2] http://data.apollo.auto/

- Vehicle CAN (velocity / accelerations / yaw rate / steering wheel angle / wheel speeds)
- Mobileye camera (object / lane information)
- Continental-30x radar front centre, rear left, rear right
- U-blox GPS
- Ibeo LIDAR

The position and viewing angle of the sensors is depicted in Figure 1. Besides these sensors also an additional forward-facing camera was used to record reference footage. The LIDAR has not been used in the analysis of the data.

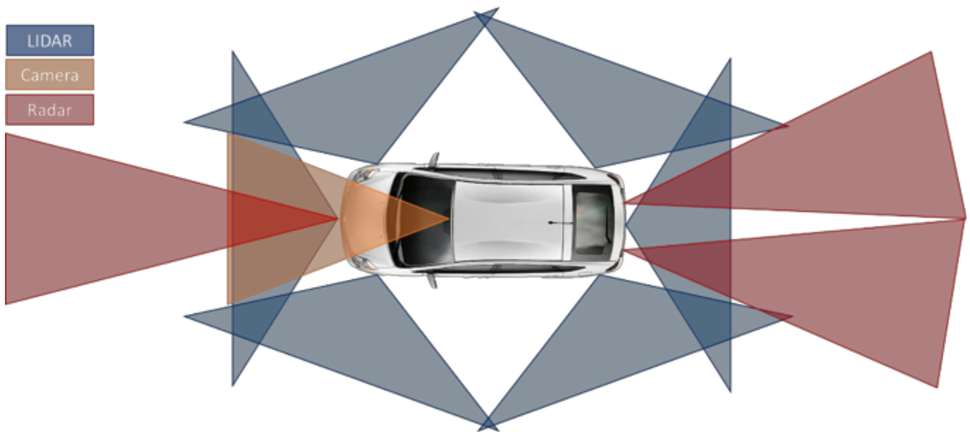

Figure 1: Field of view of the external sensors of the recording vehicle. Orange: front-looking MobilEye camera. Red: Continental-30x radar, front centre, rear left, rear right. Blue: Ibeo LIDAR.

Data pre-processing

The recorded data is converted to a uniform representation (the so-called world model) of the static and dynamic environment around the ego vehicle. In this dataset the static environment is only represented by the road markings of the ego lane. The lateral position of all road users is considered relative to these lanes. The output of the Mobileye camera is used for the road markings. This contains the type of lane marking and predicted position of the marking with certain confidence level.

The dynamic traffic is modelled with a multi-target tracker that has been developed by TNO [8]. The multi-target tracker uses the sensor output of the Mobileye camera and the 3 Continental radars (front center, rear left and rear right radar). The test vehicles were also equipped with Ibeo LIDARs, but those were not used. The multi-target tracker fuses the sensor data and provides the position and motion of detected objects. The targets are represented as points. The distance between the ego vehicle and a target in front of ego vehicle is the distance between target vehicle rear bumper center and ego vehicle front bumper center. For the distance between the ego vehicle and a target behind the ego vehicle the distance between target vehicle front bumper center and ego vehicle rear bumper center is used. For lateral position the center of the vehicle (both ego and target) is used as reference point.

The test drivers drove a fixed route in the region of Amersfoort in the Netherlands. The route has a length of approx. 46 km and takes about 50 minutes driving without delays. About 55% of the distance is highway, 40% is rural and the remaining 5% is urban area. About 55% of the route are multi-lane uni-directional roads. The route and driving direction are shown in Figure 2. Every test person drove the route 6 times, 3 times with ACC and 3 times without.

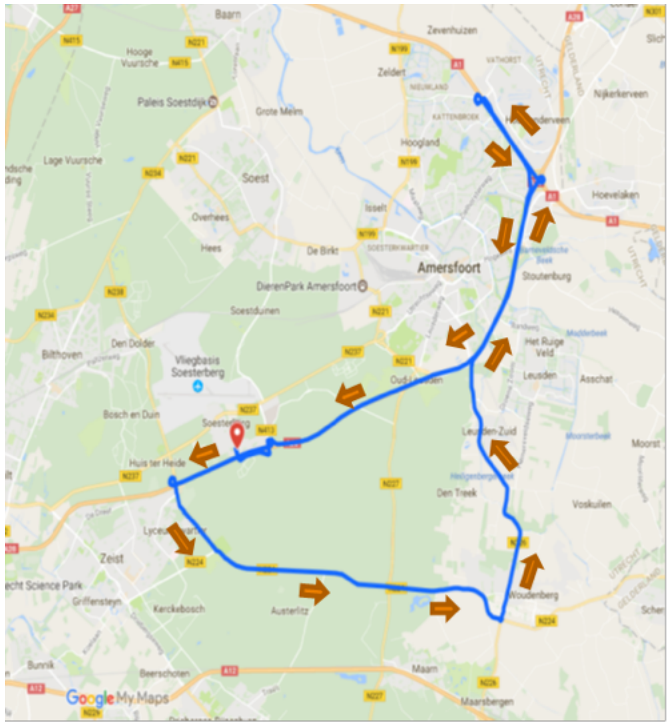

Figure 2: The route, including driving direction, that was driven by the test drivers.

Identification of scenarios

In the StreetWise methodology traffic is interpreted as a sequence of scenarios, meaning that every instance of the data is assigned to a scenario [6]. These scenarios need to be defined by a consensus among experts in order to make them as useful as possible for testing. In this work we focus on two relatively straightforward scenarios: one scenario that is centered on longitudinal interaction between two vehicles, and one centered on lateral interaction. The first scenario is the 'gap-closing' scenario. It consists of a target vehicle in front of the ego vehicle that is in the same lane as the ego and decelerates. This scenario ends when the distance between the two vehicles no longer decreases. The second scenario is the 'cut-in' scenario. In this scenario a target vehicle moves from an adjacent lane to the ego lane in front of the ego vehicle, such that the target becomes the lead vehicle of the ego vehicle. Figure 3 shows a graphical representation of the two scenarios.

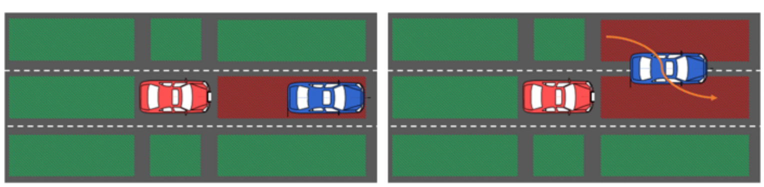

Figure 3: *Left*: Gap-closing scenario. *Right*: Cut-in scenario.

As described in [6], we define activities as building blocks and construct scenarios by combining activities of different road users. Activities can fall into two categories: longitudinal and lateral. Longitudinal activities can be either acceleration, cruising or deceleration. Lateral activities are defined with respect to the lane and can be either lane following, turn (or lane change) left or turn (or lane change) right. These 6 activities cover all the allowed movement of a vehicle on the road and are sufficient to describe any possible trajectory. The activities are identified in the data for the ego and all the targets that are detected around the ego. The trajectory of a road user is described by at least two (i.e. longitudinal and lateral) activities at all times.

Scenarios are found by combining activities with the relative position and speed of every target. We use template matching on a graphical network to efficiently find the scenarios in the dataset. In this bottom-up approach, given the right template to search for, any scenario can be detected straightforwardly without the need to write a separate algorithm for every scenario. The activity detection and scenario mining algorithms will be detailed in a forthcoming publication.

Identification of critical scenarios

For all scenarios the minimal set of parameters needed to describe the activities and the scenarios is stored. This includes a full description of the time evolution of every activity of the ego and every target, the relative positions of the targets with respect to the ego, the relative speeds of the targets with respect to the ego, and the absolute position of the ego. This set of parameters can be used to determine the safety criticality of the scenarios found in the data. Many possible safety indicators have been proposed [9][10]. As an example, we consider in this work the following safety criticality indicators:

- Start longitudinal distance [m]: the longitudinal distance between the ego and the target at the start of the scenario.
- Maximal deceleration during the scenario [m/s^2].
- Minimal Time-To-Collision (TTC) [s]: the time to collision is the time it takes for the rear vehicle to cover current longitudinal distance between rear and front vehicle, also taking into account the possible distance covered by front vehicle. The TTC is computed in the following way:
  TTC [s] = inter-vehicle-distance [m] / (rear vehicle velocity – front vehicle velocity) [m/s].
- Maximal lateral speed during the scenario [m/s].

RESULTS

We have applied the scenario identification algorithms to the 6000 km of public-road driving. In this section we describe the results and give an example of the analysis of criticality of a scenario based on the safety criticality indicators described in the previous section.

Braking in front

We have identified 1460 braking in front scenarios in the data. An example of the relevant signals for this scenario is shown in Figure 4. The target vehicle has initially a higher speed than the ego, before it starts decelerating. About 1 second after the longitudinal distance starts the decrease, the ego vehicle decelerates until the distance between the vehicles is 8 meters, at which point the target accelerates again.

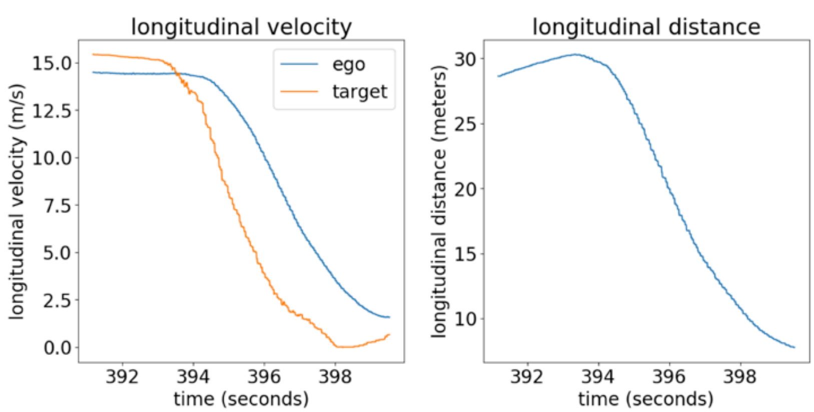

Figure 4: *Left*: Longitudinal speed as function of time for the ego and the target. *Right*: Inter-vehicle distance as function of time.

By comparing the safety criticality parameters of this scenario with the probability density functions (PDF) of these parameters constructed from all scenarios in the data, the relative safety criticality of this scenario can be assessed.

In Figure 5 the longitudinal distance at the start of the scenario, the maximal deceleration of the target and the minimal TTC are shown.

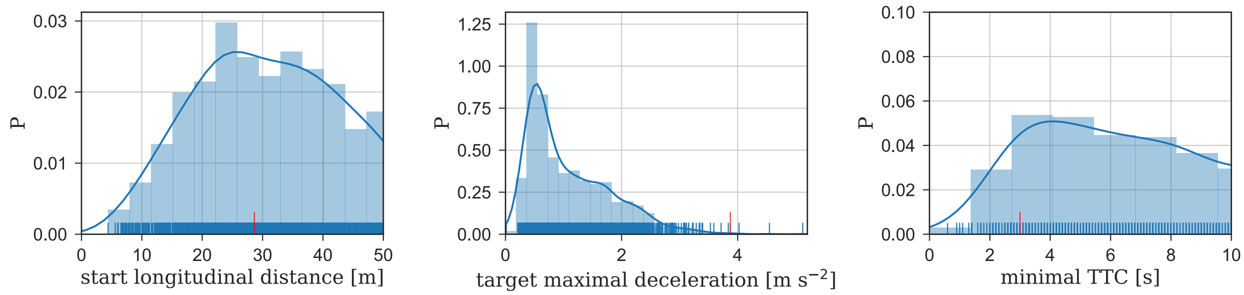

Figure 5: Probability densities of safety indicators for the braking-in-front scenario. Solid line is a univariate non-parametric fit of the histogram with Kernel Density Estimation using a Gaussian kernel. Vertical lines on the x-axis denote the data points. The red vertical line indicates the example shown in Figure 4. *Left*: Longitudinal distance at the start of the scenario. *Centre*: Maximal deceleration of the target during the scenario. *Right*: Minimal time to collision during the scenario.

The maximal deceleration of the target is among the highest found in the dataset. However, due to the relatively high inter-vehicle distance at the start of the scenario, this does not result in a safety critical scenario. This is reflected in the minimal TTC that is above 2 seconds. The drawback of only using the TTC for safety analysis is that it is not always defined, even in cases where the target might still be dangerously close to the ego [9]. This analysis shows that it is not sufficient to rely on a single parameter to judge the safety criticality of a scenario.

Cut in

We have identified 403 cut-ins in the dataset. An example of a cut-in scenario with the relevant signals is shown in Figure 6. The lateral speed of the target increases at the start of the scenario indicating the lane change. Although the longitudinal speed of the target is initially much lower than that of the ego, the target quickly accelerates and as a result the longitudinal distance is never less than 17 meters during the scenario.

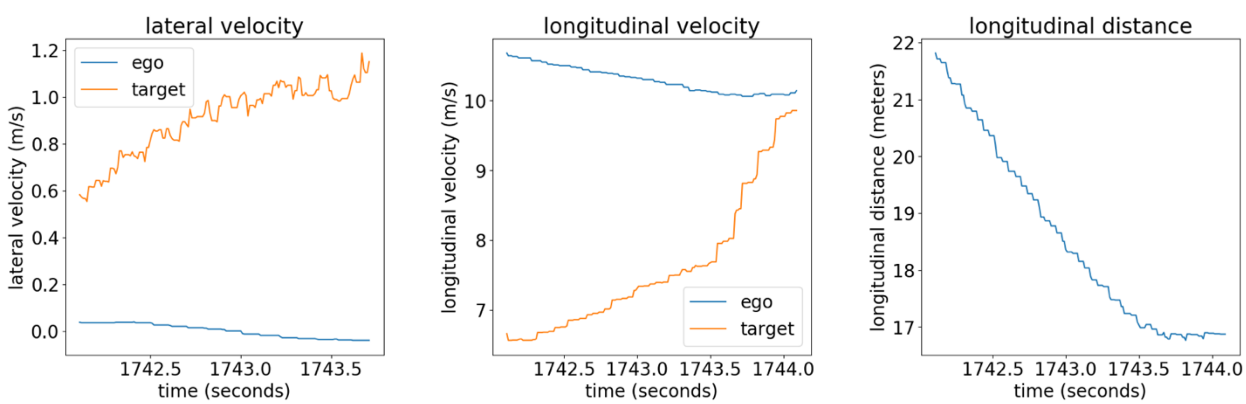

Figure 6: *Left*: Lateral speed as function of time for the ego and the target. *Centre*: Longitudinal speed for the ego and the target. *Right*: Inter-vehicle distance as function of time.

To determine the safety criticality of this example, in Figure 7 we show the PDFs of 3 safety indicators. These indicators show that even though the lateral speed of the target was relatively high and the longitudinal distance at the start of the scenario was below average, this example is not safety critical, as the minimal TTC of more than 5 seconds shows. However, as noted earlier, relying only on TTC for defining safety criticality has severe drawbacks.

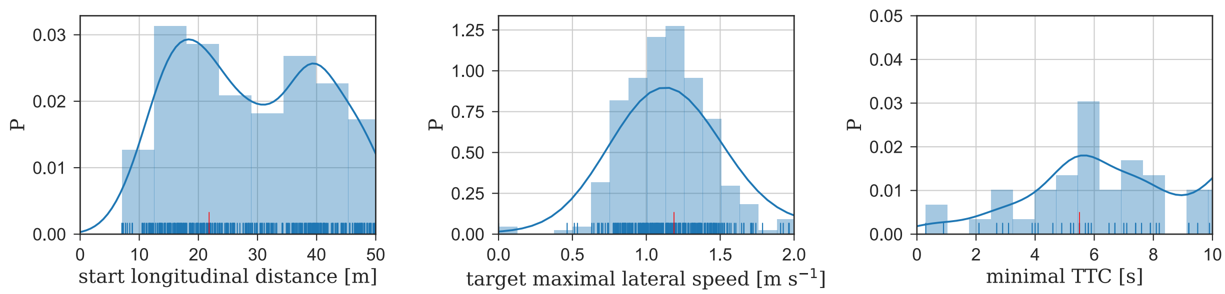

Figure 7: Probability densities of safety indicators for the cut-in scenario. Solid line is a univariate non-parametric fit of the histogram with Kernel Density Estimation using a Gaussian kernel. Vertical lines on the x-axis denote the data points. The red line indicates the example shown in Figure 6. *Left*: longitudinal distance at the start of the scenario. *Centre*: Maximal lateral speed of the target during the scenario. *Right*: Minimal TTC during the scenario.

CONCLUSIONS AND DISCUSSION

We have presented a dataset of driving on the public road that consists of 6000 kilometers of a mix of highway (55%), rural (50%) and urban (5%) driving and contains information on the ego vehicle CAN; the GPS position; information on the objects around the ego vehicle from radar and camera; and road lanes and lines. The dataset will be made publicly available at www.tno.nl/streetwise.

In addition, we have presented the results of a bottom-up approach to scenario mining in this dataset. By first detecting activities in the data that serve as building blocks, scenarios can be identified in the data in a scalable manner. With the input of experts about what a certain scenario entails, a template of the scenario can be defined that can immediately be used in the scenario mining algorithm to extend the scenario catalogue. The two scenarios described in this work only describe a very small portion of the data, but we expect to add more scenarios in the near future, working towards the goal of assigning every instance of data to at least one scenario.

Finally, we have presented a method for determining the safety criticality of scenarios based on the probability density functions of a set of safety indicators. By comparing where different safety indicators are in the distributions of all scenarios, the safety criticality of the scenario can be quantified. The dataset presented in this paper is too small for a thorough statistical analysis and does not contain any critical scenarios, we plan to extend the analysis with more data in the future.

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CHANGES IN CRASH PROTECTION WITH VEHICLE MODEL YEAR

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ABSTRACT

NASS 1993-2015 was queried for frequency of exposed vehicles with belted driver injuries separated by injury severity and vehicle model year. Vehicle model-years were aggregated by 3 model year groupings – 1985 -1994; 1995-2000; 2001-2015. These percentages of the crash exposed populations for the 3 groups were: 27%, 34% and 39%. The total exposed population was 27,347,705. The total and Mean AIS 3+ HARM for each model year grouping was calculated for each crash mode – frontal, near-side, far-side, rear and rollover. Changes in total AIS 3+ HARM distribution and Mean AIS 3+ HARM by crash mode and model year grouping were reported.

The largest source of AIS 3+ HARM to belted drivers in the 2001-2015 NASS population remains the frontal crash mode. Near-side and rollover injury rates have dramatically decreased in recent model years. Frontal and far-side crash mode injury rates have decreased slightly and rear has remained relatively constant, but at a low injury rate.

The data suggests that for light trucks, the near-side Mean AIS 3+ HARM has increased during the 2001-2015 model years. However, the level remains below that of passenger cars which have experienced dramatic reductions in near-side Mean AIS 3+ HARM during the same period.

BACKGROUND

The analysis to follow examines vehicle safety trends based on changes to the HARM that was present in groupings of motor vehicles from three successive time periods. The concept of HARM was introduced in a landmark paper by key NHTSA staff [Malliaris, 1982]. A frequent alternative to the use of HARM is to categorize all severe injuries greater than AIS 3 in a single group labeled AIS3+ injuries. An issue with this categorization is that the AIS 3+ population is overwhelmed by AIS 3 injuries and the AIS 4+ population is not given increased priority. Alternatively, the HARM weighting scheme is applied to injuries of different severity based on the average cost of the injury. This injury weighting system has the advantage of increasing the priority for preventing the most severe injuries.

The mean HARM is defined as the total HARM for a grouping divided by the exposure for that grouping. The mean HARM is a measure of the combined injury risk and has been widely used to conduct benefits analyses. The mean HARM is a weighted injury risk and is useful for determine how the safety has changed. HARM and mean HARM were used extensively at NHTSA and elsewhere in the 80's and 90's to assess priorities for safety systems. GM Australia used HARM calculations in designing the first air bag introduced in Australia and the Australian Ministry of Transport used HARM to establish frontal and side impact regulations [Fildes, 1992].

The analysis in this paper follows the methodology of an earlier analysis by Eigen [Eigen, 2007]. However, the Eigen analysis examined HARM to injured body regions and, therefore, considered all of the multiple injuries that were coded for each individual. The present analysis uses the Malliaris methodology and considers only the most severe injury to each occupant.

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In 2012, NHTSA stopped doing reconstructions for NASS/CDS included vehicles 10 years old and older at the time of the crash. For that reason, even though the vehicles would be stored in the dataset, the general area of damage (GAD) and principal direction of force (PDOF) were not computed for these vehicles. These components of the collision deformation classification (CDC) were used in this analysis to categorize cases into crash modes. Consequently some of the very oldest vehicles were excluded from the counts by crash mode for crashes occurring in 2012 and later.

Another limitation of this longitudinal HARM analysis is that it assumes that the mean crash severity has not changed with model year.

METHODS AND DATA SOURCES

The source for exposure and injury data was the NASS/CDS (National Automotive Sampling System/Crashworthiness Data System) years 1993 to 2015. NASS/CDS is a weighted estimate of tow-away crashes occurring in the United States. The NASS/CDS weighted data contains approximately 59 million drivers of passenger cars, SUV's, passenger vans or light trucks (pickups) who were exposed to crashes. NASS/CDS data were disaggregated by vehicle model year and crash mode. Since this study focused on the safety changes for belted drivers, only vehicles with belted drivers were included. The resulting exposed population of belted drivers including those with unknown injury was 27,347,705.

The resulting data permitted the assessment of changes in injury distributions and rates by model year, crash mode and body region for belted drivers. The front, side and rear crash mode categories excluded all rollovers. The rollover crash mode contains all rollovers including those with planar impacts as an earlier or later event.

The HARM calculations applies a weighting factor to each AIS 3+ injury in the database. The weighting factor is proportional to the cost of the occupant's most serious injury. In general, minor and moderate injuries (AIS 1 and 2) are high frequency, events that tend to cloud the analysis of serious injury reduction by safety systems. For this reason, AIS 1 and 2 injuries were excluded from the AIS 3+ HARM calculations. The AIS 3+ HARM, measured in equivalent fatalities, was based on NHTSA's data on average cost of injuries. The equivalent fatality measurement is obtained by normalizing the average cost of a given injury by the cost of a fatality. The average cost of each injury severity was obtained from a Table E-1 in the 1995-1997 NASS/CDS Summary [NHTSA 2001]. The injury cost values are: MAIS 3, $98,011; MAIS 4, $221,494; MAIS 5, $697,533; and MAIS 6, $822,328.

In order to examine how the HARM content has changed with model year, it is necessary to examine how the injury rate or some equivalent factor has changed. The rate of AIS 3+ injuries is a commonly used injury risk factor. For the 1985 to 2015 population of interest the distribution of AIS 3, 4, 5 and 6 was 74%, 18%, 8% and 2%, respectively. When HARM weights are applied, the distributions become: 40%, 22%, 29% and 9%. By applying HARM weighting, the influence of AIS 3 injuries is reduced and the more severe injuries are given added priority. The Mean AIS 3+ HARM per exposed occupant provides an injury rate similar to the AIS 3+ rate but with more priority on the AIS 4+ injuries.

The Mean HARM for each category of interest was calculated by dividing the HARM suffered by drivers by the number of drivers exposed to that category. The Mean HARM results were multiplied by 100 to simplify the presentation.

The total and mean AIS3+ HARM for each model year grouping was calculated for each crash mode – frontal, near-side, far-side rear and rollover. The data was further disaggregated by vehicle class – passenger cars (PC), sport utility vehicles (SUV), light trucks (LT) and minivans (MV). The distribution of belted drivers by vehicle class was: PC-66%; SUV-16%; LT-11% and MV-7%. Since the entire populations of LT, SUV and MV constituted about one third of the vehicle population and they were combined in a single group. Changes in total AIS 3+ HARM distribution and Mean HARM by crash mode, model year grouping and vehicle class were computed and reported.

RESULTS

Vehicle model-years were aggregated by 3 model year groupings – 1985-1994; 1995-2000; 2001-2015. The NASS/CDS was queried for all injuries by AIS including AIS 0 (no injury) and unknown injury. This total population was 27,347,699. The total AIS 3+ HARM for the three model year groupings were 27%, 34% and 39%. The total AIS 3+ HARM for each model year grouping was calculated for each crash mode – frontal, near-side, far-side, rear and rollover. Changes in total AIS 3+ HARM distribution and Mean AIS 3+ HARM by crash mode and model year grouping were reported.

Figure 1 shows the total AIs3+ HARM distribution by crash mode and how it has changed with the model year groupings. The percentages for each model year grouping add to 100%, consequently the Figure shows the distribution for each model year grouping but not the total content for that group.

The changes in Mean AIS 3+ HARM by Crash Mode and Model Year Groupings are displayed in Figure 2.

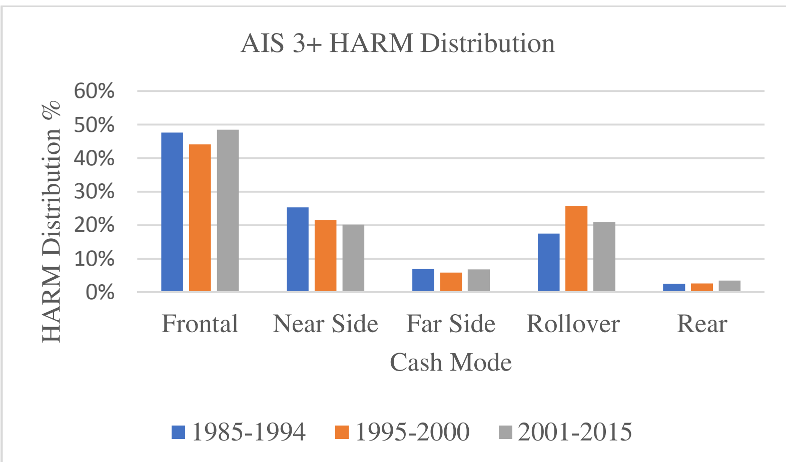

Figure 1. Distribution of Restrained Driver AIS 3+ HARM by Crash Mode and Vehicle Model Years

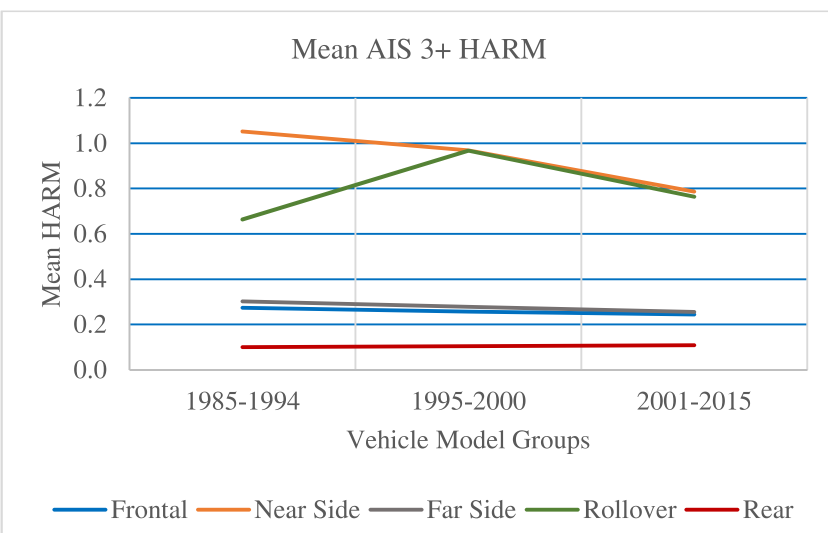

Figure 2. Distribution of Restrained Driver Mean AIS 3+ HARM by Crash Mode and Vehicle Model Years

Table 1 shows how the distribution AIS 3+ HARM has varied among vehicle types for the three vehicle model year groupings.

Table 1.
Distribution of Belted Drivers and AIS 3+ HARM by Vehicle Classes and Model Year Groups

	Pass Car		Lt Truck, SUV, Van	
Model Years	Drivers	HARM	Drivers	HARM
1985-1994	67.1%	71.7%	32.9%	28.3%
1995-2000	68.0%	71.1%	32.0%	28.9%
2001-2015	63.7%	67.2%	36.3%	32.8%

Table 2 shows how the distribution mean HARM has varied among vehicle types for the three vehicle model year groupings.

Table 2.
Belted Driver Mean AIS 3+ HARM by Crash Mode and Model Year Groups for Passenger Car and Light Truck, SUV and Van Groupings

Lt Truck, SUV, Van					
Model Year	**Frontal**	**Near Side**	**Far Side**	**Rollover**	**Rear**
1985-1994	0.275	0.413	0.241	0.445	0.065
1995-2000	0.242	0.407	0.245	0.720	0.026
2001-2015	0.208	0.749	0.192	0.701	0.050
Average	0.236	0.547	0.220	0.647	0.047
Pass Car					
Model Year	**Frontal**	**Near Side**	**Far Side**	**Rollover**	**Rear**
1985-1994	0.272	1.377	0.319	0.958	0.111
1995-2000	0.263	1.154	0.288	1.204	0.126
2001-2015	0.265	0.804	0.281	0.971	0.135
Average	0.266	1.081	0.294	1.058	0.126

DISCUSSION

Figure 1 shows that the largest source of AIS 3+ HARM to belted drivers in the 2001 and later NASS population remains the frontal crash mode. Figure 2 indicates that the reduction in Mean AIS 3+ HARM has been relatively small for frontal crashes. Table 2 shows that for frontal crashes, most of the reductions in Mean AIS 3+ HARM have been in vehicles other than passenger cars.

Figure 2 shows that near-side and rollover injury rates have dramatically decreased for recent vehicle model years. Frontal and far-side crash mode injury rates have decreased slightly and rear has remained relatively constant, but at a low injury rate.

Table 1 permits the comparison of belted driver exposure and total AIS 3+ HARM distributions by crash mode for the three model year groupings. Each row adds to 100%, so the extent of safety improvements cannot be determined from this table. It may be noted that passenger cars still comprise the largest fraction of vehicles in the NASS/CDS – 63.7% in the 2001-2015 model year grouping. They also account for 67.2% of the total AIS 3+ HARM.

Safety initiatives that may have influenced the side crash mode improvements include the IIHS side impact rating, the NHTSA FMVSS 214 upgrade, and widespread incorporation of air curtains. The changes to comply with standards may have been more extensive for cars than for light trucks. The reason for the increase in near-side Mean AIS 3+ HARM for the non-passenger car category cannot be explained from the data in this paper. However, the near-side Mean AIS 3+ HARM for the combined group of light truck, SUV and van was lower than the passenger car near-side Mean AIS 3+ HARM.

For rollovers, the large reduction in Mean AIS 3+ HARM occurred in both vehicle groupings. Safety initiatives that may have influenced rollover improvements include the roof strength rating by IIHS, FMVSS 216 upgrade, voluntary incorporation of air curtains that function in rollover and widespread introduction of electronic stability controls.

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HARMONIZED PRE-CRASH SCENARIOS FOR REACHING GLOBAL VISION ZERO

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ABSTRACT

Crash data are essential for the development and introduction of new of active safety systems. At first, the target population of a new system is evaluated to understand the situations in which the system shall become active. The respective crashes are then analyzed and requirements towards the system development are derived. Finally, an effectiveness evaluation validates the potential benefit of the system in real-world crashes.

Multiple in-depth databases are available for different regions of the world. They are generally based on different crash collection and data coding methods. Thus, comparable data analysis is hard to achieve. This is however necessary for a systematic worldwide approach towards reaching "Vision Zero".

Crash scenarios describe the scene of the crash including the participants and their respective actions and intentions. They are the basis for developing sensor-based active safety systems.

The paper discusses possibilities of analyzing in-depth crash data and deriving harmonized crash scenarios. Different databases and their limitations are considered, and a scenario catalogue is proposed.

This catalogue will enable various stakeholders to compare and analyze crash scenarios of different regions and countries. The catalogue serves as a new and efficient tool to enhance the policy making for vehicles and the development of safety technology to drive "Vision Zero" worldwide.

INTRODUCTION

Crash data are needed to evaluate the benefit of safety systems in real-world crashes. The field-of-action is analyzed in which the system can become active to avoid or mitigate crashes, and essential requirements for the system development are derived. Additionally, the potential effectiveness of the safety system within its defined field-of-action is evaluated. For both development phases, a classification of crashes based on common characteristics, before and during the collision, is needed. Such common characteristics can be the trajectories of crash participants or the actual collision geometrics.

To classify traffic crashes, a set of pre-defined crash scenarios can be used. The commonly used terms scene, situation and scenario differentiate by the added level of detail. A scene describes all players and their local and dynamic properties within the surrounding environment. A situation additionally includes goals and values of the players. Besides the properties of the scene and the situation, a scenario also contains actions of the players and other decisive events [1]. Generally, a crash scenario describes the course-of-events that lead to a traffic crash, based on intentions and movements of the participants and other events and circumstances, at the scene and within the environment of the crash, and including the collision outcome. Thus, crash scenarios are well-suited for the description and definition of a safety system.

Vehicle safety systems are divided into primary, secondary and tertiary systems, with active safety systems (ADAS) addressing the primary safety by performing driver warnings and active interventions in the vehicle dynamics. This is based on a critical assessment due to ego kinematics data and object information provided by environment sensors. Therefore, a classification of crashes into crash scenarios, that are to be used for ADAS development, should be done using common sensor-relevant properties in the pre-crash phase. These are mainly the positions and movement directions of the crash participants.

Crash types describe the conflicts that lead to traffic crashes. They are generally represented by pictograms which show the first conflict between two traffic participants, regardless whether other participants are involved. Crash types are used to systematically classify and group traffic crashes. Each crash is classified by the respective crash causer and non-causer. The crash types are partly characterized by a very high level of detail [2]. Due to this segmentation they are generally unfavorable to represent the overall crash occurrence in a compact way.

This paper shows a method to cluster crash types into crash scenarios, considering characteristics and limitations of active safety systems. The focus shall be on the usability of the defined crash scenarios during the development of active safety systems. A scenario catalogues is proposed based on the Cyclist-AEB Testing System (CATS) [3]. The method is demonstrated using in-depth databases from four of the biggest markets worldwide (USA, Germany, China, Japan). As an example, traffic crashes between passenger cars and motorcycles are analyzed and visualized.

METHOD

Active safety systems prevent crashes by direct or indirect intervention in the longitudinal or lateral vehicle dynamics based on sensor information in the pre-crash phase. A classification of traffic crashes that is based on the crash type definition is therefore particularly suitable for defining the field-of-action for an ADAS.

For this paper, the authors used data from USA, China and Japan. Depending on the database used, the authors were able to identify variables which classify the crash configuration and are suitable for clustering. Table 1 gives an overview of the databases and the respective variables used for the scenario generation.

Table 1.
Databases used for the analysis and the respective variables for scenario generation

Database	**Country**	**Variables**	**Reference**
GIDAS	Germany	UTYP, UTYPA, UTYPB	[4]
FARS	USA	ACC_TYPE, PEDCTYPE, BIKECTYPE	[6]
ITARDA	Japan	SIP-code	[7]
CIDAS	China	UTYP, UTYPA, UTYPB	[5]

The GIDAS database describes the three-digit crash type UTYP for each recorded crash and classifies the two participants in the causal conflict as UTYPA and UTYPB. In general, the causing crash participant is coded as UTYPA. The exception are crashes with pedestrians, who are always coded as UTYPB regardless of the question of guilt. Based on the parameters UTYP, UTYPA and UTYPB, the crashes are clustered into crash scenarios.

In [8] the methodology to derive a scenario catalogue based on the GIDAS database has been extensively documented. Each step of the methodology is almost exactly applicable to the data found in CIDAS and ITARDA database. The authors propose a scenario mapping for the ITARDA data in Appendix 1. An example for the ITARDA data is given in Figure 1. Note that scenario C1 describes crossing scenarios from nearside, thus left-hand driving in Japan must be considered.

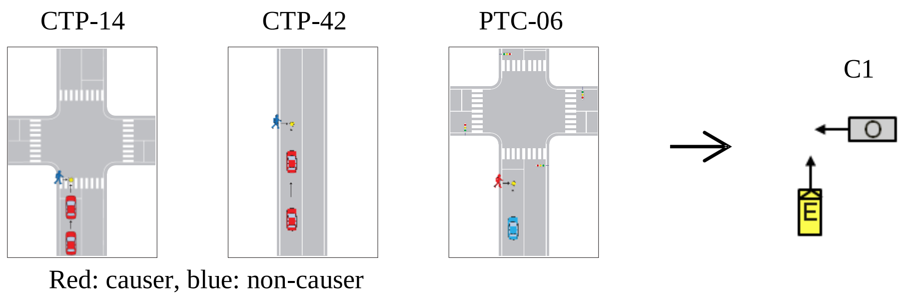


Figure 1. Example of scenario C1 using SIP code an ITARDA data

The FARS database differs in many ways from the previously mentioned databases (GIDAS, ITARADA, CIDAS). Therefore, in this paper the authors propose a methodology to derive a scenario catalogue based on the FARS database. Figure 2 describes the necessary steps of the method when using FARS. In the following text, the authors are using the terminology of FARS variable as described in Appendix 2.

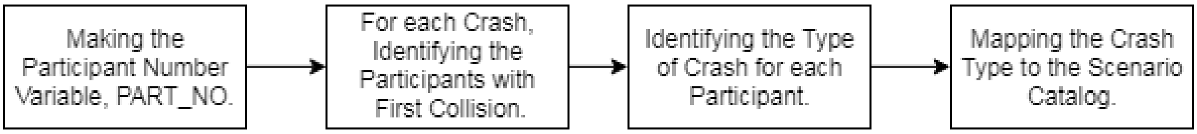


Figure 2. Generation of scenarios based on FARS data

Introduction of a new variable in FARS

The FARS database describes the type of crash at the level of the vehicle for each of the motorized vehicles. It does not contain a causal conflict and it does not contain a participant variable equivalent to the GIDAS data. A comparison of the database hierarchies of both GIDAS and FARS is visualized in Figure 3.

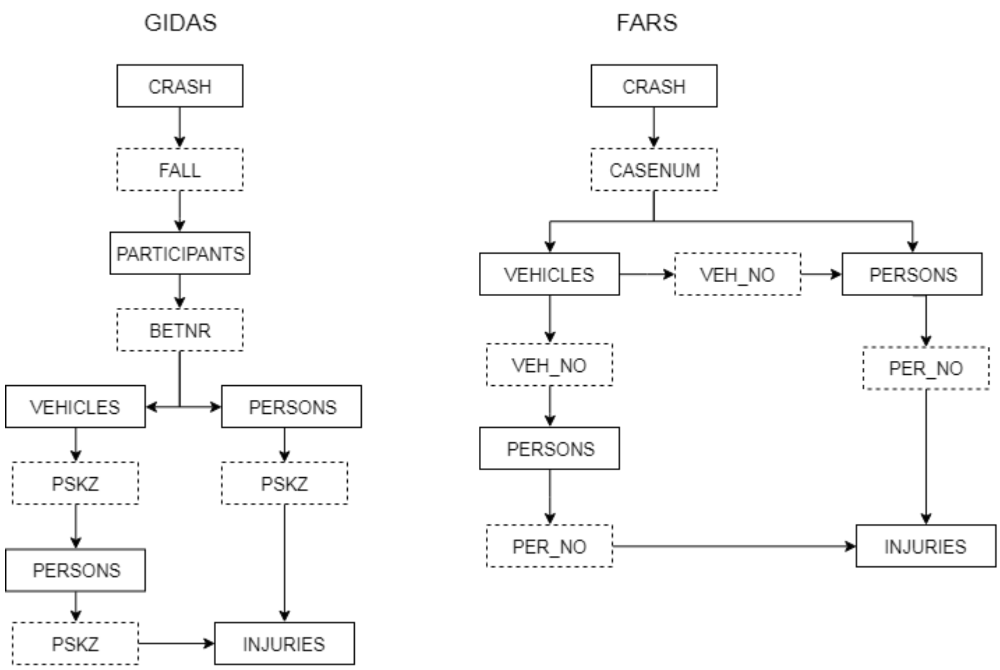


Figure 3. Comparison of GIDAS and FARS database hierarchies

For instances, in GIDAS, a conflict between a vehicle and a pedestrian is classified as a crash between two participants. In contrast, for FARS this would be considered as a single crash given that only one motorized vehicle was involved. To harmonize the data and to be able to apply the proposed scenarios found in [8], one of the primary goals was the introduction of a "participant" layer in the FARS data, which takes the number of the vehicle and the number of the pedestrian/bicyclist in a crash as an input, and then maps them into a participant number.
To this end we merge the person and vehicle data sets. Then for each state cases, the following equation is proposed, and it gives a solution to this problem.

$$Participant\ Number = \begin{cases} \text{VEH\_NO (num. of vehicle)}, & If\ \text{VEH\_NO} \neq 0 \\ max(\text{VEH\_NO}) + PER\_NO, & If\ \text{VEH\_NO} = 0 \end{cases} \quad \text{(Equation 1)}$$

For the Equation 1, suppose a State Case with n Vehicles, $\{V_1, V_2, \ldots, V_n\}$, and Persons, $\{P_j^k\}$ for k in $\{0,1,\ldots,n\}$, where P_j^k represents the Person j in the Vehicle k; if $\text{k} = 0$, the Person is a Pedestrian or Bicyclist.

It follows from the above equation that the participant number is the same for the vehicles. We do not consider the case where $\text{k}, \text{j} = 0$, since this case reduces to a conflict among motorized vehicles. For $\text{k} = 0$, the pedestrians/bicyclist case, that is $\{P_j^0\}_{1 \le j \le m}$, the participant number is $\text{j} + \text{n}$ for all the j, as n corresponds to the maximum number of vehicles. Hence, the total number of participants is given as follows.

$$\#\{P_j^0\}_{1 \le j \le m} + \#\{V_1, V_2, \ldots, V_n\} = m + n \ \text{(if j} \neq 0\text{) (Equation 2)}$$

A visualization of the above described process can be found in Figure 4.

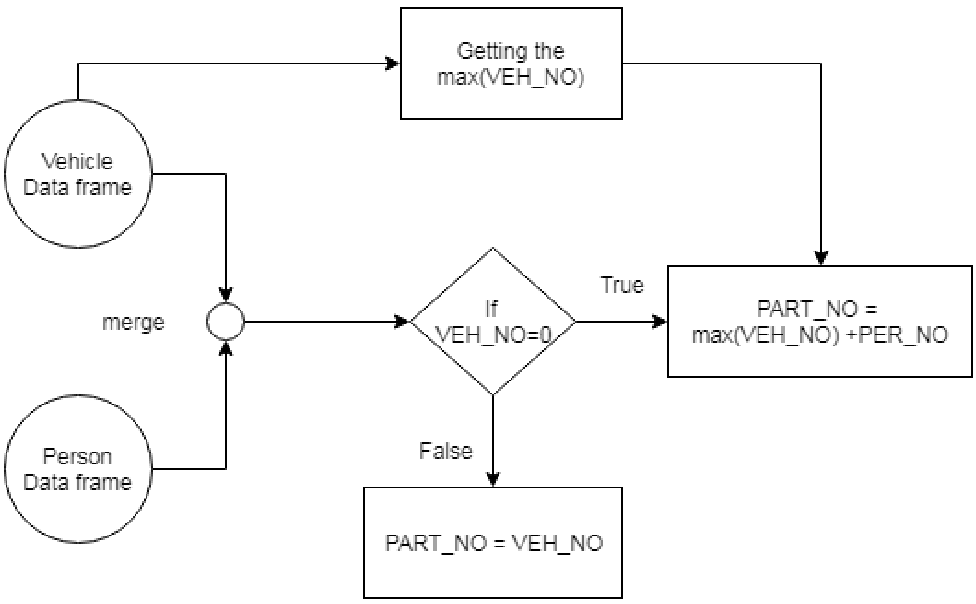


Figure 4. Generation of the participant variable from the number of vehicles and pedestrian.

Table 2 shows the above visualized process for a specific example taken from FARS 2015.

Table 2.
Example for the introduction of a new variable in FARS

ST_CASE	VEH_NO	PER_NO	PART_NO
10712	1	1	1
10712	2	1	2
10712	0	1	3 (*2+1 = max (VEH_NO)+PER_NO*)
10712	0	2	4 (2+2)
10712	0	3	5 (2+3)

Identifying the participants with the first collision

The next step is the identification of the participants with the first collision in a crash to apply the proposed scenarios. Since the authors could not identify a variable indicating the participants directly, this information was obtained using different steps. We select the first two participants in the crash using the lowest possible number in the event variable, EVENTNUM, from the VEVENT data set.

If the first participants are vehicles, we use the VNUMBER1 and VNUMBER2 variables to infer the causal conflict. The limitation with this approach is that this field is only applicable when the event is a collision between two motor vehicles.

If the first participants are a vehicle and pedestrian/bicyclist, we use, depending of the case, PEDCTYPE and BIKECTYPE for the analysis. One of the limitations with this approach is the lack of information to get a complete classification, particularly on the direction of travel of the pedestrian and cyclist. Thus, if there is a doubt about who the causer of the crash could be, the authors assume that the motorized vehicle is the causer of the crash. However, this is regardless of the question of who the (legally) guilty participant of a crash is, like it can be found in GIDAS. The overall process is visualized in Figure 5. To see our assumptions for the cause conflict in the vehicle/pedestrian and vehicle/bicyclist conflict, see Table 2 and Table 3.

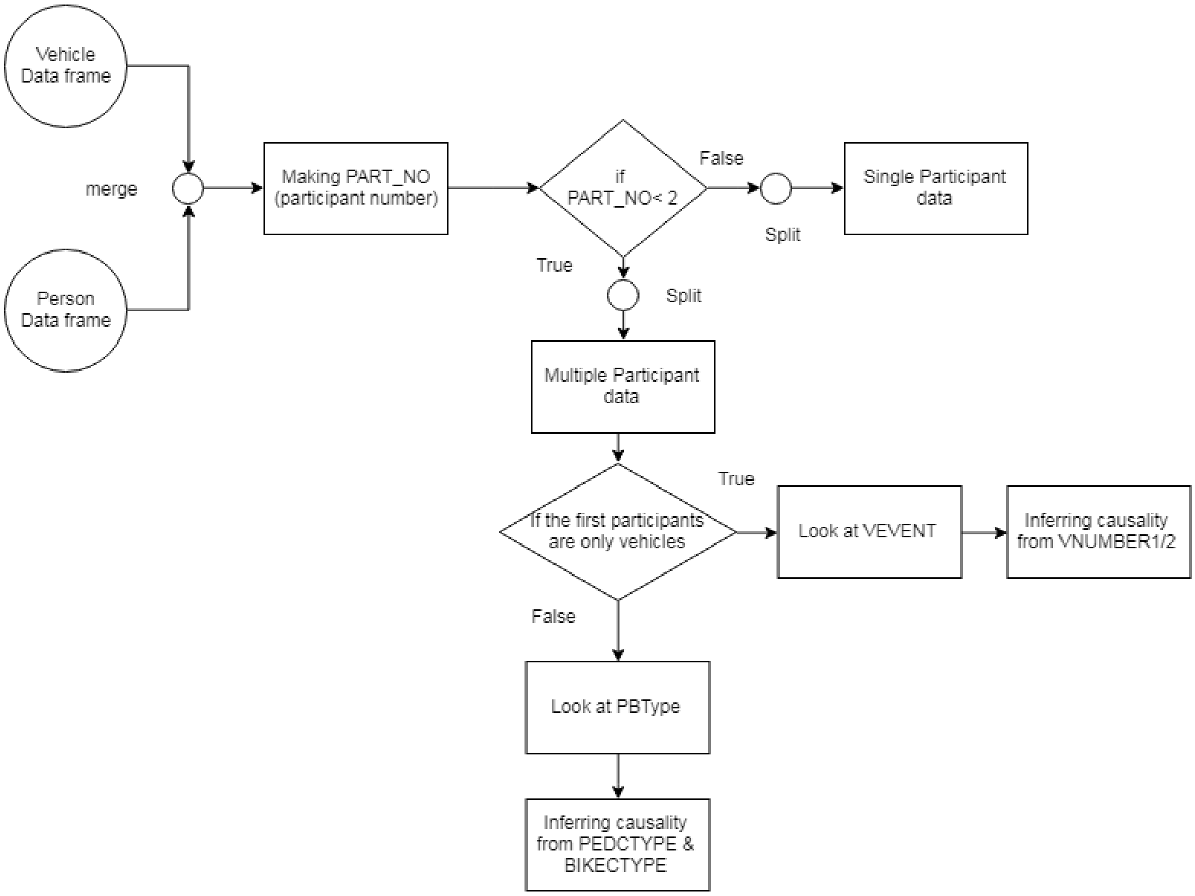


Figure 5. Identifying participants with the first collision in the crash.

Table 3.
PEDCTYPE indicates pedestrian causation in vehicle/pedestrian conflict

PEDCTYPE	**Title**	**Description**
160	Pedestrian Loss of Control	is used when the pedestrian stumbled, fell or rolled into path of a vehicle due to surface conditions, medical issue, blackout or unconsciousness, alcohol or drug impairment, falling asleep, or other mishap.
313	Lying in Roadway	is used when the pedestrian is lying in the roadway when involved with a collision with a motor vehicle. This includes someone sitting, getting up, asleep/unconscious, kneeling, etc.
742	Dart-out	is used when the pedestrian walked or ran into the roadway and was involved in a collision with a vehicle where the driver's view of the pedestrian was blocked until an instant before impact. A dart-out can only occur if there is some documented visual obstruction (e.g., parked vehicle, building or vegetation).

Table 4.
BIKECTYPE indicates bicycle causation in vehicle/bicycle conflict

BIKECTYPE	**Title**	**Description**
114, 115, 116	Bicyclist Turning Error	is used when the bicyclist made a left turn/right at an intersection or a commercial driveway, cut the corner and entered the opposing traffic lane (travel lane, bike lane, paved shoulder, parking lane) occupied by the motorist.
122, 123, 124	Bicyclist Lost Control	is used when the bicyclist lost control due to mechanical problems, alcohol, drug impairment, surface condition, improper breaking, etc.
142,153, 311, 312, 313, 318, 319	Bicyclist Ride-out	is used when the bicyclist rode from a driveway access into the path of a motor vehicle
155	Bicyclist Ride-Through	is used when the case materials indicate that the motorist had the right-of-way and the bicyclist did not stop at a sign (stop or yield) or flashing light-controlled intersection.
156, 157, 159	Bicyclist Failed to Clear	is used when the bicyclist entered the intersection on green, did not clear the intersection before the signal changed for the cross-street traffic giving those operators the right-of-way, and was involved in a collision with a vehicle whose view was not obstructed by standing or stopped traffic
250	Wrong way/Wrong side	is used when the bicyclist was traveling the wrong way on a one-way roadway or on the wrong side of a two-way roadway and collided with a motor vehicle.

Applying the scenario catalogue to FARS

After these steps, we have a dataset which satisfies all the premises to apply the proposed crash scenarios. An example of the catalogue mapping is shown in Figure 6. For each of the crashes, the solid red point represents the participant to which the scenario "C1" is attributed. Notice that only one of the involved vehicles belongs to the scenario.

Passing the variables in Table 1 of the processed data through the mapping in Appendix 3 results in a list of scenarios for a comparison with other regions.

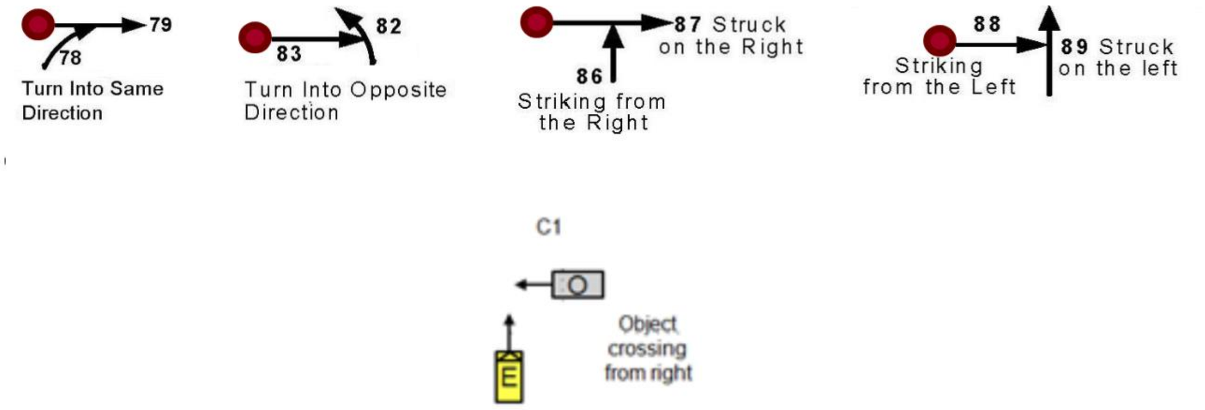


Figure 6. Mapping crash types for scenario "C1" as defined in [8]

RESULTS

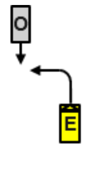
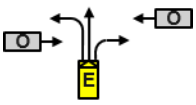
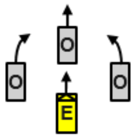
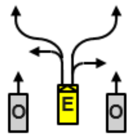
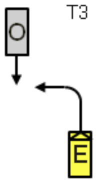
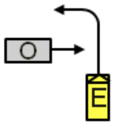
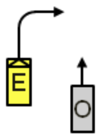
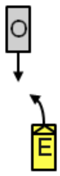
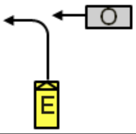
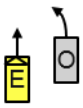
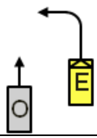
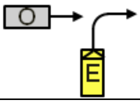
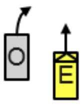
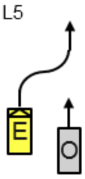
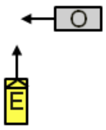
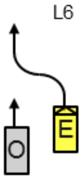
FARS describes 92 different crash types for motorized vehicles (ACC_TYPE), 56 for pedestrians (PEDCTYPE) and 78 for bicyclists (BIKECTYPE). This totals more than 220 crash types to describe the overall traffic crashes in the USA. Using a proven methodology [8] this paper shows that with slight modifications for the FARS database a mapping of nearly all FARS crash types to an existing harmonized pre-crash catalogue is possible.

This mapping allows for a reduction of the overall number of crash type categories from over 220 to 22 (-90%). For Japan this reduction is even greater since there are currently 255 SIP-Codes defined in ITARDA (-91%). As for Germany and China there are almost 300 crash types (UTYP) defined in the database, which means a reduction of about 92%. The complete overview of the mapping for the ITARDA variable SIP-Code and the FARS variable ACC_TYPE can be found in Appendix 1 and Appendix 3, respectively. The mapping for GIDAS (UTYP) has already been published in [8].

Besides reducing the number of categories, another benefit of the harmonized pre-crash scenarios can be found in the comparability of traffic crashes between countries, regions, databases, etc. The authors are not aware of any studies that have shown a practical mapping between more than two databases up to this point in time.

To demonstrate the practicability of the harmonized pre-crash scenarios, crashes between passenger cars (including light trucks) and motorcycles were analyzed across four different databases. For this example, the scenarios are clustered further into bundles to simplify the visualization and to allow a better comparability. In Table 5, the scenario bundles are displayed.

Table 5.
Scenario Bundles

Turning farside 	Crossing 	Runup 	Rear 	Lane Change 	Oncoming same 	Oncoming adjacent 
T3 	T4 	L1 	L4 	T1 	On1 	On2 
	T9 	L2 		T5 		
	T10 	L3 		L5 		
	C1 			L6 		
	C2 					

From the point of view of the cars and the motorcycles, the complete accident occurrence can be presented using the proposed scenario bundles. This shows how the scenario catalogue can be applied to various participants types. In Figures 7 and 8 both, the cars and the motorcycles are depicted in the role of the ego vehicle.

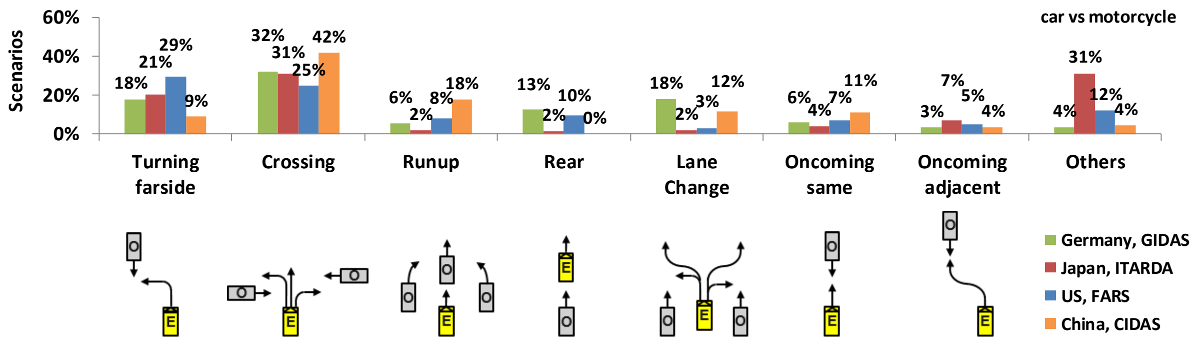


Figure 7. Car perspective: Ego is car, object is motorcycle

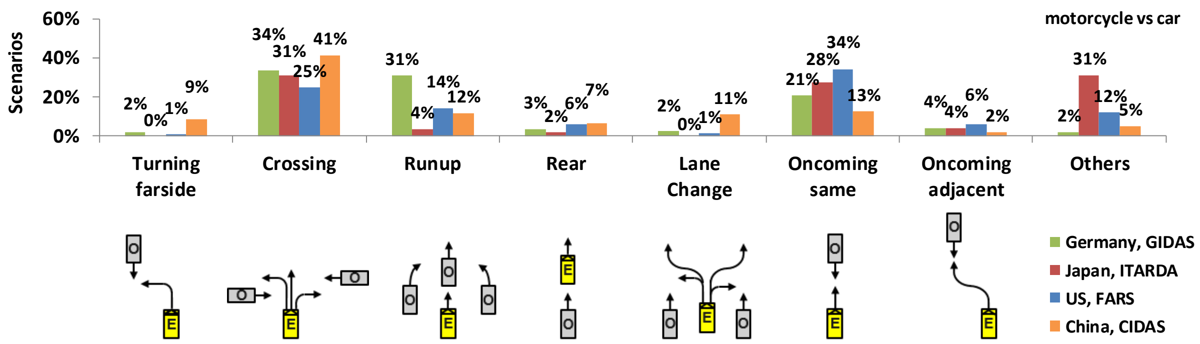


Figure 8. Motorcycle perspective: Ego is motorcycle, object is car

Appendix 4 gives an overview of all scenarios for crashes with car vs. motorcycle participation in four countries (Germany, USA, China, Japan).

At this level of the analysis of traffic scenarios it is already possible to derive the most relevant scenarios for a specific crash constellation. In the example above, "Crossing" scenarios are the most relevant in all four crash databases with "Turning farside" scenarios as second most relevant (Figure 7). Looking from the motorcycle perspective at the same crashes, "Crossing" followed by "Oncoming same" scenarios are the most relevant.

Following this high-level analysis, which can be used for identifying for example consumer test scenarios, data analysts can also take a deeper dive into the existing data to provide input for the requirements of advanced driver assistance systems (ADAS) and of advanced rider assistance systems (ARAS®).

CONCLUSIONS

The crash scenarios are consolidating for regions by combining them into a common form PCAS scenarios. Since the GIDAS and FARS coding hierarchy differs, it requires an extra effort to map the existing data upon the proposed scenarios. The limitations found within the FARS data are as follows:

i) Non-motorized participants (Pedestrian and Bicyclist) do not have a crash type in the ACC_TYPE variable.
ii) Crash type for non-motorized participants needs to be obtained through PEDCTYPE and BIKECTYPE and adjust to each of the cases.
iii) Changes in the data throughout the years (ACC_TYPE is introduced after 2010).

Nevertheless, the methodology presented in this paper shows a systematic way to deal with these limitations.

Since the FARS coding does not explicitly state if the pedestrian or cyclist was at fault (causer), we had to make the choice based on the parameter descriptions (See Table 3 and 4). Mapping results shown in Appendix 3 is incomplete because we are unable to map directly a FARS value into a PCAS scenario since some values are coded unknown (i.e. specifics unknown, specifics other). However, the authors understand that improvement in the classification as well as the processing of the data still can be made. We may improve the method by using the pre-crash variables to get further details of the critical events which lead to the collision.

Considering the challenge of properly mapping the N/A's presented in Appendix 3, more research is needed to analyze and understand these parameters. We found that our algorithm works for the years 2015 to present; however, the database has significant changes for 2010 and prior which would need further analysis.

The crash scenario catalogue presented in this paper is the result of an analytical approach of available in-depth crash data worldwide. Existing crash classifiers of different databases are used to create a harmonized dynamic scenario description. This enables a comparability of crash research results regardless of regional differences in data collection and coding formats. Therefore, harmonized safety system development and simulation methods and tools can be utilized.

The scenario generation has been demonstrated on four different crash databases. The focus of this paper lays on the US fatality database FARS. The detailed mapping of the German GIDAS crash data is explained in [8], which can also be applied to the Chinese CIDAS data. Due to its simplicity, the Japanese ITARDA SIP crash codes can directly be mapped to the proposed crash scenarios. SIP codes are defined by 255 typical accident types with more than three fatalities; these cover around 80% of fatal accidents in Japan, however, accident types with less than 3 fatalities are not considered.

OUTLOOK

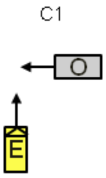
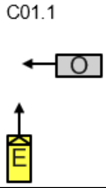
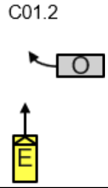
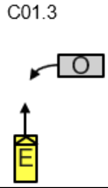
This paper describes a method to cluster crash types to a harmonized set of scenarios, by looking at each crash from the perspectives of the causer and of the non-causer and by considering additional pre-crash information. This inductive approach will naturally leave a quantity of crashes that cannot automatedly be mapped to crash scenarios, since the available classification is not sufficient, see Table 6. To further increase the respective percentages, additional research should be performed to add further available crash parameters. Ultimately, manual re-coding might be needed to reach 100% coverage, which however will be difficult to justify for existing data. It is therefore suggested that the proposed scenario catalogue is introduced as a standard crash parameter to all relevant worldwide databases and is consequently populated for all new cases.

Table 6.
Percentage of crash participants classified by automatic mapping method

Database	Region	Percentage covered
GIDAS	Germany	75%
FARS	US	70%
ITARDA	Japan	82%
CIDAS	China	75%

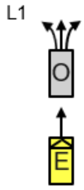
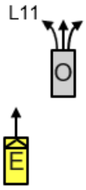
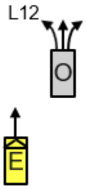
The crash scenarios allow for a dynamic crash description from the perspective of the ego vehicle. They include ego movement and object direction, however do not differentiate between possible object intentions. In V2V communication systems, the object intention is communicated over the air, therefore the crash dynamic scenarios should be extended to reflect this extra information. An extension to the scenario definition with additional object intentions is proposed. Table 7 gives an example for scenario C1 "Crossing from right" with added object intentions.

Table 7.
Scenario C1 "Crossing from right" with different object intentions

No object intention	Object going straight	Object turning right	Object turning left
			

The proposed scenario catalogue has been developed by aggregating crash types from different crash databases. The catalogue does not cover normal driving scenarios that are not crash relevant. To allow the classification of all real-world driving data, such as normal driving, near miss incidents and crashes, the scenarios catalogue is further extended. Therefore, non-crash relevant scenarios are added. Table 8 shows following-scenarios with traffic objects in same or adjacent lanes.

Table 8.
Scenarios L1, L11, L12 "Run-up in same lane", "Following in adjacent lane"

Run-up in same lane	Following in adjacent lane	
		

The proposed scenario catalogue should be applied to a maximum number of worldwide crash and naturalistic driving databases (NDD). Table 9 lists several databases that are suggested for further research.

Table 9.
Possible variables for scenario generation in other databases

Database	**Region**	**Variables**	**Reference**
RASSI	India	PRECREV, PRECRA, PRECRB	[9]
iGLAD	Worldwide	ACCTYPE, ACCTYPEA, ACCTYPEB	[10]
SHRP2 NDS	USA	Crash Type	[11]
TUAT NDS	Japan	Incident / Collision Type	[12]

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APPENDICES

Appendix 1: Scenario mapping Japan for crashes with at least 3 fatalities (SIP code)

Code	Causer	Non-causer	Code	Causer	Non-causer	Code	Causer	Non-causer
CTC-01	C2	C1	CTC-11	On2	N/A	CTC-20	On1	On1
CTC-02	C1	C2	CTC-12	On2	On1	CTC-21	On2	On1
CTC-03	On1	T3	CTC-13	L1	L4	CTC-22	On2	On1
CTC-04	T3	On1	CTC-14	L1	L4	CTC-23	On2	On1
CTC-05	On2	On1	CTC-15	On2	On1	CTC-24	On2	On1
CTC-06	C2	C1	CTC-16	L1	L4	CTC-25	L1	L4
CTC-07	C1	C2	CTC-17	On2	On1	CTC-26	L1	L4
CTC-08	T4	C1	CTC-18	On2	On1	CTC-27	On1	On1
CTC-09	T9	C2	CTC-19	On2	On1	CTC-28	On1	On1
CTC-10	T3	On						

Code	Causer	Non-causer	Code	Causer	Non-causer	Code	Causer	Non-causer
CTM-01	C2	C1	CTM-09	T4	C1	CTM-16	On2	On1
CTM-02	C1	C2	CTM-10	T3	On1	CTM-17	L1	N/A
CTM-03	On1	On2	CTM-11	On2	On1	CTM-18	L1	L4
CTM-04	T5	L2	CTM-12	L5	L3	CTM-19	T4	N/A
CTM-05	T3	On1	CTM-13	T3	On1	CTM-20	L5	L3
CTM-06	C2	C1	CTM-14	On2	On1	CTM-21	T3	On1
CTM-07	C1	C2	CTM-15	L5	L3	CTM-22	L5	L3
CTM-08	T10	C2						

Code	Causer	Non-causer	Code	Causer	Non-causer	Code	Causer	Non-causer
CTB-01	C2	C1	CTB-11	T1	L2	CTB-20	On1	On1
CTB-02	C1	C2	CTB-12	T3	On1	CTB-21	L1	L4
CTB-03	T1	L3	CTB-13	On1	On1	CTB-22	C2	C1
CTB-04	T2	On1	CTB-14	L1	L4	CTB-23	C1	C2
CTB-05	T5	L2	CTB-15	C2	C1	CTB-24	L5	L3
CTB-06	T3	On1	CTB-16	C1	C2	CTB-25	L5	L3
CTB-07	L1	L4	CTB-17	C2	C1	CTB-26	On1	On1
CTB-08	C2	C1	CTB-18	L1	L4	CTB-27	C2	C1
CTB-09	C1	C2	CTB-19	L1	L4	CTB-28	C1	C2
CTB-10	T14	C2						

Code	Causer	Non-causer	Code	Causer	Non-causer	Code	Causer	Non-causer
CTP-01	C2	C1	CTP-18	C1	C2	CTP-35	C1	C2
CTP-02	C1	C2	CTP-19	T1	C2	CTP-36	L1	N/A
CTP-03	T2	C1	CTP-20	T5	C1	CTP-37	L5	L3
CTP-04	T1	C2	CTP-21	T3	C2	CTP-38	L6	L2
CTP-05	T5	C1	CTP-22	L1	N/A	CTP-39	C2	C1
CTP-06	T3	C2	CTP-23	T3	N/A	CTP-40	C1	C2
CTP-07	T3	C2	CTP-24	L5	L3	CTP-41	C2	C1
CTP-08	C2	C1	CTP-25	C1	C2	CTP-42	C1	C2
CTP-09	C1	C2	CTP-26	C2	C1	CTP-43	C1	C2
CTP-10	T3	C2	CTP-27	C1	C2	CTP-44	L1	N/A
CTP-11	L1	N/1	CTP-28	T3	C2	CTP-45	L5	L3
CTP-12	L5	L3	CTP-29	C1	C2	CTP-46	C1	C2
CTP-13	C2	C1	CTP-30	L1	N/A	CTP-47	L1	N/A
CTP-14	C1	C2	CTP-31	T3	N/A	CTP-48	B1	N/A
CTP-15	T5	C1	CTP-32	L1	N/A	CTP-49	B1	N/A
CTP-16	T3	C2	CTP-33	L5	L3	CTP-50	B3	C2
CTP-17	C2	C1	CTP-34	C2	C1			

Code	Causer	Non-causer	Code	Causer	Non-causer	Code	Causer	Non-causer
MTC-01	C2	C1	MTC-06	C1	C2	MTC-10	On2	On1
MTC-02	C1	C2	MTC-07	T4	C1	MTC-11	On2	On1
MTC-03	On1	T3	MTC-08	T3	On1	MTC-12	L1	L4
MTC-04	T3	On1	MTC-09	On2	On1	MTC-13	L5	L3
MTC-05	C2	C1						

Code	Causer	Non-causer	Code	Causer	Non-causer	Code	Causer	Non-causer
BTC-01	C2	C1	BTC-04	C1	C2	BTC-06	L6	L3
BTC-02	C1	C2	BTC-05	C1	C2	BTC-07	L6	L3
BTC-03	C2	C1						

Code	Causer	Non-causer	Code	Causer	Non-causer	Code	Causer	Non-causer
PTC-01	C1	C2	PTC-05	C1	C2	PTC-08	C1	C2
PTC-02	C2	C1	PTC-06	C2	C1	PTC-09	C2	C1
PTC-03	C1	C2	PTC-07	L4	L5	PTC-10	N/A	L1
PTC-04	C2	C1						

Code	Causer	Non-causer	Code	Causer	Non-causer	Code	Causer	Non-causer
HCTC-01	L1	L4	HCTC-04	L1	L4	HCTC-07	L1	L4
HCTC-02	L1	L4	HCTC-05	On2	On1	HCTC-08	On2	On1
HCTC-03	L1	L4	HCTC-06	L1	L4			

Code	Causer	Non-causer	Code	Causer	Non-causer	Code	Causer	Non-causer
HCTM-01	L1	L4						

Code	Causer	Non-causer	Code	Causer	Non-causer	Code	Causer	Non-causer
HCTP-01	C1	C2						

Appendix 2: FARS Terminology

For this paper the following data files and variables are used from FARS, year 2015 (FARS Analytical User's Manual 1975 – 2016).

Accident: This data contains information about crash characteristics and environmental conditions at the time of the crash. There is one record per crash.

> **ST_CASE**: This data element is the unique case number assigned to each crash. It appears on each data file and is used to merge information from the data files together.

Vehicle: This data file contains information describing the in-transport motor vehicles and the drivers of in-transport motor vehicle who are involved in the crash. There is one record per in-transport motor vehicle.

> **VEH_NO**: This data element is the consecutive number assigned to each vehicle in the case. It is used in conjunction with the ST_CASE data element to merge information from vehicle level data files.

> **ACC_TYPE**: Identifies the attribute that best describes the type of crash this vehicle was involved in based on the "First Harmful Event" and the pre-crash circumstances.

Person: This data file contains information describing all persons involved in the crash including motorists (i.e., drivers and passengers of in-transport motor vehicles) and non-motorists (e.g., pedestrians and pedal cyclists). There is one record per person.

> **PER_NO**: This data element is the consecutive number assigned to each person in the case (i.e., each occupant, pedestrian, or non-motorists involved in the crash). It is used in conjunction with the ST_CASE data element (and sometimes the VEH_NO data element) to merge information from person level data files.

Vevent: This data file contains the sequence of events for each in-transport motor vehicle involve in the crash.

> **VNUMBER1 & 2**: This data element identifies the "Vehicle Number" (VEH_NO) of this in-transport motor vehicle described in this event. This is the vehicle described in "Sequence of Events" for this event. If Vehicle #1 (V1) impacts Vehicle #2 (V2), then we have at least 2 Vevent records.

VEH_NO	EVENTNUM	VNUMBER1	SOE	VNUMBER2
1	1	1	12	2
2	1	1	12	2

> The explanation of these 2 records is as follows:
> V1 was involved in event 1 where V1 impacts V2
> V2 was involved in event 1 where V1 impacts V2

> **EVENTNUM**: This data element is the consecutive number assigned to each harmful and nonharmful event in a crash, in chronological order.

PBType: This data file contains information about crashes between motor vehicles and pedestrians, people on personal conveyances and bicyclists. There is one record for each pedestrian, bicyclist or person on a personal conveyance.

> **PEDCTYPE**: This data element summarizes the circumstances of the crash for this pedestrian.

> **BIKECTYPE:** This data element summarizes the circumstances of the crash for this bicyclist.

Using the above variables, the data sets, and the formula 1, we can infer the variable PART_NO (Participant number). Thus, a participant number is a number assigned to each of involved parties in a given crash (pedestrian, bicycle, car type). This shall not be mistaken by the PER_NO or the VEH_NO, however is obtained from these two.

Appendix 3: Scenario mapping proposal for USA (FARS)

Crash Type	Scenario
1	D1
2	D1
3	D1
4	N/A
5	N/A
6	D2
7	D2
8	D2
9	N/A
10	N/A
11	L1
12	O2
13	L1
14	O2*
15	N/A
16	N/A
20	L1
21	L4
22	L4
23	L4
24	L1
25	L4
26	L4
27	L4
28	L1
29	L4
30	L4
31	L4
32	N/A
33	N/A
34	D3*
35	D3*
36	D3*
37	D3*
38	D3*
39	D3*
40	D3*
41	D3*
42	N/A
43	N/A
44	L2*
45	L3*
46	L5
47	L6
48	N/A
49	N/A
50	On2
51	On1
52	N/A
53	N/A
54	D3*
55	D3*
56	D3*
57	D3*
58	D3*
59	D3*
60	D3*
61	D3*
62	N/A
63	N/A
64	On2
65	On1
66	N/A
67	N/A
68	T2/T3*
69	On1
70	T1
71	L3
72	T5
73	L2
74	N/A
75	N/A
76	T9
77	C2
78	T10
79	C1
80	T14
81	C2
82	T4
83	C1
84	N/A
85	N/A
86	C2
87	C1
88	C1
89	C2
90	N/A
91	N/A
92	B
93	L4*
98	N/A
99	N/A

Note: Scenarios with * indicate that the mapping needs to be optimized.

Appendix 4: Overview of all scenarios for crashes "Car vs. Motorcycle" in four major countries

Car vs. motorcycle crashes from the perspective of the car

Scenario	**Share in %**			
	Germany (KSI)	**USA (K)**	**China (KSI)**	**Japan (K)**
T1	0.1	0.5	6.0	0.0
T2	0.0	0.0	0.7	0.0
T3	18.1	29.5	9.0	22.8
T4	14.6	9.7	9.0	2.0
T5	9.7	1.8	3.0	0.0
T9	2.2	0.9	0.0	0.0
T10	2.2	0.9	0.7	0.5
T14	0.2	0.2	0.0	0.0
C1	6.4	4.0	13.4	10.8
C2	6.8	9.5	18.7	12.2
L1	3.4	5.8	6.7	2.7
L2	1.5	0.8	9.7	0.0
L3	1.0	1.8	1.5	0.0
L4	12.6	9.6	0.0	1.1
L5	2.6	0.6	2.2	1.6
L6	5.6	0.4	0.7	0.5
On1	5.9	7.2	11.2	9.3
On2	3.4	4.9	3.7	2.5
S1	0.0	0.0	0.0	0.0
S2	0.0	0.0	0.0	0.0
B	1.2	0.2	0.7	0.0
N/A	2.3	11.9	3.0	34.1
Total	**100**	**100**	**100**	**100**

Germany: GIDAS 2005-2018, weighted to national crash statistics

USA: FARS 2015, not weighted to national crash statistics

China: CIDAS 2014 - 2018, not weighted to national crash statistics

Japan: ITARDA 2013, not weighted to national crash statistics

Car vs. motorcycle crashes from the perspective of the motorcycle

Scenario	Share in %			
	Germany (KSI)	USA (K)	China (KSI)	Japan (K)
T1	0.1	0.0	0.7	0.0
T2	0.0	0.0	0.0	0.0
T3	2.3	1.2	8.9	2.3
T4	1.2	0.6	3.0	0.0
T5	0.6	0.1	6.7	0.0
T9	0.0	0.1	3.0	0.0
T10	0.2	0.1	0.0	0.0
T14	0.0	0.2	0.7	0.0
C1	24.8	19.8	25.2	14.0
C2	7.4	4.3	10.4	11.5
L1	12.9	9.6	0.0	0.0
L2	15.4	2.4	4.4	0.0
L3	2.8	2.1	7.4	2.0
L4	3.4	5.9	6.7	2.7
L5	0.9	0.6	0.7	0.0
L6	0.9	0.6	3.0	0.0
On1	20.9	34.4	12.6	31.6
On2	4.0	6.0	2.2	0.7
S1	0.0	0.0	0.0	0.0
S2	0.0	0.0	0.0	0.0
B	0.0	0.0	0.0	0.0
N/A	2.2	11.9	4.4	35.2
Total	**100**	**100**	**100**	**100**

Germany: GIDAS 2005-2018, weighted to national crash statistics

USA: FARS 2015, not weighted to national crash statistics

China: CIDAS 2014 - 2018, not weighted to national crash statistics

Japan: ITARDA 2013, not weighted to national crash statistics

MEASURING STATES' ALIGNMENT TO THE MODEL MINIMUM UNIFORM CRASH CRITERIA (MMUCC) 5TH EDITION

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ABSTRACT

In 1998, the National Highway Traffic Safety Administration (NHTSA) and the Governors Highway Safety Association (GHSA) developed the Model Minimum Uniform Crash Criteria (MMUCC), a voluntary guideline to encourage greater crash data uniformity by identifying a minimum set of motor vehicle crash data elements and attributes that States should collect and include in their State crash data system. NHTSA relies on State crash data for the Fatality Analysis Reporting System (FARS). FARS is a nationwide census providing NHTSA, Congress, and the American public yearly data regarding fatal injuries suffered in motor vehicle traffic crashes. States have implemented MMUCC differently, often combining or deleting attributes, which causes problems with data uniformity when attempting to aggregate data across States. The purpose of this paper is to describe methods used to measure States' alignment to MMUCC 5th Edition, examine the variance of States' crash data to MMUCC data elements, and describe how NHTSA will use the results of this analysis to inform future editions of MMUCC with the goal of improving the quality of FARS data.

INTRODUCTION

In 1998, NHTSA published the MMUCC, a voluntary guideline to collect data on motor vehicle crashes that can generate the information necessary to improve highway safety within each State and nationally. Early editions of MMUCC lacked guidance on implementation, which led to each of the 50 States, the District of Columbia (DC), and the U.S. Territories enacting MMUCC differently. Between the 4th and 5th Editions, NHTSA created a methodology to measure States' alignment to MMUCC, which was later updated and incorporated into the MMUCC 5th Edition. In 2018, NHTSA mapped the crash data elements and attributes from all States, DC, and Puerto Rico to the MMUCC 5th Edition and established the first baseline measurement of alignment to MMUCC. The results of this mapping exercise provide NHTSA a framework for offering States and territories technical assistance and training to increase their alignment to MMUCC, and will inform future changes to NHTSA's crash data publications, from MMUCC to the Fatality Analysis Reporting System (FARS) / Crash Report Sampling System (CRSS) Coding and Validation Manual.

BACKGROUND

NHTSA uses police-reported motor vehicle traffic crash data to conduct research, analyze traffic crash trends, support safety programs, and make data-driven decisions daily. Understanding States' crash data capabilities are reporting is critical to ensuring accuracy for all data-driven programs. Historically, each State developed their own methods for collecting, managing, and analyzing data on motor vehicle crashes. Consequently, crash data varied substantially between States. The lack of uniform data elements and attributes made it challenging to understand national crash trends. In 1975, NHTSA began collecting a census of fatal crashes using the FARS to provide an overall measure of highway safety. NHTSA trained analysts in each of the 50 States, DC, and Puerto Rico to convert the State data sources into FARS data codes.

Similarly, in 1988, NHTSA began the National Automotive Sampling System General Estimates System (NASS GES), a program to collect a nationally representative sample of police-reported motor vehicle crashes of all severities (fatal, injury, property-damage-only) to identify traffic safety problem areas, provide a basis for regulatory and consumer initiatives, and form the basis for cost and benefit analyses of traffic safety initiatives. The NASS GES and its replacement the Crash Reporting Sampling System (CRSS), requires analysts to recode the crash data collected from different States into a standard format. Early on, it was apparent that the substantial variability in State crash data made it costly and challenging to produce national crash datasets.

In 1998, NHTSA and GHSA published the first MMUCC. This provided States voluntary guidance on the minimal set of standardized data elements and attributes necessary to describe the characteristics the vehicles, the persons, and the environment involved in motor vehicle crashes,. NHTSA and GHSA encouraged States to adopt MMUCC to increase crash data uniformity. Greater standardization of crash data enables State highway safety agencies to more efficiently and cost-effectively share data with other agencies in their State (such as public safety), compare their crash data with other States, and, exchange crash data with federal data systems. Since the initial release of the MMUCC Guideline in 1998, NHTSA and GHSA have revised MMUCC four times in response to technological changes and evolving traffic safety needs. Early editions of the MMUCC Guideline did not provide States with implementation guidance, resulting in each State adopting MMUCC differently. As States developed their own data collection guidelines regarding what crash data to collect, what is a reportable crash, and what data to maintain on their Crash Databases, the variance between States' crash data increased. As a result, States often use different formats and names for data elements and attributes or they may combine (or split) elements and attributes.

In 2014, NHTSA and GHSA recognized the need to develop a methodology for measuring the alignment of the crash data States collected on their Police accident reports (PAR) and the data entered and maintained on Crash Databases to the data elements and attributes in the MMUCC Guideline. Through extensive consultation with the State stakeholders at the Association of Traffic Records Information Professionals (ATSIP) International Traffic Records Forum, NHTSA and GHSA developed a methodology to map the data elements and attributes from States PARs and their crash databases to MMUCC. This process recognized that while State data systems often use different terminology and formatting, different data sets can often be mapped to the MMUCC data elements and attributes. Thus, if an element or attribute on a State PAR or in its Crash Database did not match a MMUCC element or attribute verbatim, but is essentially the same, it is considered "mapped" to MMUCC. In 2015, NHTSA published *"Mapping to MMUCC: A Process for Comparing Police Crash Reports and State Crash Databases to the Model Minimum Uniform Crash Criteria,"* [1] a set of rules to assist States in evaluating their alignment to MMUCC.

In 2017, NHTSA and GHSA published the 5th Edition of MMUCC [2], which included updated mapping rules to address significant changes to the MMUCC content and format. In addition, the MMUCC 5th Edition no longer designated elements to be "collected at the scene," "derived," or "linked." Instead, MMUCC encouraged States to collect data elements based on the States' capabilities. States that have integrated traffic records datasets collect less data for their crash reports at the scene of a crash because they can instead link or derive data elements from other sources, such as the roadway, driver, and vehicle file. As a result, comparing a State's crash database to MMUCC is more useful than comparing a State PAR to MMUCC.

Following the publication of the 5th Edition of MMUCC, NHTSA collected crash data documentation (data dictionary, police instruction manual, database schema, and crash report forms) for all 50 States, DC, and Puerto Rico to measure how each States' crash database structure aligns to MMUCC. The objectives for this project included establishing a baseline for understanding the States' crash data capabilities, identifying the data elements and attributes that are problematic for States, providing States a measure of how they align to MMUCC and detail opportunities for improvement, and to inform future editions of MMUCC by understanding potential impacts changes might have on the States.

METHODS

Measuring the alignment of a State's crash data to MMUCC involves several steps to compare the data elements and attributes within the State crash database (the source) to the data elements and attributes in the target). Figure 1 provides a brief overview of this process. The first step involves gathering the relevant documentation, which includes the most recent version of MMUCC and documentation on the State's crash data system. Typically, a State's crash database is comprised of the corresponding data collected on police crash reports, derived from data collected on crash reports, and obtained from other data sources (e.g., a roadway database). Ideally, the State's crash data elements and attributes should contain all 115 MMUCC data elements and their attributes. If the data dictionary for the State Crash Database does not list all data elements and element attributes used in the crash database, then analysts examine the State's PAR and police instruction manual for all relevant terms and definitions needed to map to the MMUCC.

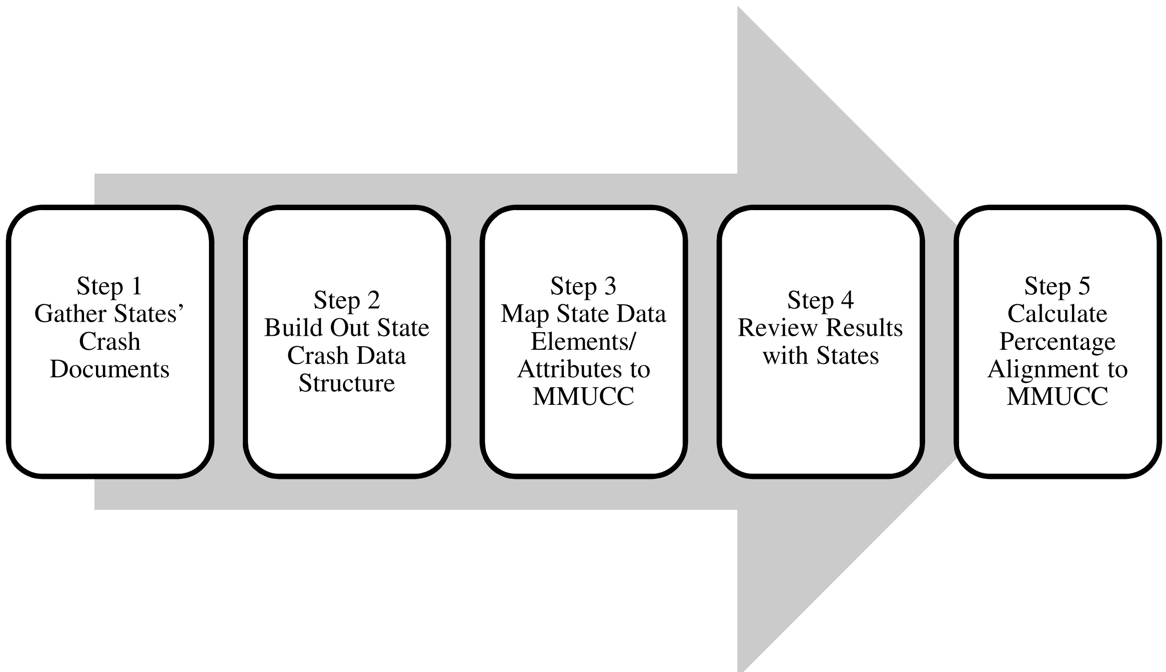

Figure 1: The MMUCC Mapping Process

The second step for measuring a State's alignment to MMUCC involves building out the target MMUCC data structure and the source State data structure to compare and evaluate the similarity of the State's data elements and attributes to those of the MMUCC. Table 1 is an example of the table used to map a State's data element and attributes for "Weather" to the MMUCC date element and attributes for "C11. Weather conditions". Since the MMUCC Guideline allows two attribute selections for "C11. Weather Conditions" the table is set up to include both subfields. Initially, analysts used an Excel spreadsheet to facilitate side-by-side comparisons of the data elements and attributes, which was cumbersome. NHTSA developed an IT application for analysts to build and update the source and target data structures, record the analyst's comments and mapping decisions, and export a final report. The application can maintain the mappings when either the target MMUCC data structure or the source State data structure are updated, which will facilitate future efforts to re-map a State's data to MMUCC when either change. This application also included many safeguards to ensure the integrity of the mapping results (i.e. color-coded mapping status notations and preventing attributes from being coded twice).

The third step involves determining how consistent the States crash data structure is with MMUCC by identifying which of the State's crash data elements and attributes can map to each MMUCC data element and attributes. Analysts apply mapping rules published in the MMUCC 5th Edition to determine if a State data attribute can be mapped, or matches MMUCC. All mapping decisions are binary at the attribute level where analysts decide whether the State's data matches MMUCC or not. The mapping process is a "top-down mapping" approach that starts with the data elements and works down to attributes. Individual elements with zero attributes (i.e., VIN) either will map to a corresponding MMUCC element/attribute or will not. While there is no partial mapping for data elements with no attributes, data elements with multiple attributes can partially map, if at least one State attribute matches an attribute for that MMUCC element. Many States collect more data elements than what MMUCC prescribes. The MMUCC mapping process is only concerned with the 115 MMUCC data elements and their associated attributes. The mapping rules include two primary sets of rules: The general rules, such as the many-to-one rule, where two State data attributes can match to one MMUCC data attribute, and the one to many rules that prohibits one State data attribute from mapping to two MMUCC data attributes. Another set of rules covers specific data elements that have unique characteristics requiring additional explanation and interpretation.

Table 1.
Mapping State Data Element "Weather" to the MMUCC "C11. Weather Conditions"

***Target:* MMUCC Data Element "C11. Weather Conditions" Selection 1**	**Ability to Map? (1 = Yes, 0 = No)**	***Source:* State Data Element "Weather"**		***Target:* MMUCC Data Element "C11. Weather Conditions" Selection 2**	**Ability to Map? (1 = Yes, 0 = No)**	***Source:* State Data Element "Weather"**
Blowing Sand, Soil, Dirt	0	(9) Blowing Sand, Soil, Dirt, or Snow *cannot be split.*		Blowing Sand, Soil, Dirt	0	*N/A*
Blowing Snow	0			Blowing Snow	0	*N/A*
Clear	0	(1) No Adverse Conditions (Clear, Cloudy) *cannot be split*		Clear	0	*N/A*
Cloudy	0			Cloudy	0	*N/A*
Fog, Smog, Smoke	1	(2) Fog (7) Smoke/Dust *includes Dust*		Fog, Smog, Smoke	0	*N/A*
Freezing Rain or Freezing Drizzle	0	*N/A*		Freezing Rain or Freezing Drizzle	0	*N/A*
Rain	1	(4) Rain		Rain	0	*N/A*
Severe Crosswinds	1	(10) Severe Crosswinds		Severe Crosswinds	0	*N/A*
Sleet or Hail	1	(6) Sleet/Hail		Sleet or Hail	0	*N/A*
Snow	1	(5) Snow		Snow	0	*N/A*
Other	0	*N/A*		Other	0	*N/A*
Unknown	0	*N/A*		Unknown	0	*N/A*

Table 1 identifies the State's data attributes that can map to the MMUCC attributes and the rules that apply. Specifically, the State's attribute *'(1) No Adverse Condition (Clear, Cloudy)'* cannot map to the MMUCC attributes '*Clear'* or '*Cloudy'* because the State combines two MMUCC attributes '*Clear'* and '*Cloudy.'* Likewise, the State attribute '*(9) Blowing Sand, Soil, Dirt, or Snow*' cannot map to the MMUCC attributes '*Blowing Snow'* or *'Blowing Sand, Soil, Dirt.'* However, the State attributes *'(2) Fog'*, and *'(7) Smoke/Dust'* can map to the MMUCC attribute '*Fog, Smog, Smoke'* without a loss in data integrity. Four attributes from the State were mapped one-to-one to a MMUCC attribute ('*Rain,' 'Sleet or Hail,' 'Snow,'* and '*Severe Crosswinds*'). According to the general mapping rules, the State attribute '*Other*' cannot map to the MMUCC *'Other'* because the State did not possess all other C11 attributes. The State did not have an attribute to map to the MMUCC attribute *'Unknown.'* Finally, the State only allows for one attribute, while the MMUCC guideline suggests States should choose up to two attributes. However, C11 provides two attribute selections, which means that any State must provide 24 total attributes (12 C11 attributes, selected twice). Therefore, this State element has five attributes that map to the 24 possible attributes in MMUCC.

After analysts completed the mappings for each State's crash data, NHTSA encouraged each State to participate in a debriefing to provide that State an opportunity to learn which of their crash data elements and attributes did not map to MMUCC. States could also use the debriefing to provide additional documentation about their crash data, which often led to revised results. NHTSA encourages States considering updating their PAR or crash database to review their MMUCC mapping report to identify opportunities to increase alignment with MMUCC.

Finally, the MMUCC mapping method results in standardized scores that measure the percentage of alignment to MMUCC at the element level, system level, and overall total. Each MMUCC data element was scored by dividing the number of attributes that the State could map to MMUCC by the total number of MMUCC attributes for that element.

$$\text{MMUCC Element Mapping Score (\%)} = \frac{\begin{array}{c}\text{Number of State Attributes}\\ \text{that Map to the MMUCC Data Element}\end{array}}{\begin{array}{c}\text{Total Number of Attributes}\\ \text{for the MMUCC Data Element}\end{array}} {}^{*}$$

In Table1, there are 24 attributes for the for MMUCC element “C11 Weather Conditions” (12 attributes, selected twice). Of these 24 attributes, the State can map five attributes. The score for this data element is calculated as follows:

$$\text{MMUCC Element Mapping Score (\%)} = \frac{5}{24} = 20.8\%$$

The score for each of the eight data sections of MMUCC were calculated by summing the scores for all the data elements in each section and dividing by the number of data elements in each section. Table 2 shows the distribution of MMUCC data elements by section

$$\text{MMUCC Section Mapping Score (\%)} = \frac{\begin{array}{c}\sum \text{MMUCC Element Mapping Scores} \\ \text{in the Section}\end{array}}{\begin{array}{c}\text{Number of MMUCC Elements} \\ \text{in the Section}\end{array}}$$

Table 2.
MMUCC Data Elements by Section

Section	**Data Elements**
Crash Section	27
Vehicle Section	24
Person Section	27
Roadway Section	16
Fatal Section	3
Large Vehicle and Hazardous Materials Section	11
Non- Motorist Section	6
Dynamic Data Element Section	1
Total	115

The score for each State’s alignment to MMUCC is the sum of each element mapping score divided by the total number of MMUCC data elements. The result is the overall State mapping percentage:

$$\text{Overall State to MMUCC Mapping Score (\%)} = \frac{\sum \text{MMUCC Element Mapping Score}}{115}$$

RESULTS

Overall, States’ alignment to MMUCC is low and varies greatly. More than half the States aligned to less than 50% of the 115 MMUCC data elements. The mean percentage of States’ alignment to MMUCC is 45.9%, with alignment ranging from a low of 9.4% to a high of 84.8% and a standard deviation of 13.66. As Figure 2 shows, a little less than half the States (46.2%) scored between 39.6% and 54.7%.

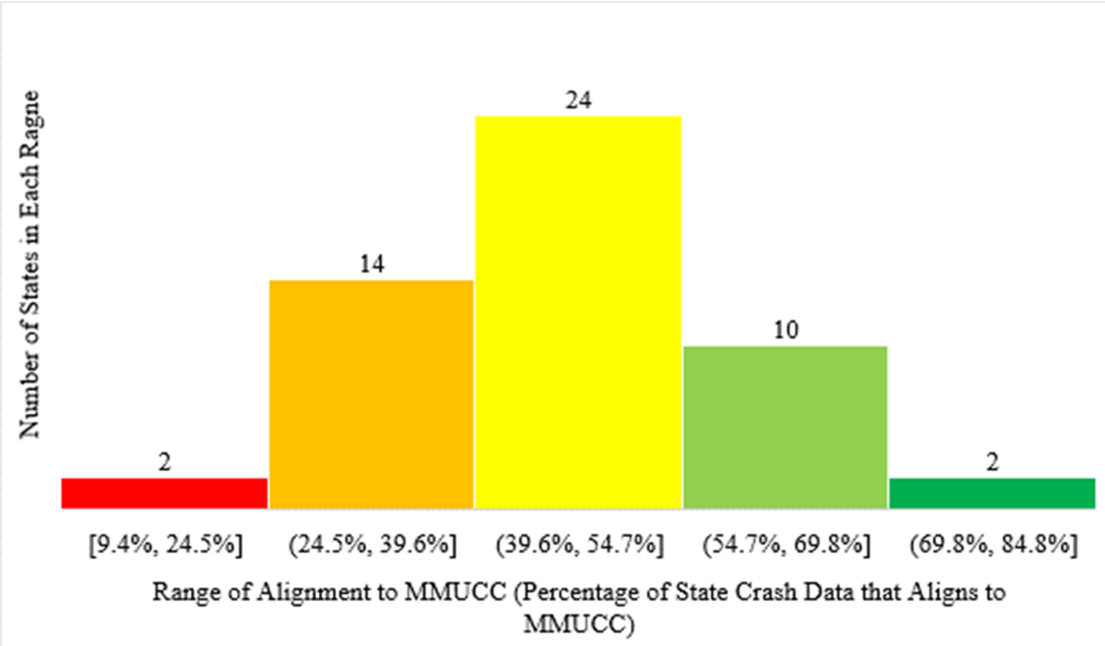

Figure 2. States' Alignment to the MMUCC 5th Edition

The MMUCC guideline includes eight sections that focus on a different type of data. As **Error! Reference source not found.**Table 3 shows, States alignment to MMUCC varies according to the different types States. States had the greatest alignment to MMUCC's crash data elements with a mean score of 70.5% ranging from a low of 32.8% to a high of 96.4%. States had the lowest alignment to the dynamic data element, which is the most recent addition to MMUCC and measures *Motor Vehicle Automated Driving System(s)*. Only one State's data was aligned 100%, and 46 States had zero alignment to this data element, resulting in a mean score of 3.4%.

Table 3.
States' Alignment to 115 MMUCC Data Elements

MMUCC Data Elements	Mean Score (%)	Median Score (%)	Lowest Score (%)	Highest Score (%)	Standard Deviation
Crash (N=27)	70.5	72.1	32.8	96.4	13.88
Vehicle (N=24)	56.7	58.3	6.7	95.4	17.61
Person (N=27	46.5	44.2	1.5	91.7	17.21
Roadway (N=16)	12.0	0.0	0.0	85.9	17.55
Fatal (N=3)	20.3	16.3	0.0	100.0	22.40
Large Vehicles and Hazardous Materials (N=11)	30.4	24.9	0.0	87.9	25.87
Non-Motorist (N=6)	28.0	26	0.0	96. 7	22.48
Dynamic Data Element (N=1)	3.4	0.0	0.0	100.0	14.56
Total (N=115)	45. 9	44.4	9.4	84.8	13.66

Collecting national data on alcohol-related crashes is central to NHTSA's work to understand risky driving behavior. Approximately one-third of all traffic crash fatalities in the United States involve drunk drivers (with blood alcohol content of .08 grams per deciliter (g/dL) or higher). MMUCC includes several data elements to capture data on alcohol-related crashes. Table 4 summarizes States alignment to MMUCC alcohol-related data elements and attributes. MMUCC data element "C25. Alcohol Involvement" is the most uniformly adopted alcohol-related element by States with a mean national alignment of 74.4% that includes 28 States that are in complete alignment with this data element, seven States with no alignment to this data element, and 17 States that can map to some of this data element's attributes. In contrast, the lowest level of alignment was for "F2. Alcohol Test Type and Results", which had a mean national score of 27.9% that includes only one State in complete alignment and 11 States with no alignment to this data element.

Table 4.
States Alignment to MMUCC Alcohol-Related Data Elements and Attributes

MMUCC Alcohol-Related Data Elements and Attributes	Mean Score (%)	Median Score (%)	N States with 0.0% Alignment	N States with 100.0% Alignment	Standard Deviation
"C25. Alcohol Involvement"	74. 4	100.0	7	28	34.35
"P19. Condition at Time of the Crash" Attribute 5, 'Under the Influence of Medications/Drugs/Alcohol'	34.0	34.4	16	2	30.21
"P20. Law Enforcement Suspects Alcohol Use"	66. 7	66.7	8	20	34.59
"P21. Alcohol Test"	55.0	65.4	11	5	35.36
"F2. Alcohol Test Type and Results"	27.9	22.2	11	1	25.94

NHTSA collects data on other risky driving behaviors, including drowsy driving, drugged driving, speeding, and distracted driving. Table 5 identifies the MMUCC data elements and attributes that relate to each risky behavior.

Table 5.
Risky Driving Behavior captured in MMUCC

Issues	MMUCC Data Elements and Attributes
Drowsy Driving	"P19. Condition at Time of the Crash" 1.1 and 1.2 *Asleep or Fatigued*
Drugged Driving	"C26. Drug Involvement", "P19. Condition at Time of the Crash Subfield 1.1 *Under the Influence of Medications/ Drugs/ Alcohol* Subfield 1.2 *Under the Influence of Medications/ Drugs/ Alcohol*, "P22. Law Enforcement Suspects Drug Use", "P23. Drug Test", "F3. Drug Test Type and Results".
Speeding	"P13. Speeding Related"
Distracted Driving	"P18. Distracted By"

As Table 6 show, States alignment to the MMUCC data elements related to risky driving behavior varies greatly with standard deviations ranging from 19.24 to 42.43. States had the greatest alignment to the MMUCC data elements related to drowsy driving (41. 4%). Data elements that States were in complete alignment to MMUCC was limited to 15 States collecting data on drowsy driving, nine States collecting data on speeding, and one State collecting data on distracted driving . No States collected data on drugged driving that aligned completely to MMUCC.

Table 6.
States Alignment to MMUCC Data Elements for Risky Driving Behavior

MMUCC Data Elements for Risky Driving Behavior	**Mean Score (%)**	**Median Score (%)**	**N States with 0.0% Alignment**	**N States with 100.0% Alignment**	**Standard Deviation**
Drowsy Driving	41.4	50.0	24	15	42.43
Drugged Driving	32.5	26.3	5	0	28.67
Speeding	30.4	0	28	9	39.12
Distracted Driving	6.3	0	42	1	19.24

NHTSA promotes road safety through grants to States and countermeasures programs, which focus on school bus safety, seat belts, teen driving, child passenger safety, non- motorist safety, and motorcycle safety. Table 7 identifies the MMUCC data elements and attributes that relate to each safety countermeasure program. Collecting this data helps States and NHTSA understand the effectiveness of safety countermeasure programs.

Table 7.
Critical Safety Issues Captured in MMUCC

Issues	**MMUCC Data Elements and Attributes**
School Bus Safety	"V10. Special Function of Motor Vehicle in Transport" Attribute 01 *'Bus – School (Public or Private)'*; "P12. Driver License Number, Class, CDL and Endorsements" Attribute 04 *'School'*.
Seat Belt Safety	"P8. Restraint Systems/Motorcycle Helmet Use" Attributes 05 *'Lap Belt Only Used'*, 06 *'None Used – Motor Vehicle Occupant'*, 07 *'Restraint Used – Type Unknown'*, *08 'Shoulder and Lap Belt Used'*, 09 *'Shoulder Belt Only Used'*, and Subfield 2 'Any Indication of Improper Use?'
Teen Driving Safety	"P16. Driver License Restrictions" Attributes 08 *'Intermediate License Restrictions'*, 09 *'Learner's Permit Restrictions'*; "P17. Driver License Status" Attribute 02 *'Non-CDL Restricted Driver license (Learner's permit, Temporary/ Limited, Graduated)'*.
Child Passenger Safety	"P8. Restraint Systems/Motorcycle Helmet Use" Attributes 01 *'Booster Seat'*, 02. *'Child Restraint System – Forward Facing'*, 03 *'Child Restraint System – Rear Facing'*, 04 *'Child Restraint – Type Unknown'* ; and Subfield 2 'Any Indication of Improper Use?'
Non Motorist Safety	"C22. Number of Non-Motorists" "P4. Person Type" Attributes 04 *'Bicyclist'*, 05 *'Other Cyclist'*, 06. *'Pedestrian'*, 07 *'Other Pedestrian (wheelchair, person in a building, skater, personal convey.)'*, 08 *'Occupant of a Non-Motor Vehicle Transportation Device'*, 09 *'Unknown Type of Non-Motorist'*, and 99 *'Unknown'*.
Motorcycle Safety	"P8. Restraint Systems/Motorcycle Helmet Use" Attributes 12 *'DOT-Compliant Motorcycle Helmet'*, 13 *'Not DOT-Compliant Motorcycle Helmet'*, 14 *'Unknown If DOT-Compliant Motorcycle Helmet'*, 15 *'No Helmet'*, 97 *'Not Applicable'*, 98 *'Other'*, 99 *'Unknown'*; and Subfield 2 'Any Indication of Improper Use?'

As Table 8 show, States' crash data alignment to the MMUCC data elements related to critical traffic safety issues was low and varies greatly. States had the greatest alignment to those MMUCC data elements related to school bus safety (56.4%) and seat belt safety (56.0%). In contrast, motorcycle safety ("P8. Restraint Systems/Motorcycle Helmet Use" per **Error! Reference source not found.**) has the least alignment by States with an average of 30. 6% alignment including nine States that cannot map anything to this data element. Of note also are the 16 States that do not map anything to the MMUCC child passesnger safety data elements.

Table 8.
States Alignment to MMUCC data Elements for Critical Traffic Safety Issues

	Mean Score (%)	Median Score (%)	N States with 0.0% Alignment	N States with 100.0% Alignment	Standard Deviation
School Bus Safety	56.4	58.3	4	12	34.15
Seat-Belt Safety	56.0	57.1	5	4	24.72
Teen Driving Safety	43.1	41.7	2	2	23.78
Child Passenger Safety	43.0	50	16	3	32.25
Non-Motorist Safety	37.9	31.4	2	0	24.66
Motorcycle Safety	30. 6	22.2	9	1	24.35

DISCUSSION

The most common issue NHTSA encountered during this MMUCC mapping project was outdated, incomplete or missing documentation, especially related to States' crash data dictionary. However, as a result of this project, many States updated or created documentation because the initial measurement of their database alignment to MMUCC was not reflective of their crash data capabilities. After receiving the new documentation, analysts updated the mapping scores to accurately reflect the contents of the primary production database. While some States took steps to improve or create documentation, several States still lack documentation about the external data systems linked to their crash database, and specifically those States lack definitions for data elements with established time-lapsed linkages with other traffic records data system, such as roadway, driver, and vehicle data systems. Conversely, States that have robust interfaces (live linkages) all had documentation in some form, and most had documentation that was fully updated and reflective of their existing system

Another common issue NHTSA encountered was discrepancies between the States' crash report form (or forms) and their database. In one instance, the mapping uncovered that a State had updated their statewide crash report form, but had failed to plan for or update their State crash database. In this case, the database could not save the new crash data elements that law enforcement collected. As a result, NHTSA finds that States may benefit from conducting regular data mappings and other data quality assessments and adjustments to keep their crash data system accurate and operational.

Lastly, some jurisdictions collected elements at different levels than suggested in MMUCC (e.g., States collected vehicle or person-level elements at the overall crash level instead). The primary problem with collecting elements at higher levels than suggested is the loss in specific data about the people, vehicles or roadways involved. For example, the State might collect "Sequence of Events" for the entire crash, which yields a single value as opposed to collecting this for each vehicle involved. Conversely, States that opt to collect elements at lower levels than suggested collect more granular data than MMUCC. This provides more detailed data for State analysts and can still be rolled up into a MMUCC aligned mapping.

Each State can use their MMUCC alignment score to develop an action plan for updating their crash report (or reporting software) and crash database. Since it may not be possible or desirable to update everything all at once, States can prioritize the elements to revise. NHTSA encourages States to establish an action plan and include the priority for change, rationale, deadline, and the person or agency responsible for each element for which they are considering a change.

CONCLUSION

The results of this mapping exercise provide NHTSA with the first nationwide understanding of State crash data capabilities, from which several initiatives are planned. First, the results form a baseline of capabilities that NHTSA plans to use to design and implement appropriate technical assistance and training to increase State alignment with MMUCC and improve data quality. Second, NHTSA plans to use the results to inform future changes to both the

MMUCC Guidelines and FARS Coding and Validation Manual. By understanding where the States' capabilities currently reside, NHTSA can make better-informed decisions regarding additions, deletions, and changes to the existing data publications that will serve to enhance alignment between the States' crash data systems and NHTSA's MMUCC Guidelines and FARS Manual simultaneously. Thirdly, NHTSA plans to repeat this exercise on a regularly recurring basis to provide consistent, relevant information to all crash data stakeholders. This will result in NHTSA having the means and opportunity to conduct research and analysis on State crash data capability changes and trends over time, leading to further enhancements of all the programs listed herein.

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NATURALISTIC STUDY OF LEVEL 2 DRIVING AUTOMATION FUNCTIONS

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ABSTRACT

Currently, there are commercially available vehicles that include features capable of providing Level 2, Partial Driving Automation as defined by SAE International. Research on the use and performance of the systems that these vehicles employ in natural settings is needed to help clarify the systems' potential benefits. The *Naturalistic Study of Level 2 Driving Automation Functions* (L2 NDS) project described herein has generated practical data to support the understanding of the use of automated lateral and longitudinal control functionality by evaluating a subset of currently available advanced technologies as drivers experience them during daily use.

The objective of the L2 NDS project was to investigate, through a naturalistic driving study, real-world driver interaction with commercially available driving automation systems. Ten vehicles equipped with both lateral and longitudinal automated features were instrumented and loaned to participants for a 4-week period. A total of 120 drivers were recruited over a 14-month data collection period. Each study vehicle was equipped with Virginia Tech Transportation Institute's NextGen Data Acquisition System, which continuously records video of the both the driver and the roadway, as well as vehicle data and automated lateral and longitudinal control activations. These data were used to analyze driving automation system use and driver performance during the study.

Focus area 1 investigated *System Performance*, including overall use of the features. Participants drove 216,585 miles, with 70,384 miles driven with both lateral and longitudinal control features active. Focus area 2 investigated *Driver-System Interaction* and involved a review of driver behaviors during driving automation system use, specifically the prevalence of non-driving tasks. Drivers were observed engaging in non-driving tasks, but these were not related to feature use. Focus area 3 investigated *Driver Performance*, which was measured by drivers' responses to Request to Intervene (RTI) alerts generated by the driving automation systems. Driver behavior was consistent with active driving/supervision of the automated features; drivers were receptive to RTI alerts. No RTIs were associated with any safety-critical events (i.e., crashes and near-crashes). In total, 5 minor crashes (no injury or visible damage) and 66 near-crashes were observed across the entire data set. No statistical relationship was observed between safety-critical event rates and feature activation level. Focus area 4 investigated *Driver Engagement*, which includes subjective feedback obtained from participants. Participants reported that they were generally comfortable and felt safe using the features, with self-reported trust increasing over the course of the study.

INTRODUCTION

The objective of the *Naturalistic Study of Level 2 Driving Automation Functions* (L2 NDS) project was to investigate, through a naturalistic driving study (NDS), real-world driver interaction with commercially available vehicles that could sustain lateral and longitudinal motion control. The study objectives were to observe and evaluate how drivers operated vehicles equipped with lateral and longitudinal driving automation features intended for operation in mixed traffic under a variety of roadway types, driving conditions, and speeds. This study was also intended to support the identification and/or refinement of human factors-related needs to help encourage the safe operation of vehicles with driving automation features.

Currently, there are several commercially available vehicle models offering optional features that automate at least some portion of lateral and longitudinal vehicle control. Depending on the make of the vehicle, different terms are used to name and describe these automated lateral and longitudinal control features. For example, the lateral control feature may be referred to as steering assist, lane keep assist, or lane centering, while the longitudinal control feature is often termed adaptive cruise control, intelligent cruise control, or advanced cruise control. In some cases, these systems activate together, while other implementations require two separate feature activations. When automated lateral and longitudinal control features are combined, the overall driving automation systems can be considered Level 2 (L2), Partial Driving Automation [1]. SAE describes the roles of the driving automation system and the driver during L2 driving automation in standard J3016, originally published in 2016:

> The Driving Automation System (while engaged): 1) Performs part of the dynamic driving task (DDT) by executing both the lateral and longitudinal vehicle motion control subtasks, and 2) Disengages immediately upon driver request.
>
> The Driver (at all times): 1) Performs the remainder of the DDT not performed by the driving automation system, 2) Supervises the driving automation system and intervenes as necessary to maintain safe operation of the vehicle, and 3) Determines whether/when engagement and disengagement of the driving automation system is appropriate, and immediately performs the entire DDT whenever required or desired. (p. 19)

The research team notes that there is ongoing discussion regarding classification and definitions of driving automation systems and features. Although the report title includes the term "Level 2," the goal of this research project was not to classify features as Level 2, but rather to determine how drivers interact with a range of driving automation features. Given the myriad of terms used to name or brand these types of automation, the general terms "automated lateral control features" and "automated longitudinal control features" are used in this paper.

The project was designed to address four main focus areas, with specific research questions assigned to each. Focus area 1 investigated ***System Performance***. Sampled and reduced data were used to provide insight into the systems' performance. Focus area 2 investigated ***Driver-System Interaction*** and involved a review of driver behaviors during driving automation system use, specifically the prevalence of non-driving tasks. Focus area 3 investigated ***Driver Performance***. Driver performance was measured by drivers' responses to Request to Intervene (RTI) alerts generated by the driving automation systems. Focus area 4 investigated ***Driver Engagement***, which includes subjective feedback obtained from participants. The project also included a Longer Drive Sub-Study focused specifically on drives longer than 2 hours.

METHODS

Two each of the following vehicles were leased for the duration of the study. Each of the selected models allowed drivers to simultaneously activate longitudinal and lateral automation features (relevant packages required are listed). As part of the lateral automation feature, all vehicles generated RTIs informing the driver to return hands to the steering wheel or otherwise administer lateral control input.

- 2017 Audi Q7 Premium Plus 3.0 TFSI Quattro with Driver Assistance Package
- 2015 Infiniti Q50 3.7 AWD Premium with Technology, Navigation, and Deluxe Touring Package
- 2016 Mercedes-Benz E350 Sedan with Premium Package, Driver Assistance Package

- 2015 Tesla Model S P90D AWD with Autopilot Convenience (software version 8.0)
- 2016 Volvo XC90 T6 AWD R with Design and Convenience Packages

Each vehicle was equipped with Virginia Tech Transportation Institute's (VTTI's) NextGen Data Acquisition System (DAS). As shown in Figure 1, the DAS continuously recorded video of the forward roadway, the driver's face, an over-the-shoulder view of the driver's hands and lap area, a view of the footwell, and a rear view. The DAS also recorded vehicle data, including speed, accelerator pedal position, brake application, acceleration, lane position, turn signal activation, and GPS coordinates.

Figure 1. Example of video views collected by the DAS

For each driving automation system, the general operational envelope was ascertained in various driving environments. The longitudinal control features utilized a forward-looking set of sensors (typically radar-based; for some vehicles, forward camera data was also included). None of the longitudinal control features directly responded to traffic ahead in adjacent lanes. Following distance could be adjusted by the driver, with following distance settings having an approximately 2–3-second headway.

Lateral control features varied in their overall capability. In some cases, the lateral control feature would initiate steering as the study vehicle approached a lane marking, while in others the system operated more akin to a "lane centering" feature, with active steering from the feature. Lateral control features utilized a forward-looking camera with a vehicle-specific machine vision algorithm to track lane markings.

Regardless of overall capability, all features required active monitoring from the driver and frequent intervention. For all vehicles, the intended use of the lateral control features required the driver's hands on the wheel to engage it, and drivers were warned not to use the driving automation systems in poor visibility conditions, weather related or otherwise. As noted, the vehicles varied somewhat in feature availability and activation; in some cases, the lateral control feature was only available if the longitudinal control feature was already engaged, or the two features engaged simultaneously. For most of the vehicles, the following feature generalizations are most relevant for the current paper:

- Driving automation systems were intended for use in highway driving environments with clear weather
- Lateral control features were generally available at speeds above 40 mph with visible lane markings
- Lateral control features were based on a vehicle-specific machine vision system to track lane markings
- Additional sensors (e.g., ultrasonic) may have been used for lateral safety systems such as blind spot warning
- Longitudinal control features were available above 20 mph
- Longitudinal control features were forward-radar based

- No vehicles included corner or side-facing radar units
- RTIs were all generated as part of the lateral driving automation feature
- Timing was based on the lack of detected steering inputs from the driver and/or crossing a detected lane marking
- RTIs were multi-modal, including both a visual and auditory component (no RTIs included a haptic component)

Although some vehicles tested included a “low speed” version of driving automation (i.e., traffic jam assist, pilot assist, autopilot), baseline epochs for this effort were sampled from the speeds outlined above for lateral and longitudinal control features. However, RTIs and safety-critical events (SCEs; i.e., crashes and near-crashes) were included from all speeds.

PARTICIPANTS

A total of 120 participants were recruited—12 participants for each of the 10 selected study vehicles. All participants were recruited from the Washington, DC region, which included both northern Virginia and Maryland suburbs. Participants were balanced across age and gender and were recruited from two age groups: 25 to 39 years old, and 40 to 54 years old, which were the age groups used in previous test track research [2]. For each set of 12 participants, six were from the younger age group (three male and three female) and six were from the older age group (three male and three female).

Drivers were compensated up to $500 as follows: 1) up to $360 if their total mileage was under or equal to 1,200 miles; or 2) $500 if they exceeded 1,200 miles. They were also lent a transponder that gave them free access to the high-occupancy toll lanes managed by Transurban.

APPROACH

Each driver was assigned to one vehicle for the duration of their 4-week participation time in the study. Drivers received training on the vehicles designed to mimic what they would receive at a dealership if purchasing a new car. Training consisted of a static orientation and a two-part test drive. The static orientation included instruction on all of the driving automation system features. During the first part of the test drive, the onsite researcher drove the study vehicle and demonstrated the driving automation features. Once the researcher completed the demonstration of the features, the participant took over driving the vehicle. The participant was then able to experience features and ask the researcher any remaining questions. After completing training, participants drove the study vehicle instead of their own vehicle during the 4-week participation period.

Participant data was saved to a secure server and analyzed once driving periods were complete. Continuously recorded data were then sampled for further annotation and analysis. Trained data reductionists reviewed the sampled recorded video, audio, and parametric data to annotate the driver, vehicle, and environmental factors that were present during each of the sample types (driving automation system use, RTI alerts, and SCEs).

DATA SAMPLING AND REDUCTION

NDSs provide continuous data recording while participants are driving. The focus of this section is to describe the approach to sampling, reducing, and analyzing continuously recorded data. Established kinematic algorithms (e.g., hard decelerations, lane departures, high yaw rates) were used to identify potential SCEs. Trained data reductionists (see below) then inspected the videos associated with these events to verify the occurrence of an SCE. For baseline driving samples, 15-second epochs were sampled from the continuously recorded data. The 15 seconds were divided into 10 seconds prior to and 5 seconds after the time of interest. Samples were taken during instances in which both the lateral and longitudinal driving automation features were engaged, during instances in which the driving automation system was available but not engaged, and during instances in which both features of the driving automation system were available but only one was engaged. Instances in which an RTI was issued were also sampled. Driving automation was available when the vehicle was traveling above the speed required for activation on a road with visible lane markings. The sampling approach was as follows:

- All periods in which the driving automation system was available for use and also active were identified using a VTTI-developed machine-vision algorithm combined with available vehicle network information.
- Up to twelve 15-second epochs per driver were randomly sampled from the periods in which the driving automation system was active (samples were stratified by each week of participation). It was determined that 12 samples per driver were needed to provide a reliable statistical estimate of driver performance, and 15-second samples allowed for the assessment of drivers' visual behavior and engagement in non-driving-related tasks; this sampling method was adapted from a previous NDS [3].
- Up to 12 epochs per driver of instances in which the driving automation system was available, but only one feature (either lateral or longitudinal) was active, were sampled. These were instances where only lateral or only longitudinal control was automated, but vehicle speed was above 40 mph and data reductionist-verified lane markings were present.
- Up to 12 epochs per driver of instances in which both functions of the driving automation system were available, but neither lateral nor longitudinal control automation was active, were sampled. These were instances where the vehicle speed was above 40 mph and data reductionist-verified lane markings were present.
- Up to 12 RTI epochs per driver per week were sampled. These were instances where an RTI was issued by the vehicle's human-machine interface.
- All SCEs that were observed in the dataset were analyzed. See the Results section below for details regarding the total number and type of SCEs (crashes and near-crashes) observed during data collection.

This sampling strategy was implemented to allow comparisons of driver behavior and roadway scenarios between levels of driving automation system engagement (when such activation was available). As noted, for each epoch type, 12 epochs per driver week were planned. In practice, 12 epochs were not observed in all cases for all vehicles; Table 2 shows the number of samples collected. In cases where there were fewer than 12 samples for a week, all instances of that activation were reduced.

Table 1.
Total epochs samples and average samples per driver

Epoch	Total	Average Samples per Driver	Average Samples per Week
Both Features Engaged	1,295	11	3
No Features Engaged, Both Features Available	1,052	9	2
One Feature Engaged, Both Features Available	1,083	9	2
RTIs	449	4	1
SCEs	71		

RESULTS AND KEY FINDINGS

The L2 NDS was intended to produce an initial understanding of commercially available driving automation systems. This project is the first study sponsored by the National Highway Traffic Safety Administration to review driver interaction with vehicles that include lateral and longitudinal automated features in real world settings. This research effort was intended to provide insight into four focus areas: System Performance (during unscripted, on-road driving), Driver System Interaction, Driver Performance, and Driver Engagement. Key findings for each focus area are summarized below.

System Performance

Across all 120 participants, a total of 216,585 miles were driven (1,805 average per participant), with 53,360 miles driven below 40 mph. The remaining 163,225 miles were driven at speeds at or above 40 mph—of these, 70,384 miles were driven with both lateral and longitudinal driving automation active, 50,454 with one feature active, and 42,431 with no features active.

The analysis of environmental factors observed indicated that, in most cases, participants were operating the driving automation system-equipped vehicles in a manner consistent with manufacturers' intended use. When operating the vehicles at speeds above 40 mph, drivers typically drove with both features active. Drivers were less likely to activate the systems in heavy traffic, on non-interstate roads, and in rainy weather conditions.

Driver System Interaction

Non-driving task prevalence was observed to be similar across all activation levels; there was no increase in non-driving tasks when both lateral and longitudinal control features were active. The most common non-driving tasks observed were interacting with a passenger and monitoring the instrument panel. Furthermore, the types of tasks performed and eyes-off-road time were also similar across activation levels. The observed prevalence of non-driving tasks was high, but it should be noted that the current study used a 15-second reduction window to assess non-driving tasks. Previous estimates of secondary tasks performed as part of the Second Strategic Highway Research Project (SHRP 2) were based on a 6-second reduction window [3]. Additionally, drivers were observed to be monitoring and/or interacting with the instrument panel (center dashboard console and instrument cluster) in about 10% of sampled cases; this is consistent with supervisory behaviors as feature activation level (e.g., on or off), settings (e.g., following distance setting), or other system status (e.g., lane marking tracking) were presented in the instrument panel.

Driver Performance

In total, there were 71 SCEs observed in the data set. Five SCEs were crashes, and 66 were near-crashes. All crashes were low severity, rated as Level 3 or Level 4 based on previously adapted SHRP 2 definitions [4] (Virginia Tech Transportation Institute, 2015). No statistical relationships were observed between SCE rates and feature activation level. No RTIs were observed in the context of any SCE. The one observed crash with both features active was a single vehicle crash in which the driver struck a toll lane access gate at low speed (the driver attempted to enter a buses-only entrance). Although both features were active at some point during the reduction window, the driver pressed the brake prior to impact, overriding the driving automation features. The driver was not distracted and had at least one hand on the wheel throughout the event. No damage to the gate or vehicle was observed in this instance.

A total of 449 RTIs were sampled; in 118 of these, drivers were observed to have hands off the wheel. Analysis of reaction times for the RTIs in which drivers had hands off the wheel showed that the average reaction time of 0.94 seconds was within an expected range based on the results of previous research (e.g., [2]). However, there were some cases that showed longer response times or no intervention from the driver. Examination of these cases revealed that drivers were exploring the boundary conditions associated with the driving automation systems (e.g., intentionally keeping hands off wheel to test RTI duration and lateral control feature capabilities). Drivers were often observed explaining system functionality to passengers in these events, which all occurred when traffic was generally free flowing, weather was clear, and drivers were looking forward and attentive.

Driver Engagement

Overall, drivers appeared to trust the driving automation systems, and were comfortable using them. Driver interviews and trust ratings gathered at specific intervals during the 4-week participation period suggested that there was little change in trust in the lateral systems, although summarized comments also indicated that there were situations reported where the lateral systems did not function as expected. Again, these limitations are consistent with how the vehicles were characterized, and it is likely that even after the features were demonstrated, participants still had a higher than realistic expectation of function. Trust in the longitudinal system did increase over time; subjective feedback suggested that drivers learned the limitations of the longitudinal system and were able to use it more effectively after understanding its limitations.

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Passenger Vehicle-Powered Two Wheeler Pre-Crash Trajectory Reconstruction and Conflict Analysis Results for Real-World Crashes in the EU and US and its Application to Advanced Crash Avoidance Technologies

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ABSTRACT

Research Question / Objective: Advanced Driver Assistance Systems (ADASs) such as Forward Collision Warning have been developed for light passenger vehicles (LPVs) to avoid and mitigate collisions with other road users and objects. These technologies may have contributed to a reduction in LPV traffic fatalities in the EU and US. However the number of powered two wheeler (PTW) fatalities has remained relatively constant in the US. To fully realize the potential safety benefits across all vehicle categories, LPV crash avoidance technologies also need to be effective in avoiding collisions with PTWs. To accomplish this, knowledge of the pre-crash LPV-PTW vehicle trajectories and conflicts is needed to guide the development and testing of effective crash countermeasures for both LPVs and PTWs.

Methods and Data Sources: Crash scenario database development tools previously developed to evaluate LPV-LPV crash countermeasure effectiveness have been extended to LPV-PTW crash scenarios. This involved using information for a large sample of LPV-PTW crashes from the EU Motorcycle Accidents In-Depth Study (MAIDS) and US Motorcycle Crash Causation Study (MCCS) databases, which are based on in-depth crash investigations and the Organisation for Economic Co-operation and Development (OECD) Common Methodology. The vehicle pre-crash trajectories were estimated based on the coded data and digitized information from the scaled pre-crash scene diagrams. The pre-crash conflict state was then analyzed based on these trajectories.

Results: The estimated pre-crash trajectories using this method indicate that LPV-PTW pre-crash trajectories and conflicts in France, Germany, Italy, and the US have many similarities, but there are some differences as well. These results indicate that conflicts in several types of pre-crash scenarios, such as the LPV turning across the PTW path in the same direction or opposite direction, begin less than 1.5 sec before impact, which may not be sufficient time for some crash countermeasures based on conflict detection and driver warnings to be effective.

Discussions and Limitations: The accuracy of the results is based on a number of assumptions, approximations, and limitations in the data and methods used. These include the accuracy and representativeness of the data based on in-depth crash investigations, as well as the domain-of-validity and accuracy of the vehicle directional control models used.

Conclusion and relevance to session submitted: Analysis of real world accident data is critical to the development and evaluation of ADAS and automated driving systems. This analysis has shown that LPV-PTW crash countermeasures need to function with shorter pre-crash conflict epochs, or in the pre-conflict phase, in order

to be effective in preventing collisions. This information may help to define requirements for LPV-PTW crash countermeasures (e.g., C-ITS V2V and Blind Spot Detection), evaluate their effectiveness, and inform the development of performance confirmation tests (e.g., New Car Assessment Programs).

INTRODUCTION

Advanced Driver Assistance Systems (ADASs) such as Forward Collision Warning (FCW), Automatic Emergency Braking (AEB), and Blind Spot Warning (BSW) have been developed for Light Passenger Vehicles (LPVs) to avoid and mitigate collisions with other road users and objects. These crash avoidance and mitigation countermeasures may have contributed to the 41% reduction in the overall number fatalities in the EU from 43,151 in 2007 to 25,651 in 2016 [1], and a 9% reduction in the overall number of traffic fatalities in the US from 41,259 to 37,461 in the same time period [2]. A main component of these overall reductions were a 42% reduction in LPV occupant fatalities in the EU from 20,744 to 11,990, and an 18% reduction in the US from 29,072 to 23,714. Powered two wheeler (PTW) fatalities, comprising mopeds and motorcycles,[1] also decreased by 42% from 7,522 in 2007 to 4,334 in 2016 in the EU, but increased by 2% in the US over the same period. In an effort to explain the differences in the PTW versus LPV fatality trends in the US, one question is whether or not LPV ADASs are as effective in avoiding collisions with PTWs compared to other road users.

Lenkeit and Smith [4] evaluated the ability of eight 2016 model year LPVs equipped with FCW to detect an exemplar motorcycle and passenger car using two tests in the US National Highway Traffic Safety Administration (NHTSA) FCW confirmation test procedures. The results of this preliminary evaluation indicated that only two of the eight LPVs tested were able to pass the NHTSA test procedure scenario with a stationary motorcycle as the principal other vehicle (POV), compared to all LPVs passing the test with a stationary passenger car as the POV. Therefore these preliminary results tend to indicate that FCW systems may not be as effective in avoiding or mitigating collisions with a motorcycle as they are with a passenger car.

Van Auken et al. ([5],[6],[7]) then estimated the pre-crash trajectories and conflicts for 101 crashes in the US and 266 crashes in the EU involving one LPV and one PTW. This analysis was based on the European Motorcycle Accidents In-Depth Study (MAIDS) database [8] and the US Federal Highway Administration’s (FHWAs) Motorcycle Crash Causation Study (MCCS) database [9]. Both of these databases were developed based on in-depth accident investigations using methodology based on the Organisation for Economic Co-operation and Development (OECD) Common Methodology [10].

Analysis of these estimated pre-crash trajectories indicated that the conflicts begin later, and therefore with smaller Time to Collision (TTC) values, compared to results for some LPV-LPV crashes. Therefore there may be less time for a driver or crash avoidance technology to avoid or mitigate a LPV-PTW crash after a conflict has been detected, compared to a LPV-LPV crash. As a result such systems may be less effective in avoiding LPV-PTW crashes.

Background

Dynamic Research, Inc. (DRI) has been developing and applying safety impact analysis methods for many years (e.g., [11]). This included the development of a comprehensive Safety Impact Methodology (SIM) in two Honda-DRI Advanced Crash Avoidance Technology (ACAT) programs for the US NHTSA. The comprehensive and general structure of this methodology and accompanying tools are well suited for the potential evaluation of LPV ADAS (e.g., FCW, AEB, and BSW) effectiveness in avoiding and/or mitigating collisions with PTWs with the extensions originally outlined in [12], as well as other applications such as pre-crash conflict analysis, the development of system requirements, and testing.

In-Depth LPV-PTW Crash Databases

Two databases that have sufficient suitable information to be integrated into this SIM methodology are from the European MAIDS study and the US MCCS study. Both of these studies had coded accident data and crash scene diagrams based on in-depth investigations.

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[1] Powered Two Wheelers comprise L1 and L3 vehicles as defined in [3]. L1 vehicles are commonly known as mopeds. L3 vehicles are commonly known as motorcycles. See the Definitions/Abbreviations Section.

The MAIDS study was conducted from 1998 through 2002 by the European Association of Motorcycle Manufacturers (ACEM) with co-funding by the European Commission. It was developed using the OECD Common Methodology [10]. All of the cases are from France, Germany, Italy, Netherlands, and Spain. Most of the MAIDS cases are from the 1999 to 2001 calendar year time period.

The MCCS study was conducted by a team from Oklahoma State University, Westat, and Dynamic Sciences, Inc. and sponsored by the Federal Highway Administration (FHWA). It was also developed based the OECD Common Methodology with adaptions to the US motorcycling conditions. All of the cases are from Orange County, California. All of the MCCS cases are from the 2011 to 2015 calendar year time period.

Project Aims

The objective of this project was to extend the SIM tools and data to include the MAIDS and MCCS data in order to better understand the pre-crash conflicts of LPV-PTW crashes, to guide the development of LPV ADASs in avoiding and mitigating collisions with a PTW, and to evaluate their effectiveness and benefits.

SAFETY AREA TO BE ADDRESSED BY THE ADVANCED TECHNOLOGIES

The objective of the ACAT SIM with the PTW extensions is to evaluate the effectiveness and benefits of LPV ADASs (e.g., FCW, AEB and BSW) in avoiding or mitigating LPV-PTW crashes. It is assumed that these technologies could address crashes where the LPV driver inattention is a contributing factor, but may also be applicable to safety-relevant cooperative ITS (C-ITS) and other technologies as well.

The size of the problem to be addressed

One of the first steps in the development and evaluation a crash avoidance technology is to determine the size of the traffic safety problem in terms of broadly defined non-technology specific crash types. The estimated numbers of fatalities that represent the size of the problem for the entire EU and US motor vehicle fleets in the 2016 calendar year by the crash category and type of vehicle involved are listed in Table 1. Some of these crashes are not expected to be addressable by specific LPV technologies such as AEB due to either the vehicle application (e.g., not an LPV), the vehicle role (e.g., struck vehicle), or other technology relevant factors. For example, the results in Table 1 indicate there were 997 PTW fatalities in the EU involving only one vehicle (i.e., did not involve an LPV). These results also indicate that there were 3,337 PTW fatalities in the EU involving one or more other vehicles, which account for 13% of all traffic fatalities in the EU. There were also 3,273 PTW fatalities in the US involving one or more other vehicles, which account for 9% of all US traffic fatalities in the US. A large portion of these cases involve an LPV, which could be potentially addressed by an LPV ADAS.

Table 1. Estimated crash problem size for the entire EU and US motor vehicle fleets in the 2016 calendar year

(A)	(B)	(C)	(D)	(E)	(F)	(G)
Crash Category	**Number of EU Fatalities[a]**			**Number of US Traffic Fatalities[b]**		
	PTW	Other =(D)-(B)	Total	PTW	Other =(G)-(E)	Total
1 Vehicle	997[c]	6,658	7,655[d]	2,065	18,415	20,480
2+ Vehicle	3,337[e]	14,659	17,996[e]	3,273	14,053	17,326
Total	4,334[f]	21,317	25,651[g]	5,338	32,468	37,806

Sources:

a Based on EU Community database on road accidents (CARE) data.

b Based on US Fatality Analysis Reporting System (FARS, [13]) data (2018-05-18) query.

c Assumed equal to 23% of all PTW fatalities based on [14], p 10, Table 5. It is assumed that none of the single vehicle crashes are pedal cycles.

d [14], p 10, Table 5.

e =Total- Single Vehicle

f [1], p 19, Table 6 (677 moped fatalities) and p 20, Table 7 (3,657 motorcycle fatalities).

g [1], p 10, Table 2.

METHODS

The analytical approach involved refining and applying the methods developed in [5],[6],[7] for the EU MAIDS and US MCCS databases. The MAIDS and MCCS databases were developed using similar, but not identical, in-depth crash investigation methods. The MAIDS database was developed according the OECD common methodology. The MCCS database was developed using a methodology incorporating both the OECD and NHTSA methods.

Overview of the Crash Scenario Database Development Tools

A conceptual block diagram of the crash scenario database tools is given in Figure 1. These tools are collectedly referred to as “Module 1” in the Honda/DRI ACAT SIM. These Module 1 tools construct a harmonized crash scenario database for use in the development and evaluation of ADASs (e.g., requirements, simulation, and testing). The inputs are archival accident data such as the MAIDS and MCCS data as indicated at the top of the figure. The resulting crash scenario database comprises text summaries (to the extent available), harmonized coded data, scene diagrams, crash geometry and pre-crash time histories as depicted by the shaded database in Figure 1. These tools are organized into three sub-modules as follows:

- Submodule 1.1 assembles a crash scenario database with a representative sample of LPVs involved in real-world crashes. Ideally the crash scenario database would include all types of crashes and severities, which could be weighted to represent all crashes involving a LPV. This sub-module extracts cases from various coded accident databases such the MAIDS and MCCS data [8],[9].
- Submodule 1.2 is a tool to download or extract crash scene diagrams for each case in the crash scenario database if available.
- Submodule 1.3 is an Automated Accident Reconstruction Tool (AART) to reconstruct the pre-crash and crash position versus time trajectories of the LPVs for each case in the crash scenario file, provided there is sufficient information available and the case is within the domain-of-validity of the AART (e.g., there is a crash scene diagram, vehicle velocity, and contact information). The resulting reconstructions can be used for simulation and testing. These results can also be used for other analyzes, such as the identification of pre-crash conflicts described in [6].

The extensions of these tools for the US MCCS and EU MAIDS data were described in [5],[6],[7].

The results described herein are based on 367 cases from the US, France, Germany, and Italy that were reconstructed using this tool. The distribution of these cases is depicted in Figure 2. Each of these cases had sufficient information in the coded data, crash scene diagram, and supporting documentation to reconstruct the case. This excluded cases where a suitable scene diagram not available or did not have sufficient information about the locations of the vehicles prior to the impact and at the point of impact.

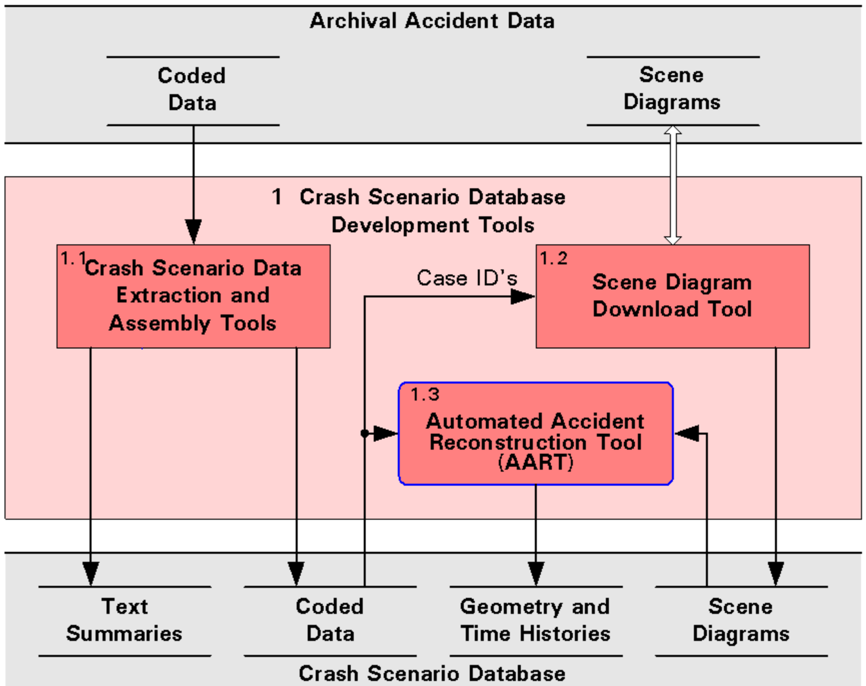

Figure 1. Crash Scenario Database Development Tools (e.g., [11]).

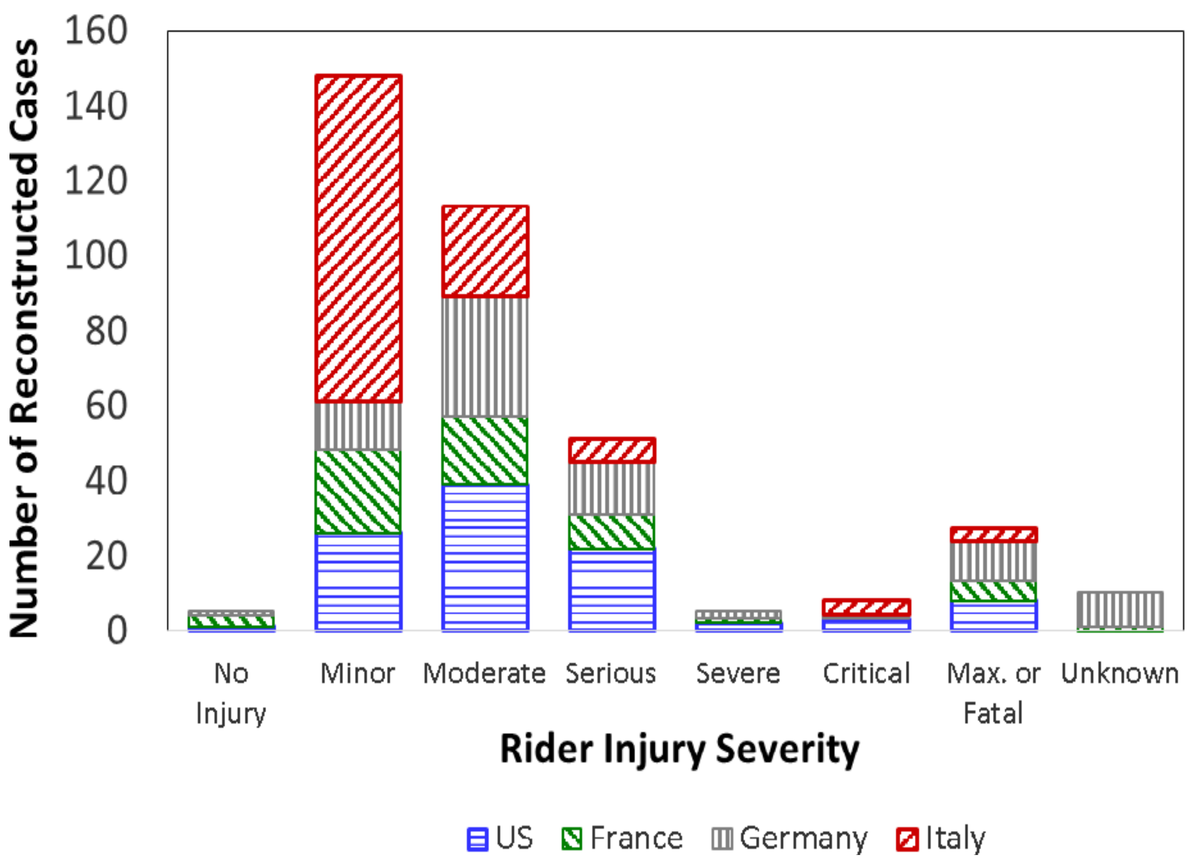

Figure 2. Number of reconstructed Cases by rider injury severity and country.

Extensions for the Current Results

The results presented herein are based on the following further refinements of the data and methods:

- Module 1.1
    - The NASS Accident Type described in Appendix A was coded for both vehicles in each of the reconstructed cases. The coded variables are VATYPE for the LPV and PATYPE for the PTW according to the conventions used in Appendix F of [11]. Reconstructed cases with similar crash types were then classified into the 24 different crash configuration groups listed in Table 2.
    - Data indicating if "*view obstructions* [were] *present and contributed to accident causation*," were extracted from the MAIDS and MCCS databases for both the LPV driver and PTW rider in order to further classify the reconstructed cases.
- Module 1.3 (Motorcycle Automated Accident Reconstruction Tool – M-AART)
    - The assumed pre-crash vehicle speeds in cases where the coded travel speed was missing or unknown to take into account coded data indicating the vehicle was traveling at a constant speed or accelerating.
    - Numerous refinements to the trajectory estimation algorithms to improve the accuracy of the estimated trajectories based on the available data. This includes new "reference trajectory" types with constant steer input rates or rider lean angle rates, which are consistent with the white process noise inputs assumed by the Kalman Filter-Smoother, provided there a are sufficient number of digitized pre-crash vehicle positions. The reference trajectories are initial solutions to the vehicle equations of motion that are used to determine locally linearized equations for the Kalman Filter-Smoother (e.g., [5]). It was also required that the PTW speed was either always less than or always greater than the critical speed of the Weir-Zellner model [16].[2] This avoids a singularity in the quasi-steady reference trajectory solution at the critical speed.

Table 2. Crash Configuration Groups based on NASS Accident Types

Crash Configuration Group based on NASS Accident Types		NASS Accident Types
Mnemonic	**Description**	**VATYPE/PATYPE**
HO/ODSS	Head-on or opposite direction side swipe	50/51, 51/50, 65/64
LPV LTAP/LD	LPV left turn across PTW path/lateral direction	82/83
LPV LTAP/OD	LPV left turn across PTW path/opposite direction	68/69
LPV LTAP/SD	LPV left turn across PTW path/same direction	72/73
LPV LTIP	LPV left turn into PTW path/same direction	76/77
LPV RE	LPV rear-end PTW	20/21, 24/25, 24/26, 28/29
LPV RTAP/SD	LPV right turn across PTW path/same direction	70/71
LPV RTIP/SD	LPV right turn into PTW path/same direction	78/79
LPV UT	LPV U-turn across PTW path	940/941…944
PTW LTAP/LD	PTW left turn across LPV path/lateral direction	83/82
PTW LTAP/OD	PTW left turn across LPV path/opposite direction	69/68
PTW LTAP/SD	PTW left turn across LPV path/same direction	73/72
PTW LTIP	PTW left turn into LPV path	77/76
PTW RE	PTW rear-end LPV	21/20, 25/24, 26/24, 29/28, 30/28
PTW RTAP/SD	PTW right turn across LPV path/same direction	71/70
PTW RTIP/OD	PTW right turn into LPV path/opposite direction	81/80
PTW RTIP/SD	PTW right turn into LPV path/same direction	79/78
SCP/L	Straight crossing path, PTW on left side of LPV	86/87, 89/88
SCP/R	Straight crossing path, PTW on right side of LPV	87/86, 88/89
SDSS/L	Same direction side swipe, PTW on the left of LPV	47/45
SDSS/R	Same direction side swipe, PTW on the right of LPV	46/45
T2/OD	Both vehicles turning/opposite direction	68/82
T2/SD	Both vehicles turning/same direction	76/78, 78/76
Other	Other	74/74, 98/98

[2] The "Norton 850" parameter values in [16] were assumed for motorcycles and the "Moped B" parameter values in [17] were assumed for mopeds.

Pre-Crash Conflict State Estimation
As previously described in [6], the state of conflict between the LPV and PTW can be estimated as a function of time before the impact based on the estimated vehicle trajectories. For the purpose of this analysis the conflict state C at time t was defined for $t \le t_{\text{impact}}$ as follows: $C(t) \triangleq \text{true}$ if the vehicles will contact each other at time t_{contact} if their linear and angular velocities remain constant between time t and t_{contact}; otherwise $C(t) \triangleq \text{false}$ if the vehicles will never contact.[3] For practical considerations the contact evaluation time interval was limited to up to 1 sec after the reconstructed impact time (i.e., $t \le t_{contact} \le t_{impact} + 1\,\text{sec}$). This definition can include momentary benign conflicts that may occur several sec before impact in addition to the final conflict, as illustrated by the example in Figure 4 and Figure 5. Of interest is the when the final conflict begins.[4]

RESULTS

The results in this section describe the estimated trajectories and conflicts for two example cases, followed by a summary for all of the cases.

Example pre-crash trajectories and state of conflict

Example Head-On Case

An example pre-crash trajectory reconstruction of a Head-On case is illustrated in Figure 3, Figure 4, and Figure 5. This case involves a moped overtaking two other PTWs and then impacting a LPV that was exiting a parking area and turning to the right onto the roadway. The coded data indicates that there were rider "*view obstructions present that contributed to accident causation*." Presumably these view obstructions were the other motorcycles. Figure 3 shows the pre-crash vehicle speeds that were assumed based on coded data. Figure 5 shows the estimated vehicle directional control inputs versus time. Figure 4 shows the resulting vehicle trajectories overlaid on the crash scene diagram. The vehicle trajectories were fit to the locations of the LPV and moped shown on the scene diagram. The estimated vehicle positions and orientations are depicted at 1 sec intervals and the movement of the cg positions are depicted by continuous curves. The control inputs and vehicle positions when $C(t) = \text{true}$ are shown highlighted in yellow. The LPV and PTW vehicle level NASS accident types illustrated in Appendix A that best describe this case were VATYPE=51 and PATYPE=50 respectively, and therefore the HO/ODSS crash configuration group according to Table 2.

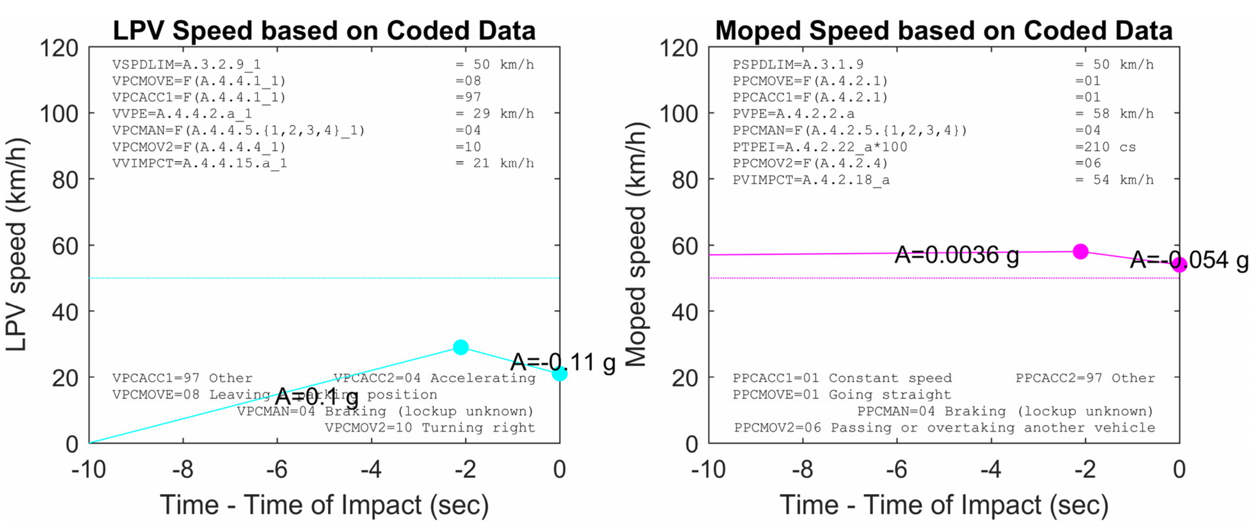

Figure 3. Assumed pre-crash speeds versus time for the exemplar head-on case based on coded data.

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[3] The PTW handlebars were included in the potential contact with the LPV. It was assumed that the handlebars were 0.89 m wide for the purpose of this conflict analysis.

[4] See footnote 9 in [6] for addition background and rationale for this conflict definition.

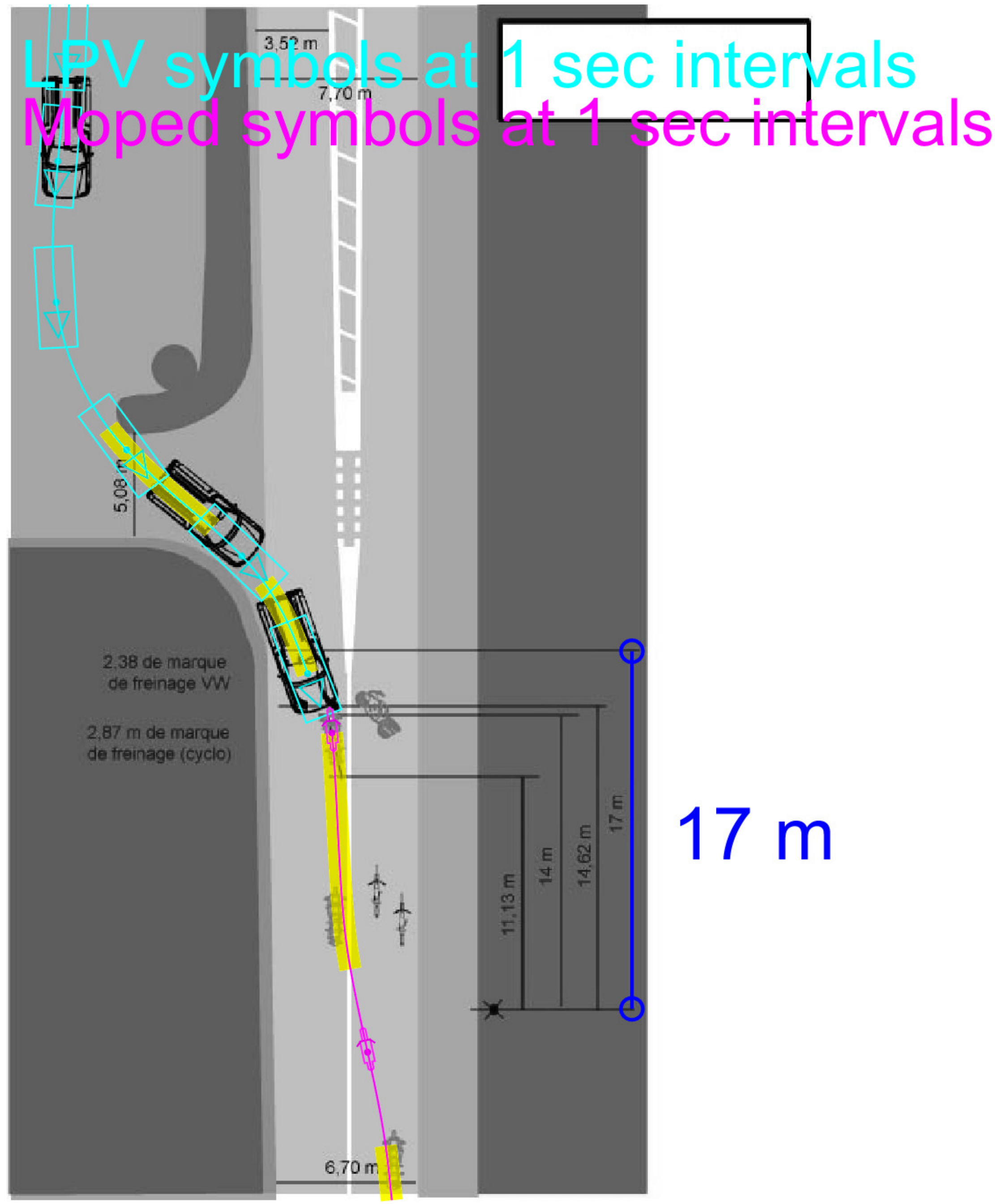

Figure 4. Estimated pre-crash trajectories for the examplar head-on case.

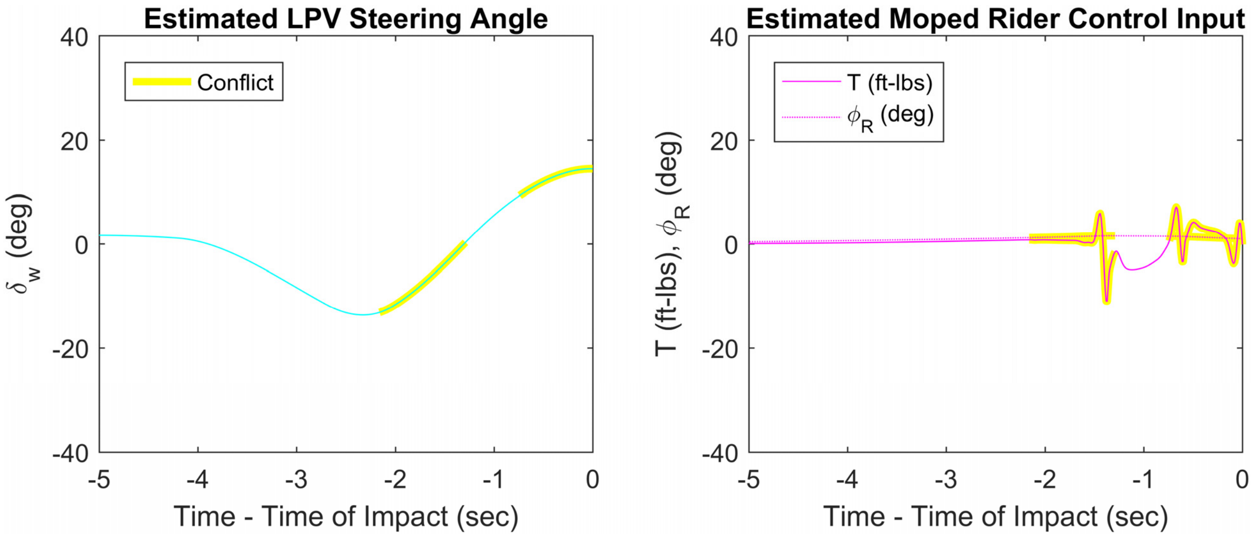

Figure 5. Directional control inputs versus time for the exemplar head-on case.

This example case illustrates the directional responses of the LPV and PTW to the vehicle control inputs. It was assumed for this case that the moped was traveling at approximately 7 km/h above the posted speed limit of 50 km/h 10 sec prior to impact.[5] At the same time a LPV was leaving a parked position. The M-AART estimated that the driver turned to the left (negative steer angle) to approach the roadway, then turned to the right (positive steer angle) to merge onto the roadway going in the opposite direction to the PTW. At the time of the coded precipitating event, 2.1 sec before impact, the coded data indicates the PTW was traveling at a constant speed of 58 km/h, and the LPV had accelerated to 29 km/h, as indicated in Figure 3. The rider then passed to the left of two other PTWs traveling in the same direction. The estimated rider passing maneuver involved first applying positive steer torque to turn to the left, then negative steer torque to turn to the right, then positive torque to recover as depicted in Figure 5. The coded data indicates both vehicles braked and the coded impact speeds were 21 km/h and 54 km/h respectively. Figure 4 shows the close agreement between the estimated vehicle trajectories and the available information. The maximum differences between the digitized LPV and PTW positions and the corresponding estimated trajectories are 0.7 m and 0.5 m respectively.

This example also illustrates both a momentary conflict which is benign and the final conflict which resulted in impact. The benign conflict occurs between t=-2.2 sec and t=-1.3 sec. This is when the LPV is headed towards the roadway and the vehicle velocity vectors intersect. The risk of collision will be small if the LPV turns to merge onto the roadway and the both vehicles stay within their respective lanes. This benign conflict ends as expected when the LPV turns to merge onto the roadway. The final conflict then begins 0.7 sec before impact. This is after the PTW crosses the lane boundary into the PTWs path. The coded data for this cases also indicates that the moped operator's view of the LPV was obstructed.

Example case with both vehicles turning

Another example pre-crash trajectory reconstruction is illustrated in Figure 6. This case involves a motorcycle turning left across the LPV path while the LPV is also turning left to follow the main roadway. Therefore both vehicles are turning left. The maximum differences between the digitized LPV and PTW positions and the corresponding estimated trajectories are 0.6 m and 0.2 m respectively. The estimated trajectories are in a state of conflict beginning 1.6 sec prior to impact. The coded data indicates that that there were LPV driver and PTW rider "*view obstructions present that contributed to accident causation*." Therefore the conflict may not have been detected because of visual obstructions. The LPV and PTW vehicle level NASS accident types illustrated in Appendix A that best describe this case were VATYPE=68 and PATYPE=82 respectively, and therefore the "T2/OD" crash configuration group according to Table 2.

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[5] The coded data for this case indicate that the moped had enhanced motor power and a modified exhaust.

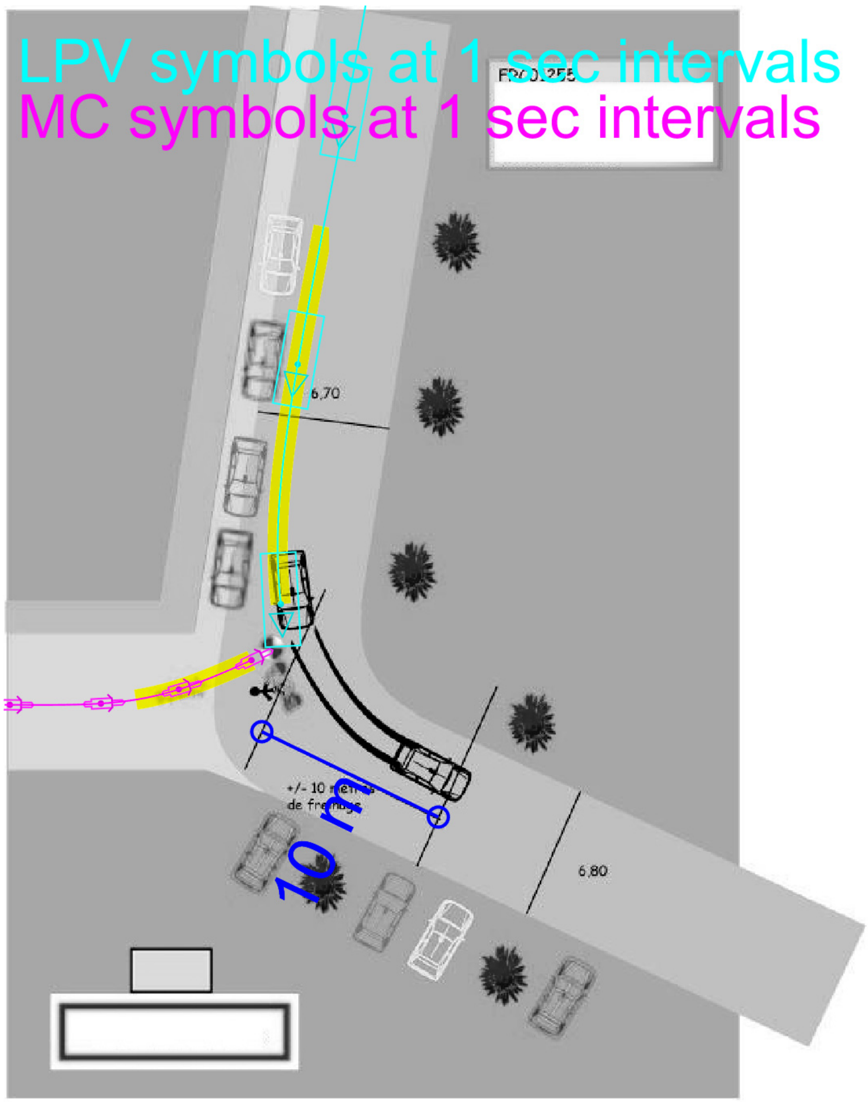

Figure 6. Estimated pre-crash trajectories and conflict for an exemplar case with both vehicles turning.

Pre-crash LPV-PTW trajectories

The estimated trajectories for the 367 reconstructed cases are summarized in Figure 7 through Figure 12. Figure 7 and Figure 8 show the results for the 266 EU MAIDS cases and 101 US MCCS data side by side. Figure 9 and Figure 10 show the results for the 242 cases involving a motorcycle and 125 cases involving a moped side by side. Figure 11 and Figure 12 show the results without and with a coded visual obstruction that contributed to the accident causation. Figure 7, Figure 9, and Figure 11 show the estimated PTW trajectories relative to the LPV in the LPV reference frame. The dotted lines show the relative positions of the PTW cg at 0.1 sec time intervals for the 3 sec prior to impact. Therefore pre-crash trajectories with higher velocities have larger spacing between the dots compared to trajectories with lower velocities. Likewise Figure 8, Figure 10, and Figure 12 show the estimated LPV trajectories relative to the PTW in the PTW reference frame. The relative vehicle positions when the conflict state $C(t) = \text{true}$ are highlighted in yellow.

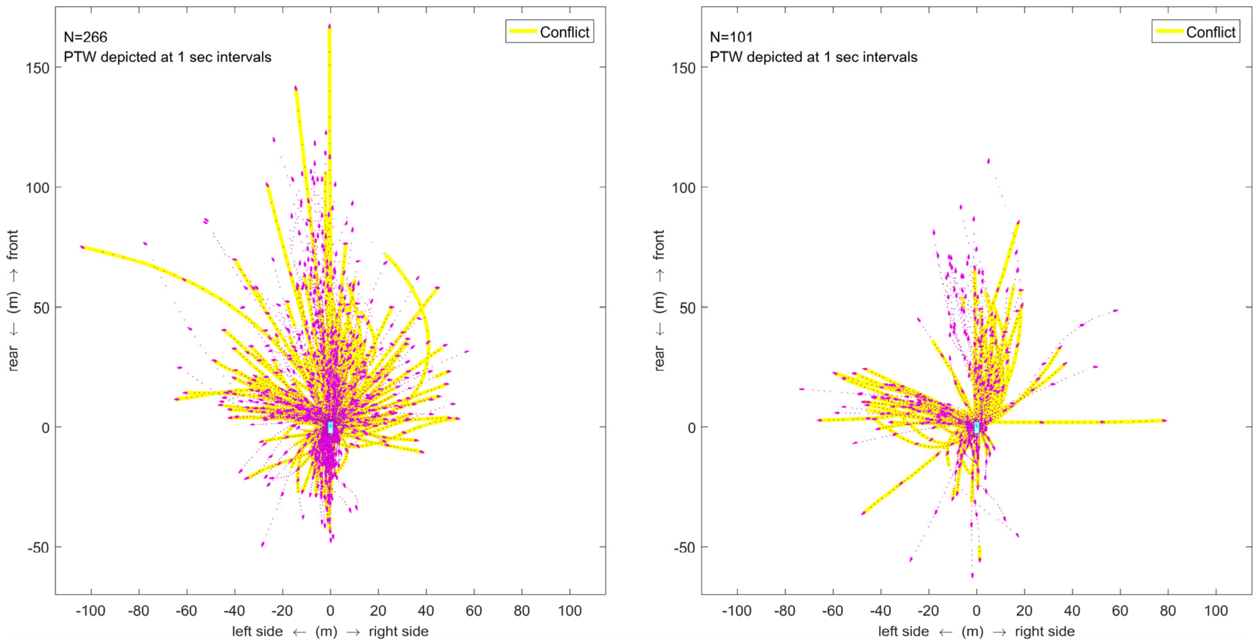

Figure 7. Estimated PTW trajectories and conflicts relative to the LPV for the 3 sec prior to impact by region (266 EU MAIDS cases on the left versus 101 US MCCS cases on the right).

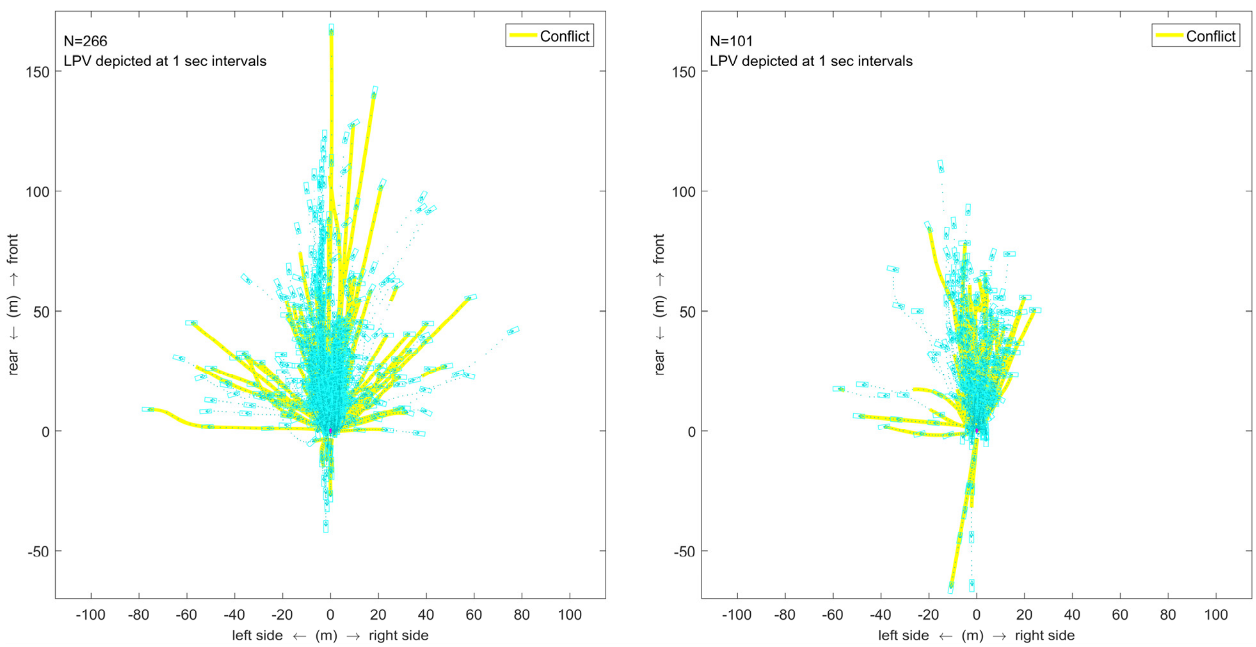

Figure 8. Estimated LPV trajectories and conflicts relative to the PTW for the 3 sec prior to impact by region (266 EU MAIDS cases on the left versus 101 US MCCS cases on the right).

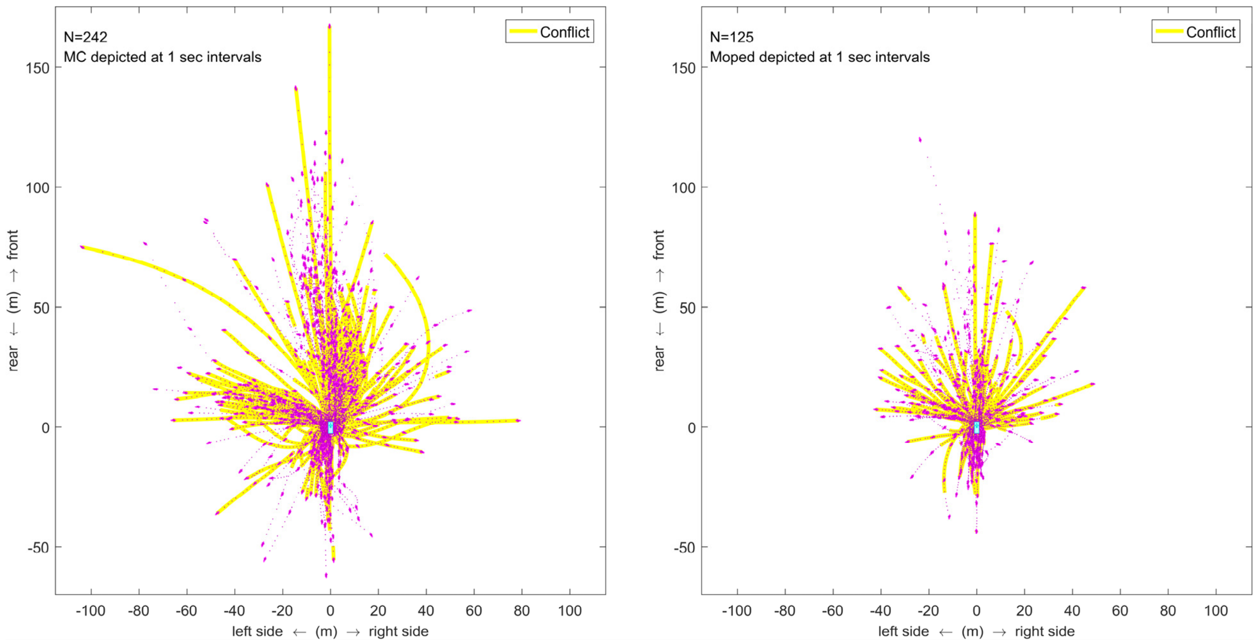

Figure 9. Estimated PTW trajectories and conflicts relative to the LPV for the 3 sec prior to impact by PTW type (242 motorcycle cases on the left versus 125 moped cases on the right).

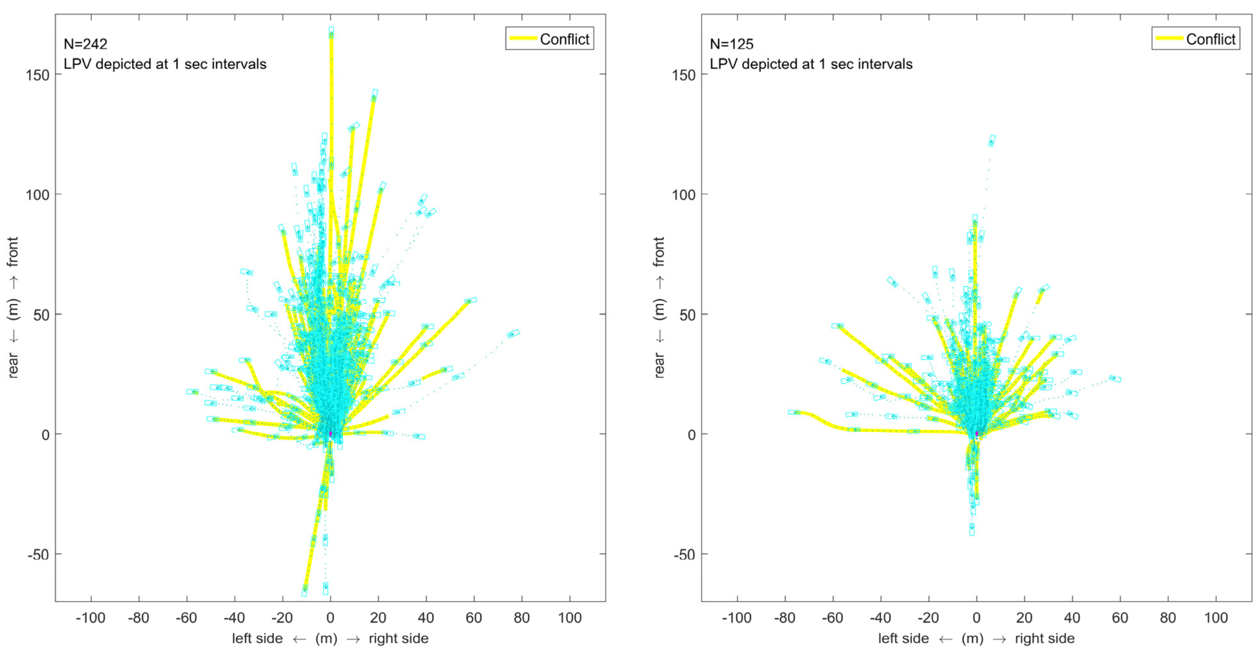

Figure 10. Estimated LPV trajectories and conflicts relative to the PTW for the 3 sec prior to impact by PTW type (242 motorcycle cases on the left versus 125 moped cases on the right).

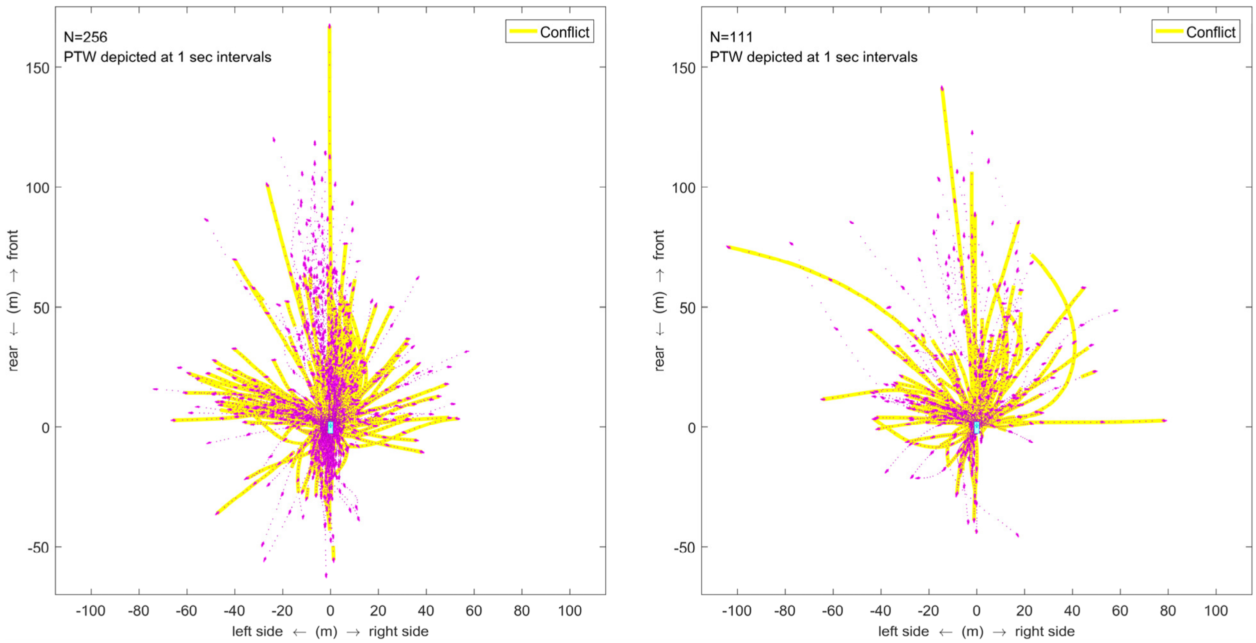

Figure 11. Estimated PTW trajectories and conflicts relative to the LPV for the 3 sec prior to impact by visual obstruction (256 cases without visual obstruction on the left versus 111 cases with visual obstruction on the right).

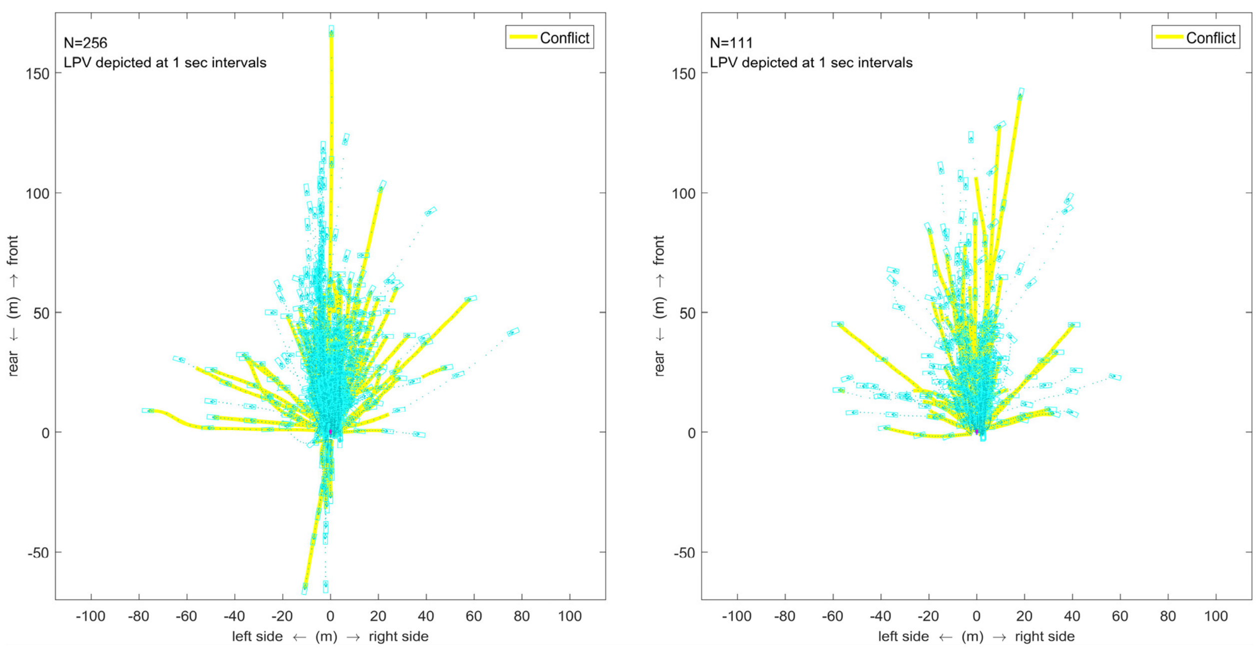

Figure 12. Estimated LPV trajectories and conflicts relative to the PTW for the 3 sec prior to impact by visual obstruction (256 cases without visual obstruction on the left versus 111 cases with visual obstruction on the right).

The results in Figure 7 and Figure 8 compare the 266 EU MAIDS cases and the 101 US MCCS cases. These results indicate that the some of the EU cases have higher relative pre-crash closing velocities than the US cases. These results also indicate that the EU cases are more broadly distributed in relative approach angle than the US cases. The smaller distribution of US cases compared to the EU cases may be partially attributed to the smaller US sample size. The US cases are primarily from a suburban sampling region with very few cases on rural roads or limited access divided highways. The EU cases were also sampled ten years before the US cases.

The results in Figure 9 and Figure 10 compare the 242 cases involving a MC to the 125 cases involving a moped. All but one of the moped cases are from the MAIDS database. These results indicate that the LPV-MC cases tend to have higher relative closing velocities than the LPV-moped cases, which is consistent with moped speed restrictions in the EU. The differences are most apparent in the longitudinal direction in the PTW reference frame. Both the MC and moped cases have a wide distribution of relative approach angles.

The results in Figure 11 and Figure 12 compare the 111 cases that had a coded visual obstruction that contributed to the conflict to the 256 cases that did not. The most noticeable difference is that none of the PTW rear-end LPV cases had a visual obstruction. This suggests that these PTW rear-end LPV cases may involve rider distraction or other factors.

Pre-crash LPV-PTW conflicts

The highlighted conflict state results in Figure 9 to Figure 12 indicate that many of the conflicts begin less than 3 sec before impact. The median start time for the MAIDS and MCCS data are 1.4 sec and 1.6 sec before impact respectively, and approximately 1.4 sec before impact overall.

The distributions of the conflict start times by crash configuration group and PTW type are illustrated in Figure 13. The crash configuration groups on the horizontal axis of this graph are defined in terms of the NASS accident type according to Table 2. The pre-crash trajectories and conflicts for each of these crash configuration groups are depicted in Appendix B. The vertical axis of this graph is the estimated conflict start time relative to the time of impact, which is a negative value. The vertical range of each box in this figure represents the 25th and 75th percentile values for the conflict start time, and the horizontal line in each box represents the median value. The number of cases for each crash configuration group are indicated by the numerical value shown above the median in each box. The graph is limited to the 5 sec epoch before impact because earlier conflict times are increasingly sensitive to the assumed vehicle speeds and estimated vehicle trajectories (many of which were extrapolated backwards in time before the digitized vehicle positions in the scene diagrams). The last 1.5 sec before impact are indicated by a light red shaded background. This shading represents the epoch where there may be insufficient time for the driver or rider to react to an ADAS warning in order to mitigate or avoid the crash, and therefore the countermeasures involving simple conflict detection and driver warning may not be effective.[6]

The results in Figure 13 indicate 10 of 21 crash configuration groups with median conflict times that began less than 1.5 sec before impact. The six largest of these groups are the LPV LTAP/OD (90 cases), LPV LTAP/SD (29), LPV UT (22), PTW RE (22), HO/ODSS (20), and LPV RTAP/SD (19), which combined represent 55% (202/367) of the reconstructed cases. The 15 cases in the other four crash configuration groups all involve the PTW turning.

[6] According to Neale and Dingus, "[w]hen a driver is looking forward, driver reaction time averages about 1.5 seconds and may be as high as 2.5 or 3.0 seconds in all but the most extreme cases" [15].

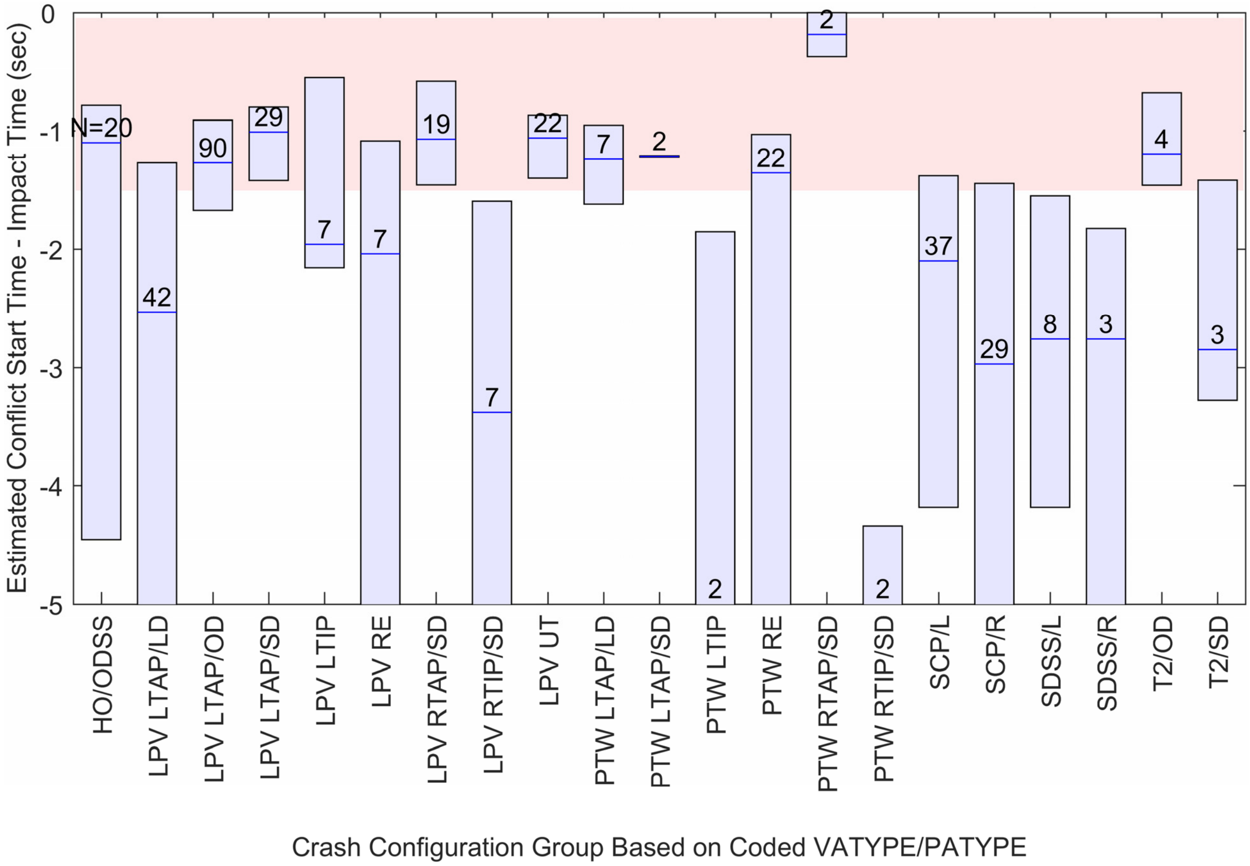

Figure 13. Distributions of estimated LPV-PTW conflict start times by crash configuration group.

<u>Comparison of EU MAIDS and US MCCS cases</u>

The estimated conflict start times are compared in further detail by data source in Figure 14. The format of Figure 14 is similar to Figure 13, but each crash configuration bar is split into pairs. The results for the EU MAIDS cases are depicted by the cyan colored boxes on the left, and the results for the US MCCS cases are depicted by the magenta colored boxes on the right.

The relative frequency of the MAIDS and MCCS cases were compared using a Pearson chi-square test. The resulting p-value=0.06 suggests that the relative frequencies of the MAIDS and MCCS cases are different, but the difference is not statistically significant at the 0.05 level.

The mean conflict start times for each pair were also compared using two-sample t-tests. The t-tests assumed that the start times in each sample are normally distributed with homogenous variance. Therefore only crash configuration groups with four or more cases were tested (i.e., two or more statistical degrees-of-freedom). The only crash configuration group with a statistically significant difference in the mean conflict start time is the LPV LTAP/OD group (p-value<0.01). This statistically significant difference is attributed to the large number of cases (90).

These results indicate that there are some differences between the two data sets, but that these differences are primarily related to the differences in the numbers of cases in each crash type rather than differences within each group. In other words, the conflict times within each crash configuration group are similar because they relative trajectories within each group are similar, as depicted in Appendix B. For example, there are more than 10 MAIDS and 10 MCCS cases in each of the LPV LTAP/LD, LPV LTAP/OD, and SCP/L groups, and the MAIDS and MCCS results for these groups are similar. Therefore we assumed that the two datasets can be combined without substantially changing the conclusions regarding conflict start times by crash configuration group.

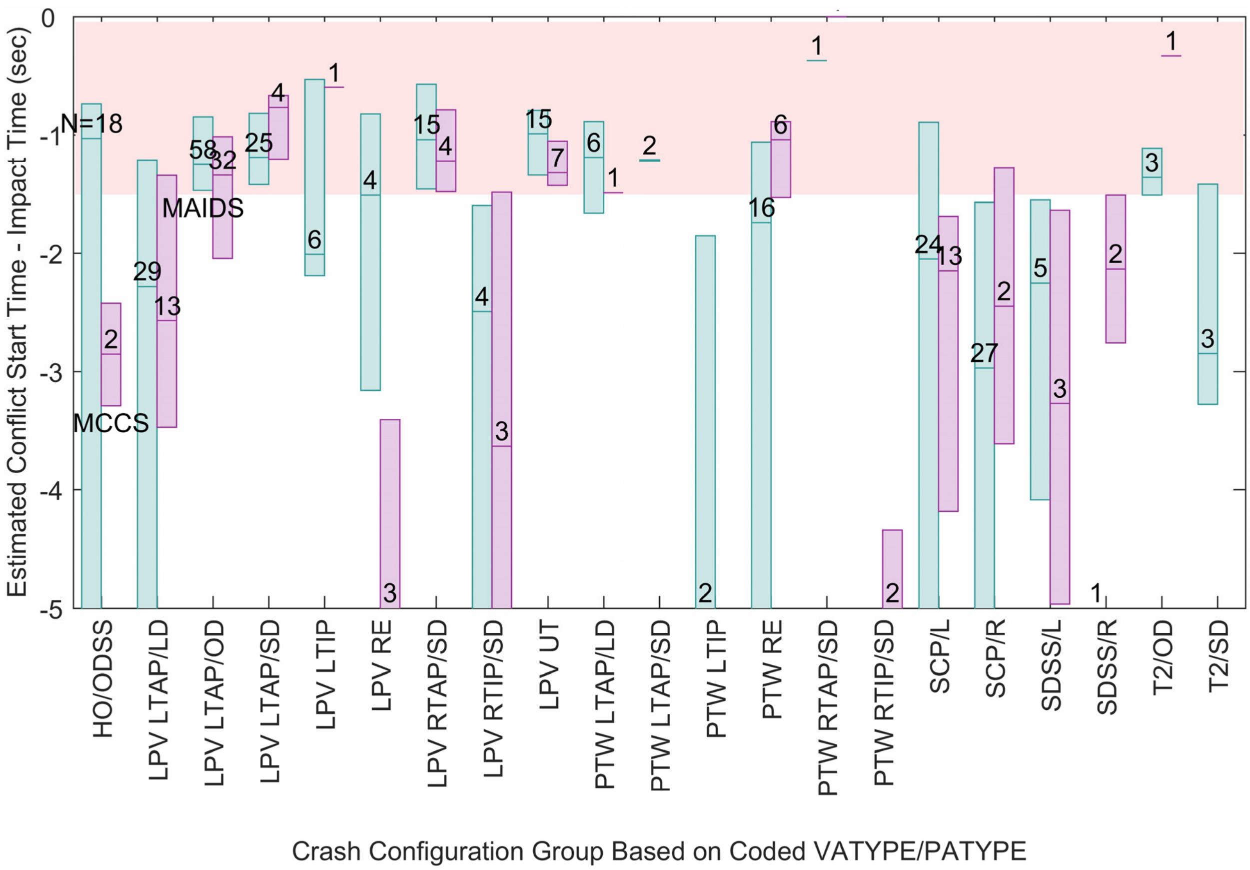

Figure 14. Estimated LPV-PTW conflict start times by crash configuration group and data source.

Comparison by PTW Type

Likewise the results in Figure 15 compare the estimated conflict start time results by PTW type. The format of Figure 15 is similar to Figure 14 but the paired bars are different. The results for motorcycles are depicted by cyan boxes on the left, and the results for mopeds are depicted by magenta boxes on the right.

The relative frequency of the MC and moped cases were also compared using a Pearson chi-square test. The resulting p-value=0.03 indicates that the relative frequencies of the MC and moped cases are statistically significantly different at the 0.05 level. However if the US MCCS cases are excluded, the resulting p-value is 0.37, which is not statistically significant.

The mean conflict start times for the MC and moped in each crash configuration group were also compared using t-tests. None of the groups had a statistically significant differences between the mean MC and moped conflict start times.

These results also indicate that the main differences between the MC and moped crash configurations are due to relative differences in sampling frequency, which may be attributed to difference in the US and EU, but the conflict start times are similar. There are more than 10 MC and 10 moped cases in each of the five LPV LTAP and SCP groups, and the MC and moped results in four of these groups are similar. Therefore we assumed that the two PTW types can be combined without substantially changing the conclusions about the conflict start time results for each crash configuration group.

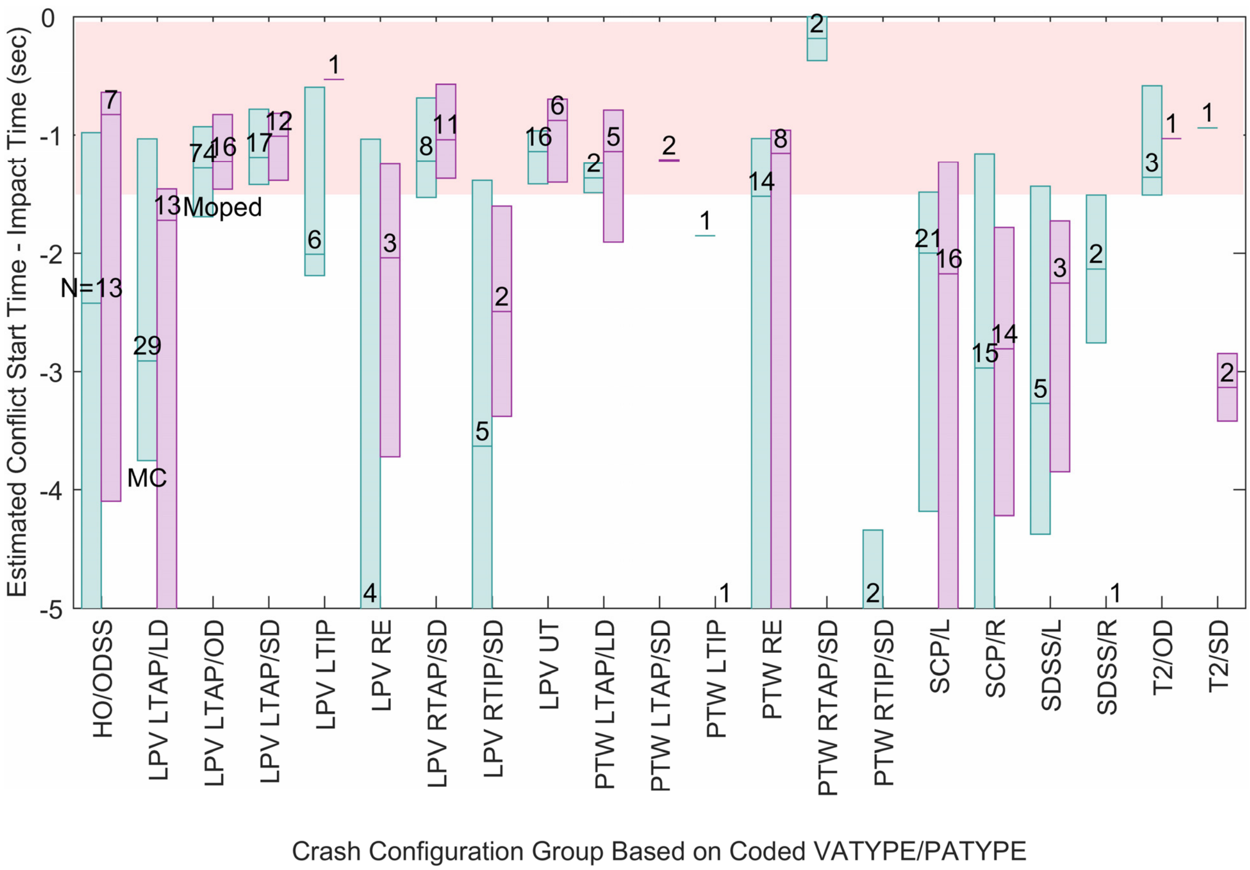

Figure 15. Estimated LPV-PTW conflict start times by crash configuration group and PTW type.

<u>Comparison by Visual Obstruction</u>

The results in Figure 16 compare the estimated conflict start time results by whether or not the coded data indicated that "*view obstructions were present and contributed to accident causation.*" The results in the cyan boxes on the left are without any visual obstruction, and the results in the magenta boxes on the right are with a view obstruction for either the LPV driver, PTW rider, or both. None of the crash configuration groups had a statistically significant difference in the mean conflict start times by visual obstruction, but the differences in the relative number of cases were statistically significantly different (p-value<0.01).

Most (86) of the 111 cases involving a visual obstruction were in the six HO/ODSS, LPV LTAP, and SCP crash configuration groups. There were 247 cases in these six groups combined, and 35% had a coded visual obstruction.

Nearly all (74) of the 79 cases in the LPV LTIP (6), rear end (7+20), RTAP/SD (18+2), and U-turn (21) groups did not have a coded visual obstruction. Therefore other factors such as operator distraction or error may be contributing to these types of crashes. It is unknown how many of the 22 U-turns were legal or not. The HO/ODSS, LPV LTAP/OD and LPV LTAP/SD groups had short conflict epochs regardless of whether or not there was a visual obstruction.

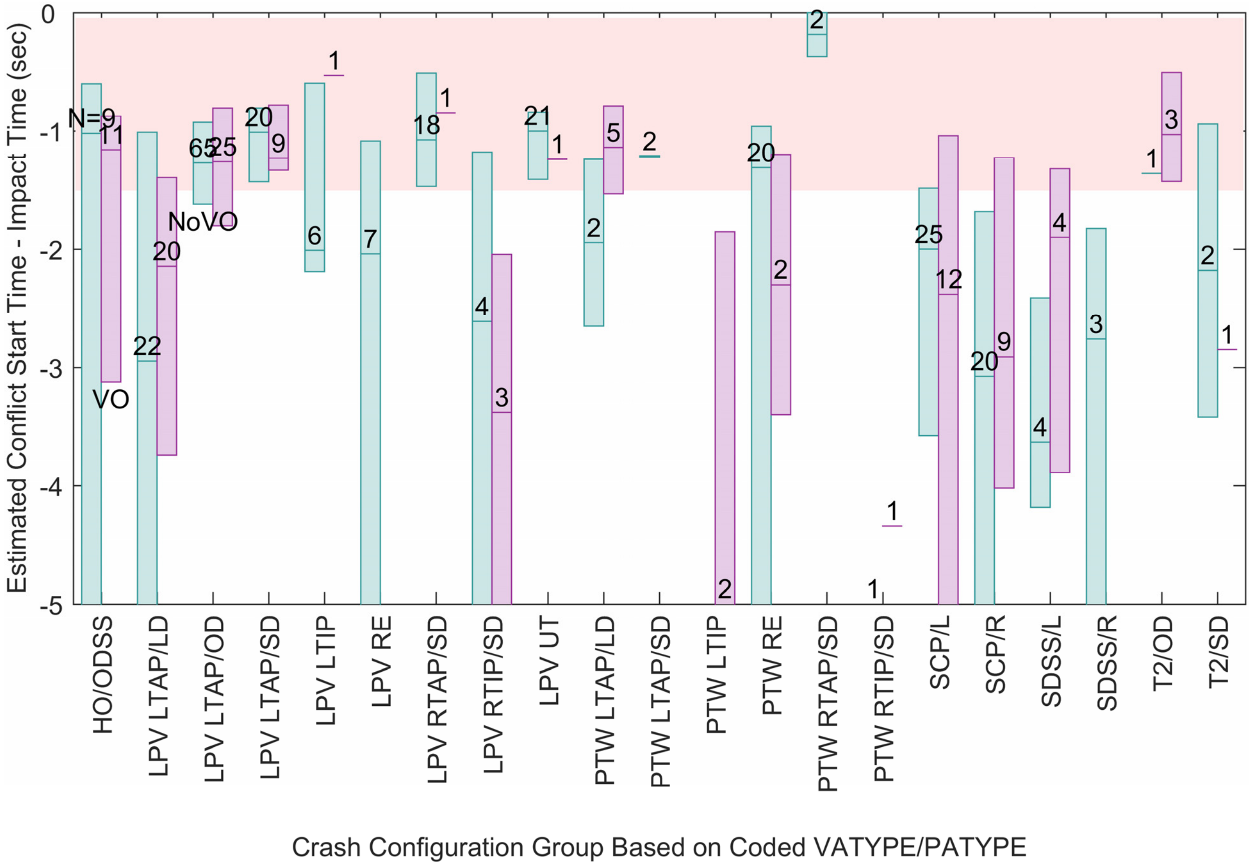

Figure 16. Estimated LPV-PTW conflict start times by crash configuration group and visual obstruction.

DISCUSSION

The effectiveness of potential conflict and crash countermeasures may depend on how soon the conflict is detected before impact. For comparison, the results in Figure 17 illustrate the distribution of conflict start times and collision effectiveness (CE) results for different technology relevant crash types (TRCTs) from a previous ADAS evaluation reported in [18]. The results for the "Primary" TRCT for which the crash avoidance countermeasure was intended to address, and three "secondary" TRCTs in which the technology designer thought the system might also be effective. A CE value of 0 indicates the technology is not effective in avoiding any of the crashes, which is undesirable. A CS value of 1 indicates the technology completely eliminates all of the crashes with the crash type, which is desirable. These results indicate that the crash avoidance countermeasure tends to be more effective for TRCTs with earlier conflict start times. Similar effectiveness results were observed in [11],[19].[7]

[7] The collision effectiveness results in Figure 17 are based on simulated cases that have been weighted to represent the US fleet in the 2009 calendar year. The conflict start times are based on the unweighted unique cases in the simulation sample. Results for the other secondary TRCTs are not shown due to insufficient numbers of reconstructable cases for the evaluation reported in [18].

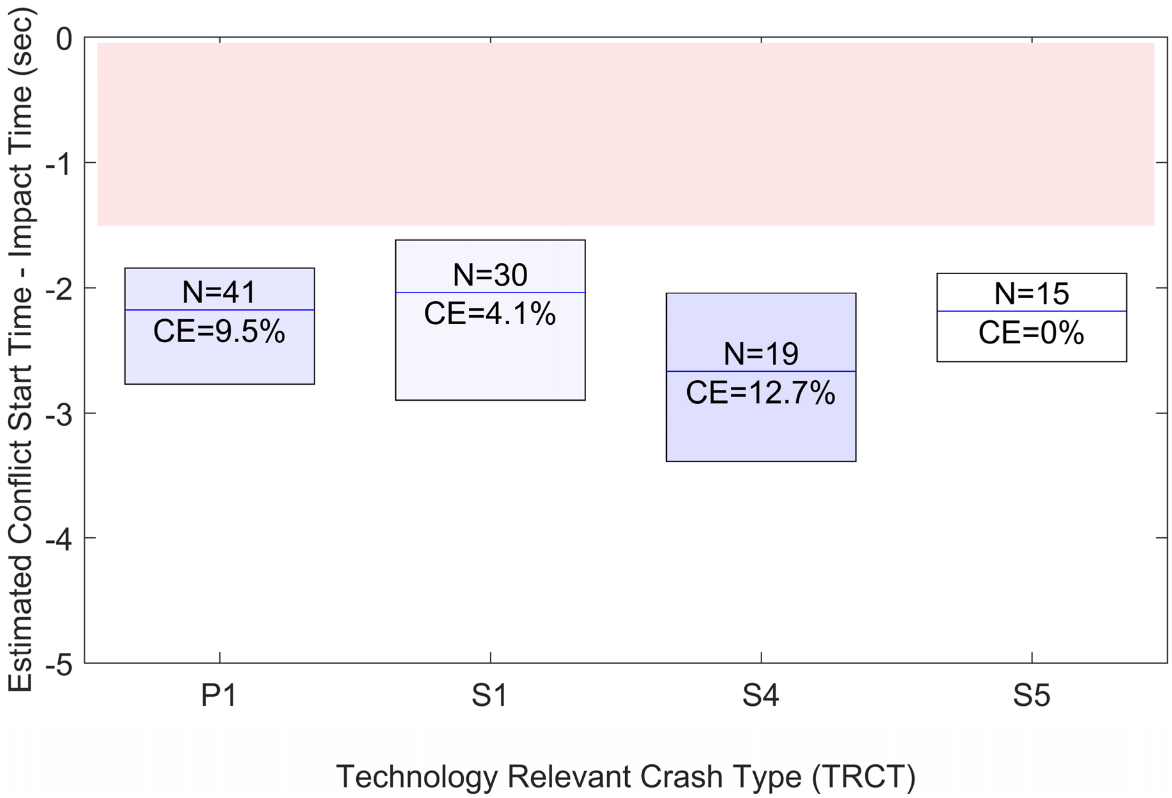

Figure 17. Boxplot distributions of estimated LPV-LPV conflict start times for a pre-production crash avoidance technology.

As previously described, the results in Figure 13 indicate several crash configuration groups with short pre-crash conflict times. The quartile and median times for the 90 LPV LTAP/OD cases were 0.9, 1.3, and 1.7 sec before impact respectively. The results in Figure B3 indicate that the cases from the front left tended to have short conflict times, and there would have been insufficient time to detect and warn the driver before a collision

The quartile and median times for the 29 LPV LTAP/SD cases were 0.8, 1.0, and 1.4 sec before impact respectively. The results in Figure B4 indicate many cases where the PTW may have been in the LPV blind spot during the conflict. However a BSW system might not have been able to detect a conflict and warn the driver with sufficient time to avoid a collision.

Other potential countermeasures could be ADASs such as AEB that are not affected by the driver response time, or by detecting and warning the driver about the impending conflict sooner. The conflict could be detected sooner by changing the vehicle "contact" criteria to include close encounters or use more advanced sensors and algorithms. However this could also result in false alarms, which is undesirable.

Impending conflicts could also be detected sooner and avoided or mitigated if the vehicle operators can see each other and properly communicate their intended paths before the conflict starts. One way to achieve this is by maximizing visual scanning strategies and vehicle conspicuity, and proper use and detection of turn signals. This could also be enhanced by safety-relevant cooperative C-ITS V2V communications systems such as Motorcycle Approach Indication (MAI) and Motorcycle Approach Warning (MAW)[20].

C-ITS also has the potential to address conflicts that cannot be detected early due to visual obstructions (e.g., the exemplar cases). The results in Figure 16 indicate that many HO/ODSS, LPV LTAP, and SCP crashes involved a visual obstruction, but there were also other crash configuration groups that did not.

LIMITATIONS

The accuracy of the results are based on a number of assumptions, approximations, and limitations in the data and methods used, many of which are described in [5], [6], [7], [11]. These include the accuracy and representativeness of the MAIDS and MCCS data, as well as the accuracy of the vehicle directional control models used.

SUMMARY/CONCLUSIONS

Pre-crash trajectories have been estimated for 367 crashes involving a light passenger vehicle (LPV) and a motorcycle or moped for the purposes of evaluating the effectiveness and benefits of crash avoidance technologies in avoiding or mitigating these types of crashes. This was accomplished by extending methods and tools to address LPV-PTW crashes. Pre-crash trajectories of 266 cases in the MAIDS database from France, Germany, and Italy and 101 cases in the US MCCS database were reconstructed using a new Motorcycle Automated Accident Reconstruction Tool (M-AART). The resulting pre-crash trajectories of the PTW as viewed from the LPV were broadly distributed in approach angle, with a possible gap from the right rear quadrant (i.e., between the 3 and 6 o'clock directions). The US MCCS data also exhibited a gap between the 10 and 11 o'clock directions. There were relatively few cases where the LPV approached the PTW from the rear (e.g., rear-end).

Further analysis of these estimated pre-crash trajectories indicate that the conflicts begin later, and therefore with smaller TTC values, compared to LPV-LPV crashes that were reconstructed for previous ADAS evaluations. This may be partially due to the smaller length and width of PTWs compared to LPVs, in which LPV-PTW close encounters do not result in a collision, but the same LPV-LPV trajectory would. Therefore LPV-PTW countermeasures may need to address the pre-conflict phase in order to be effective.

It was also observed that 30% of the cases involved a visual obstruction as reported in the crash databases. Many of the cases with a visual obstruction were in the HO/ODSS, LPV LTAP, or SCP crash configuration groups. These cases could potentially be addressed by C-ITS countermeasures such as MAI and MAW.

Only five of the 79 cases in the LPV LTIP, rear end, RTAP/SD, and U-turn crash configuration groups had a coded visual obstruction that contributed to the crash causation. Therefore other factors such as operator distraction and error may be contributing to these types of crashes.

This information can be used to guide further LPV-PTW crash avoidance research, including collecting and analyzing additional on-scene in-depth pre-crash and crash data, field operational experiments, driving simulator experiments, modeling and simulation. The results of this research can potentially help to define requirements for LPV-PTW conflict and crash countermeasures (e.g., BSW, C-ITS) and the development of performance confirmation tests (e.g., New Car Assessment Program (NCAP)). These pre-crash scenarios can also be integrated into the ACAT SIM Crash Sequence Simulation Module in order to estimate the safety benefits and effectiveness of potential countermeasures.

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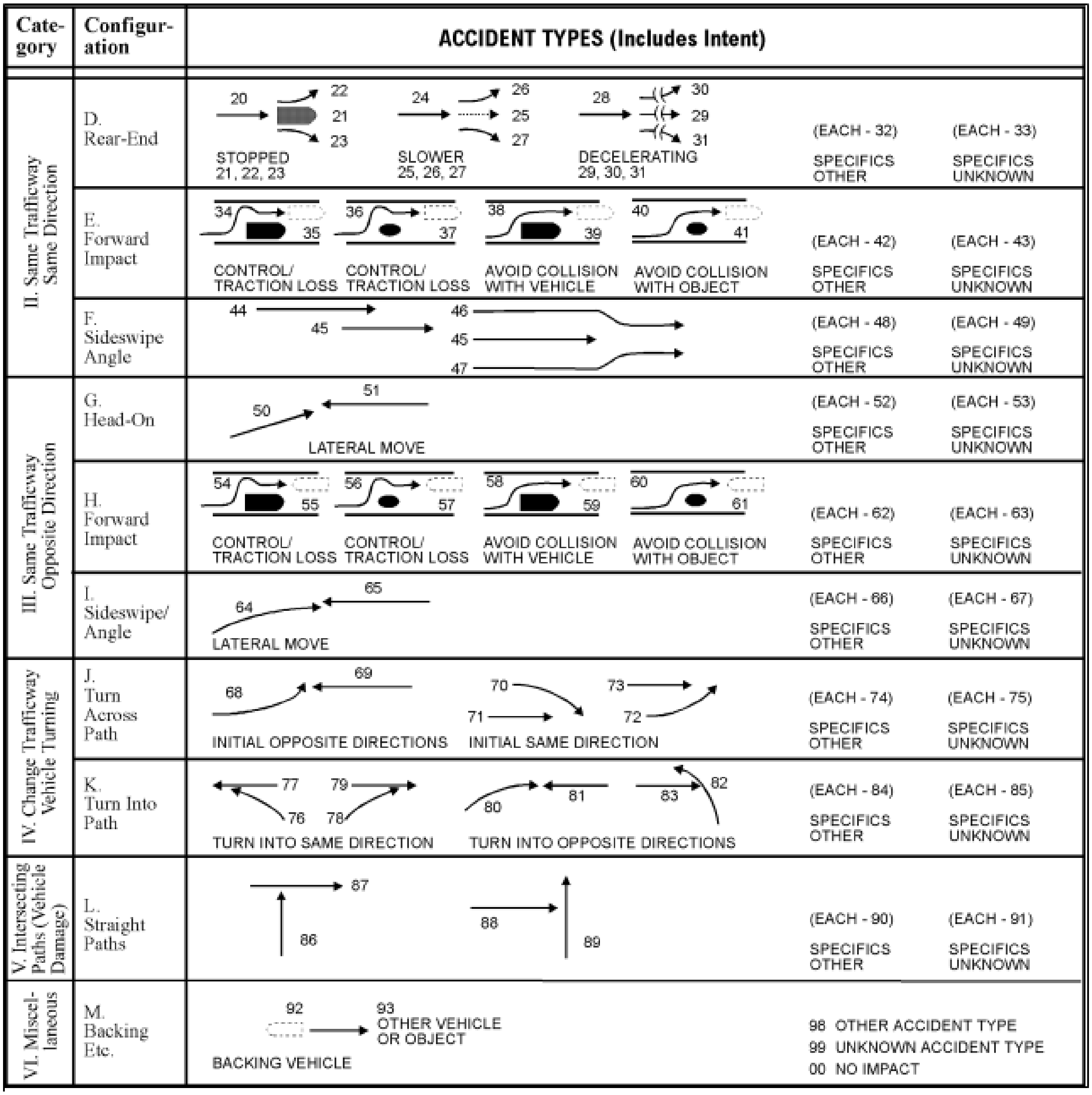
DEFINITIONS/ABBREVIATIONS

AART	Automated Accident Reconstruction Tool (Honda-DRI ACAT SIM Module 1.3).
ACAT	Advanced Crash Avoidance Technology.
ACEM	European Association of Motorcycle Manufacturers (https://www.acem.eu/).
ADAS	Advanced Driver Assistance Systems.
AEB	Automatic Emergency Braking.
BSW	Blind Spot Warning.
$C(t)$	The estimated state of conflict at time t based on the vehicle positions and velocities at time t. $C(t)$ is true if and only if the vehicles will eventually contact if their velocities remain constant.
CE	Collision Effectiveness – a measure of the ability to avoid a crash.
cg	Center of gravity
C-ITS	Cooperative Intelligent Transportation System.
DRI	Dynamic Research, Inc. (http://www.dynres.com/).
FCW	Forward Collision Warning.
FHWA	US Department of Transportation Federal Highway Administration (https://www.fhwa.dot.gov/).
L1	"A two-wheeled vehicle with an engine cylinder capacity in the case of a thermic engine not exceeding 50 cm^3 and whatever the means of propulsion a maximum design speed not exceeding 50 km/h" as defined in UN/ECE/TRANS/WP.29/78 Rev 2. (i.e., a moped).
L3	"A two-wheeled vehicle with an engine cylinder capacity in the case of a thermic engine exceeding 50 cm^3 or whatever the means of propulsion a maximum design speed exceeding 50 km/h" as defined in UN/ECE/TRANS/WP.29/78 Rev 2. (i.e., a motorcycle).
LPV	Light passenger vehicle, comprising passenger cars, light trucks and vans.
M-AART	A specialized version of the ACAT SIM AART for LPV-PTW crashes.
MAI	Motorcycle Approach Indication, a C-ITS V2V technology.
MAIDS	Motorcycle Accidents In-Depth Study [8] (http://www.maids-study.eu/).
MAW	Motorcycle Approach Warning, a C-ITS V2V technology
MC	Motorcycle (L3 vehicle).
MCCS	Motorcycle Crash Causation Study [9].
NASS	National Automotive Sampling System (https://www.nhtsa.gov/research-data/national-automotive-sampling-system-nass).
NCAP	New Car Assessment Program (e.g., EuroNCAP)
NHTSA	US Department of Transportation National Highway Traffic Safety Administration (https://www.nhtsa.gov/).
OECD	Organisation for Economic Co-operation and Development (https://www.oecd.org/).

POV	Principal other vehicle.
PTW	Powered two wheeler, comprising L1 and L3 vehicles.
SIM	Safety Impact Methodology.
TRCT	Technology Relevant Crash Type.
TTC	Time-to-Collision.
V2V	Vehicle-to-Vehicle [Communications].

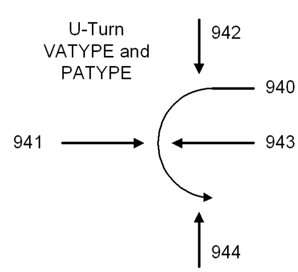
APPENDIX A – NASS ACCIDENT TYPES FOR TWO-VEHICLE COLLISIONS

VATYPE and PATYPE Accident Type Codes



Category	Configuration	ACCIDENT TYPES (Includes Intent)		
II. Same Trafficway Same Direction	D. Rear-End	20, 22, 21, 23 STOPPED 21, 22, 23; 24, 26, 25, 27 SLOWER 25, 26, 27; 28, 30, 29, 31 DECELERATING 29, 30, 31	(EACH - 32) SPECIFICS OTHER	(EACH - 33) SPECIFICS UNKNOWN
	E. Forward Impact	34, 35 CONTROL/ TRACTION LOSS; 36, 37 CONTROL/ TRACTION LOSS; 38, 39 AVOID COLLISION WITH VEHICLE; 40, 41 AVOID COLLISION WITH OBJECT	(EACH - 42) SPECIFICS OTHER	(EACH - 43) SPECIFICS UNKNOWN
	F. Sideswipe Angle	44, 45; 46, 45, 47	(EACH - 48) SPECIFICS OTHER	(EACH - 49) SPECIFICS UNKNOWN
III. Same Trafficway Opposite Direction	G. Head-On	50, 51 LATERAL MOVE	(EACH - 52) SPECIFICS OTHER	(EACH - 53) SPECIFICS UNKNOWN
	H. Forward Impact	54, 55 CONTROL/ TRACTION LOSS; 56, 57 CONTROL/ TRACTION LOSS; 58, 59 AVOID COLLISION WITH VEHICLE; 60, 61 AVOID COLLISION WITH OBJECT	(EACH - 62) SPECIFICS OTHER	(EACH - 63) SPECIFICS UNKNOWN
	I. Sideswipe/ Angle	64, 65 LATERAL MOVE	(EACH - 66) SPECIFICS OTHER	(EACH - 67) SPECIFICS UNKNOWN
IV. Change Trafficway Vehicle Turning	J. Turn Across Path	68, 69 INITIAL OPPOSITE DIRECTIONS; 70, 71, 72, 73 INITIAL SAME DIRECTION	(EACH - 74) SPECIFICS OTHER	(EACH - 75) SPECIFICS UNKNOWN
	K. Turn Into Path	76, 77, 78, 79 TURN INTO SAME DIRECTION; 80, 81, 82, 83 TURN INTO OPPOSITE DIRECTIONS	(EACH - 84) SPECIFICS OTHER	(EACH - 85) SPECIFICS UNKNOWN
V. Intersecting Paths (Vehicle Damage)	L. Straight Paths	86, 87; 88, 89	(EACH - 90) SPECIFICS OTHER	(EACH - 91) SPECIFICS UNKNOWN
VI. Miscellaneous	M. Backing Etc.	92 BACKING VEHICLE; 93 OTHER VEHICLE OR OBJECT	98 OTHER ACCIDENT TYPE 99 UNKNOWN ACCIDENT TYPE 00 NO IMPACT	

Source: NASS GES Analytical User's Manual, 1998-2000.



APPENDIX B – PRECRASH TRAJECTORIES AND CONFLICTS BY CRASH CONFIGURATION GROUP

The estimated pre-crash trajectories and conflicts for the 3 sec prior to impact are illustrated in Figures A1 through A24 for the 24 crash configuration groups defined in Table 2. The graph on the left side of each figure depicts the position of the PTW relative the LPV in the LPV frame, and is a subset of the cases depicted in Figure 7. The graph on the right side of each figure depicts the position of the LPV relative to the PTW in the PTW frame, and is a subset of the cases depicted in Figure 8. The yellow highlighting indicates the positions that are in a state of conflict defined herein as $C(t) = \text{true}$.

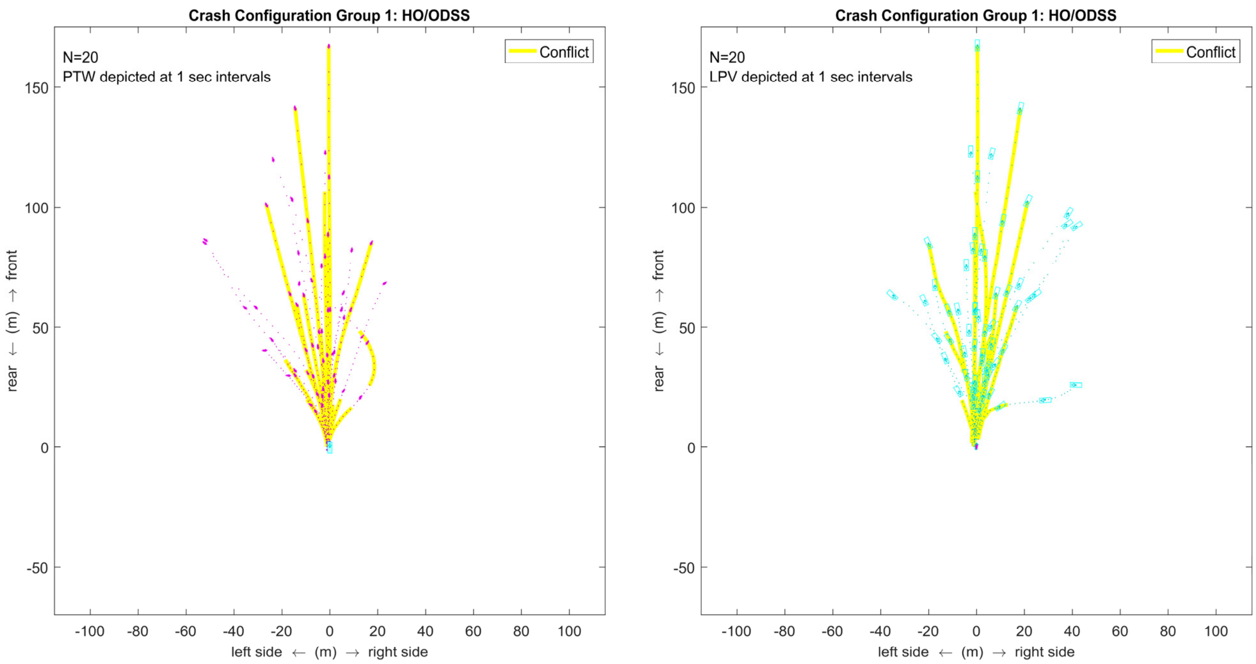


Figure B1. Head-on or opposite direction side swipe

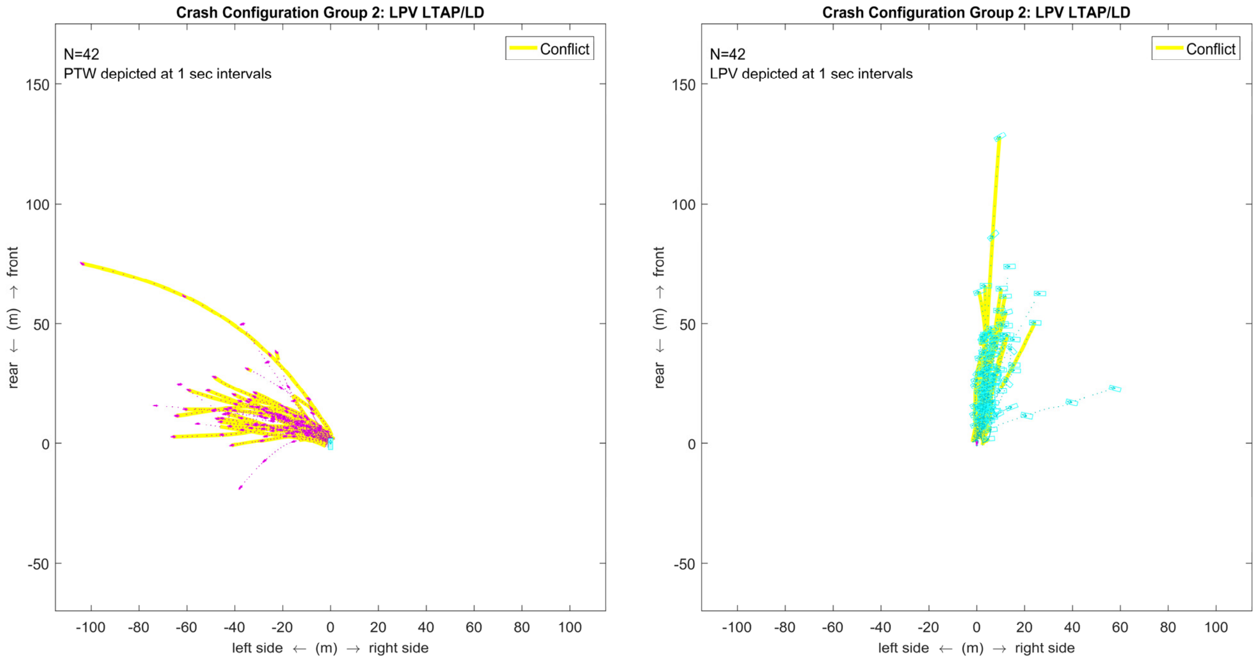


Figure B2. LPV left turn across PTW path/lateral direction

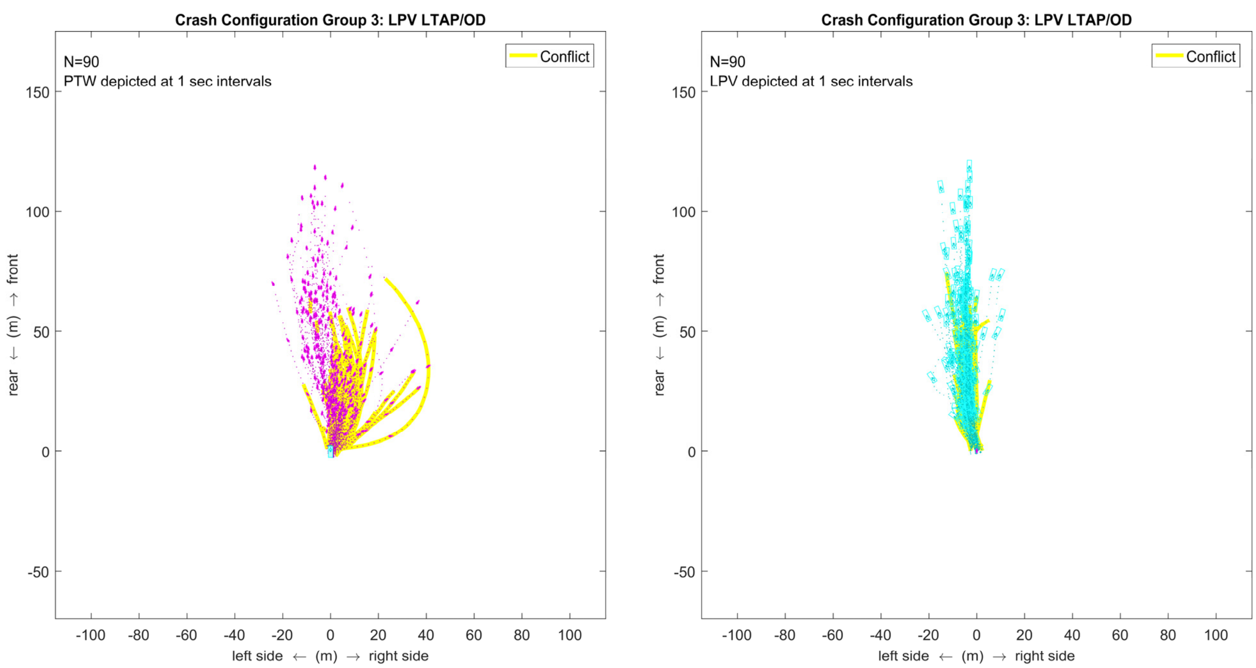


Figure B3. LPV left turn across PTW path/opposite direction

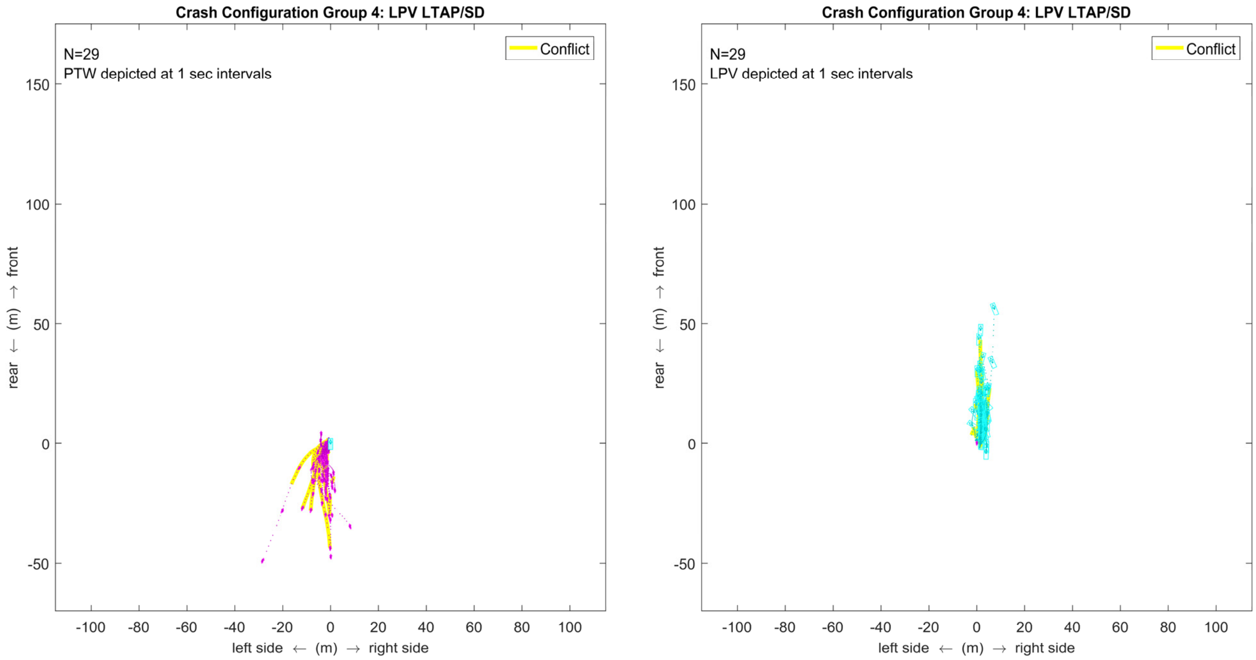


Figure B4. LPV left turn across PTW path/same direction

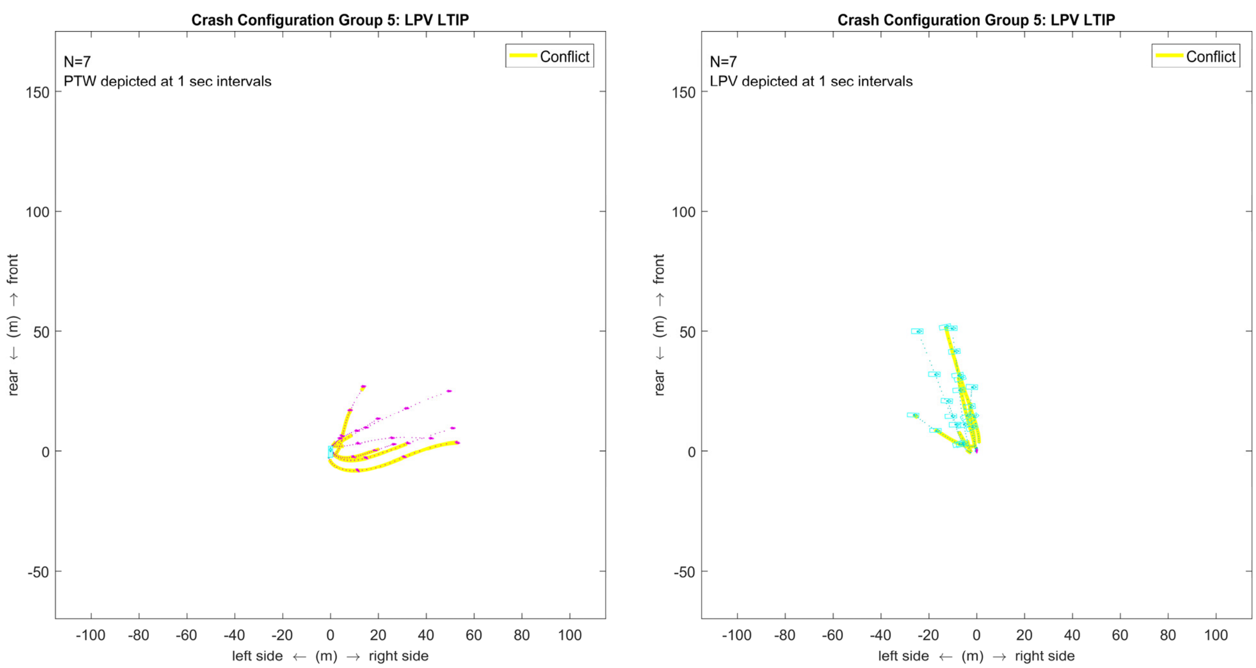


Figure B5. LPV left turn into PTW path

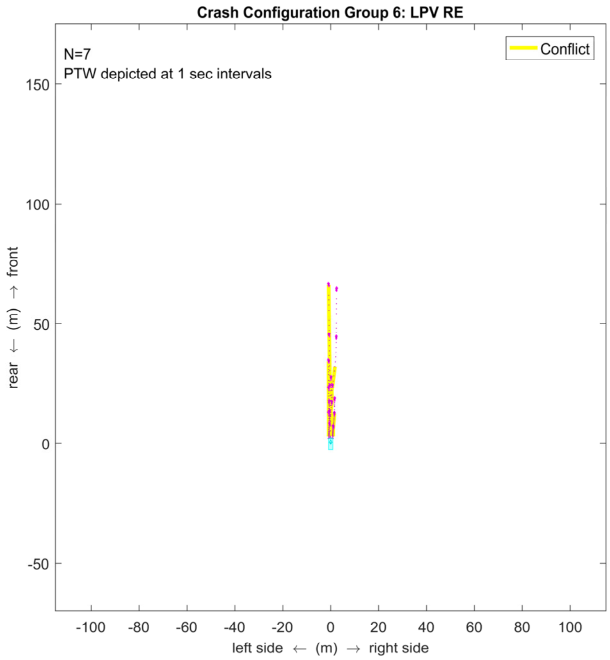


Figure B6. LPV rear-end PTW

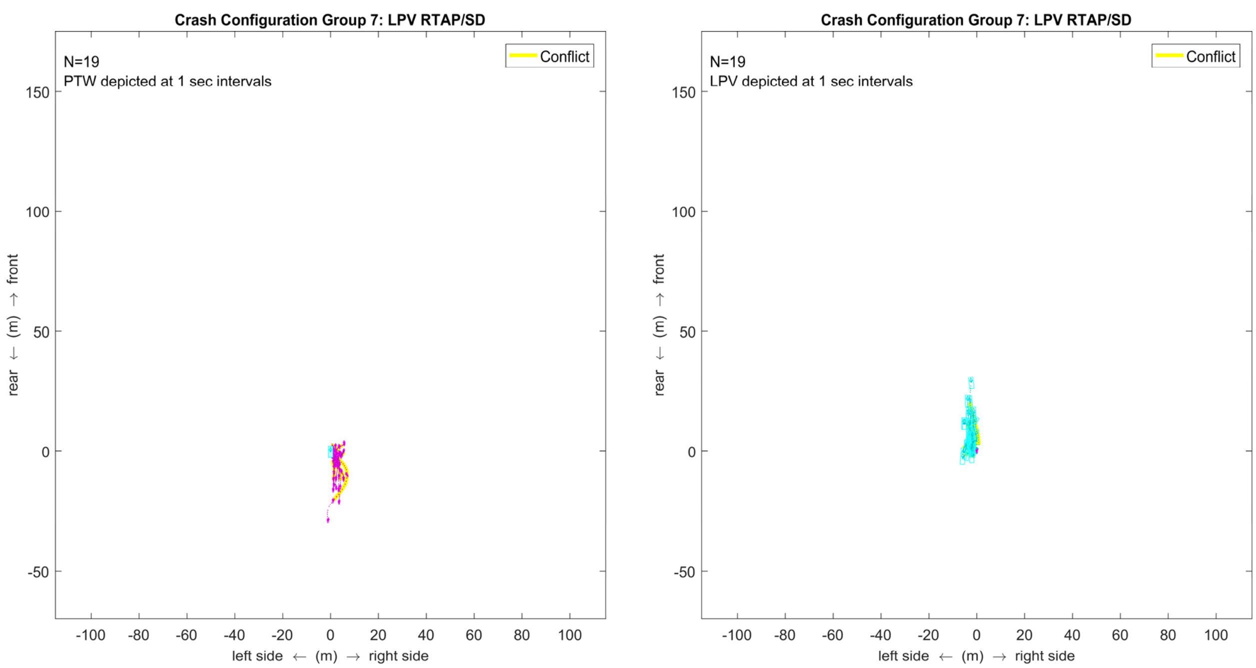


Figure B7. LPV right turn across path/same direction

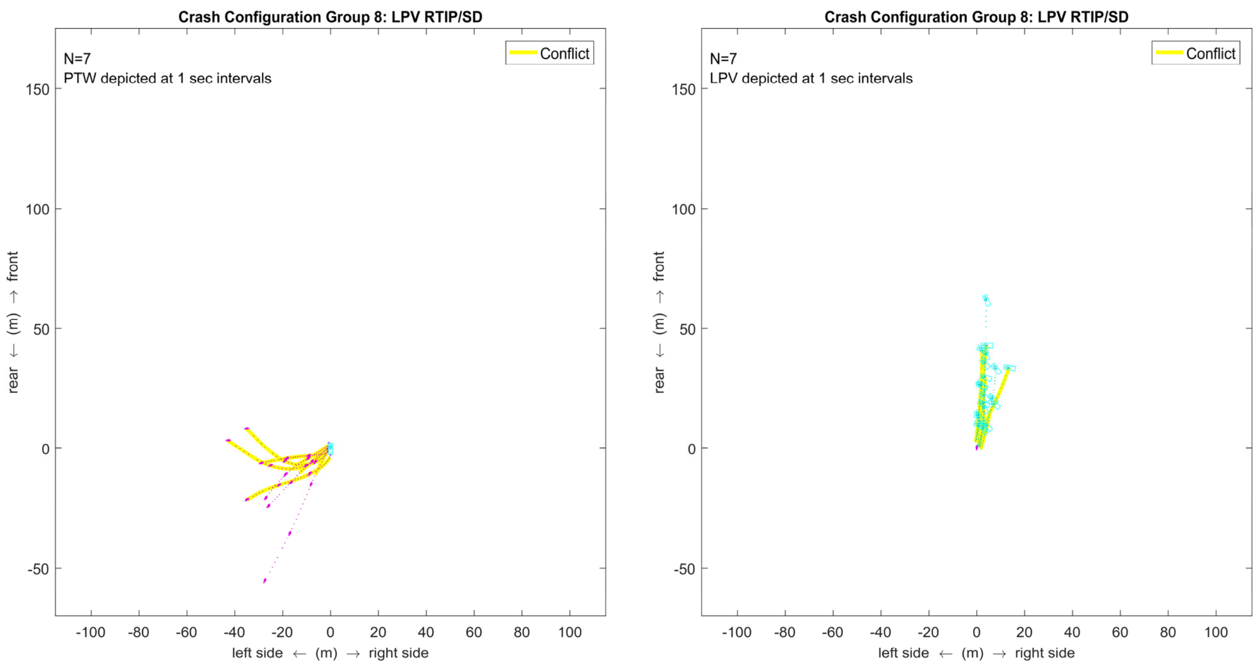


Figure B8. LPV right turn into path/same direction

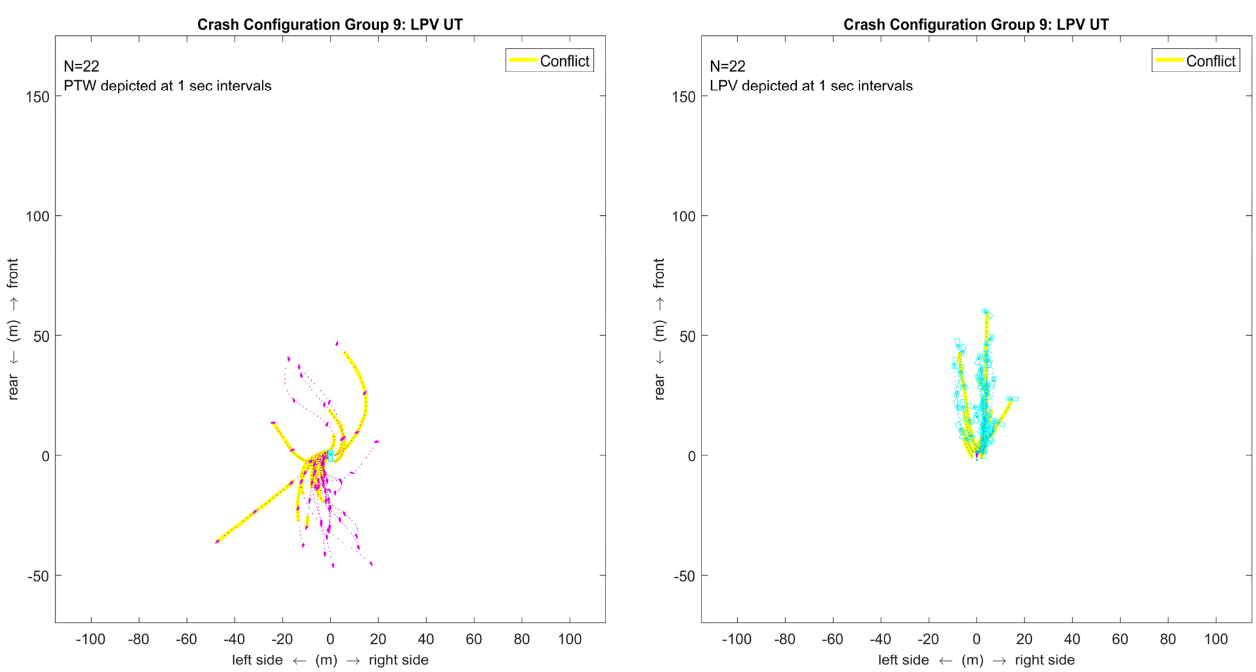


Figure B9. LPV U-turn across PTW path

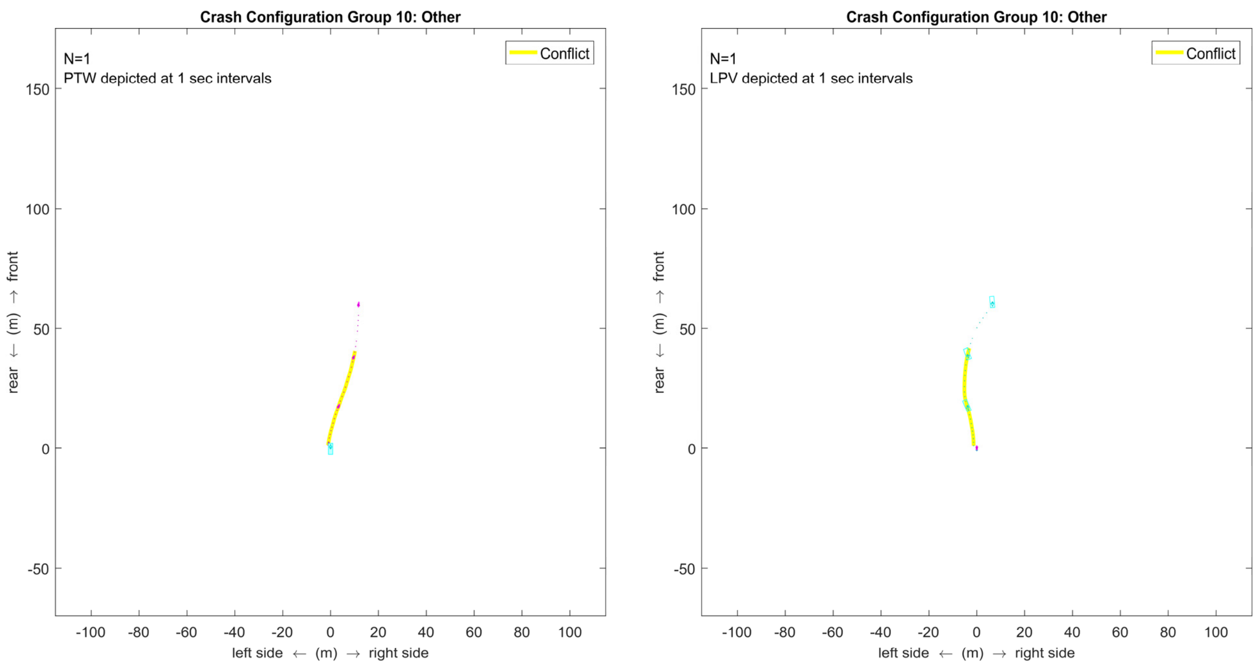


Figure B10. Other crash type

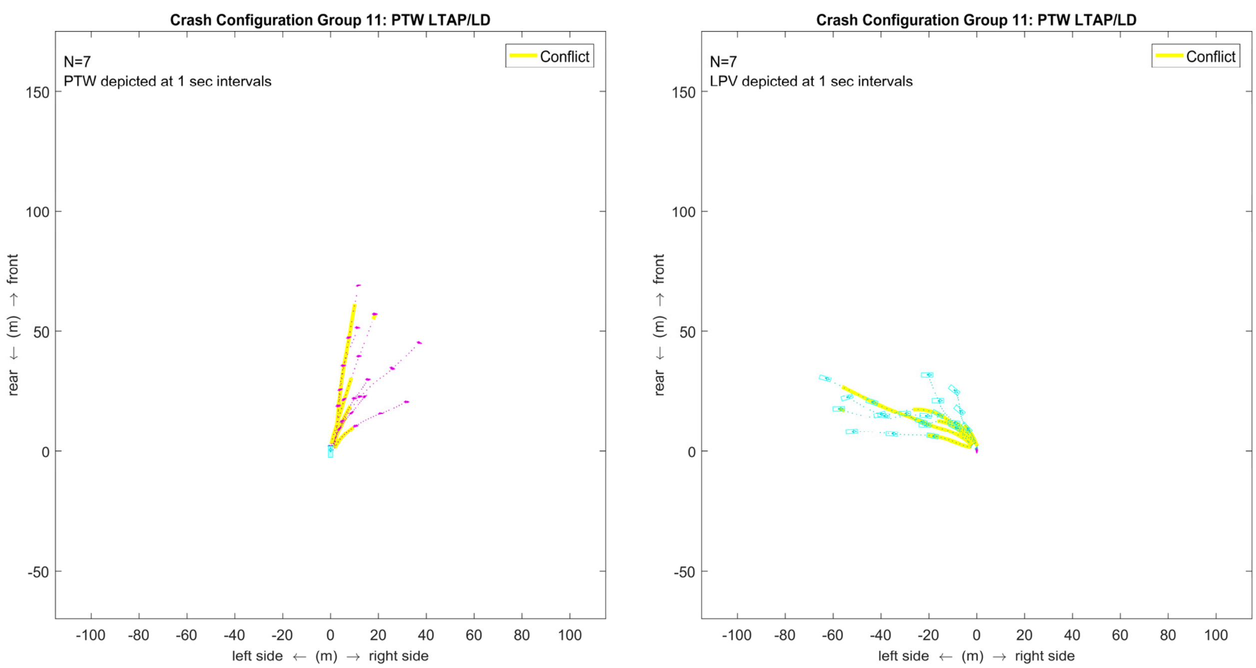


Figure B11. PTW left turn across LPV path/lateral direction

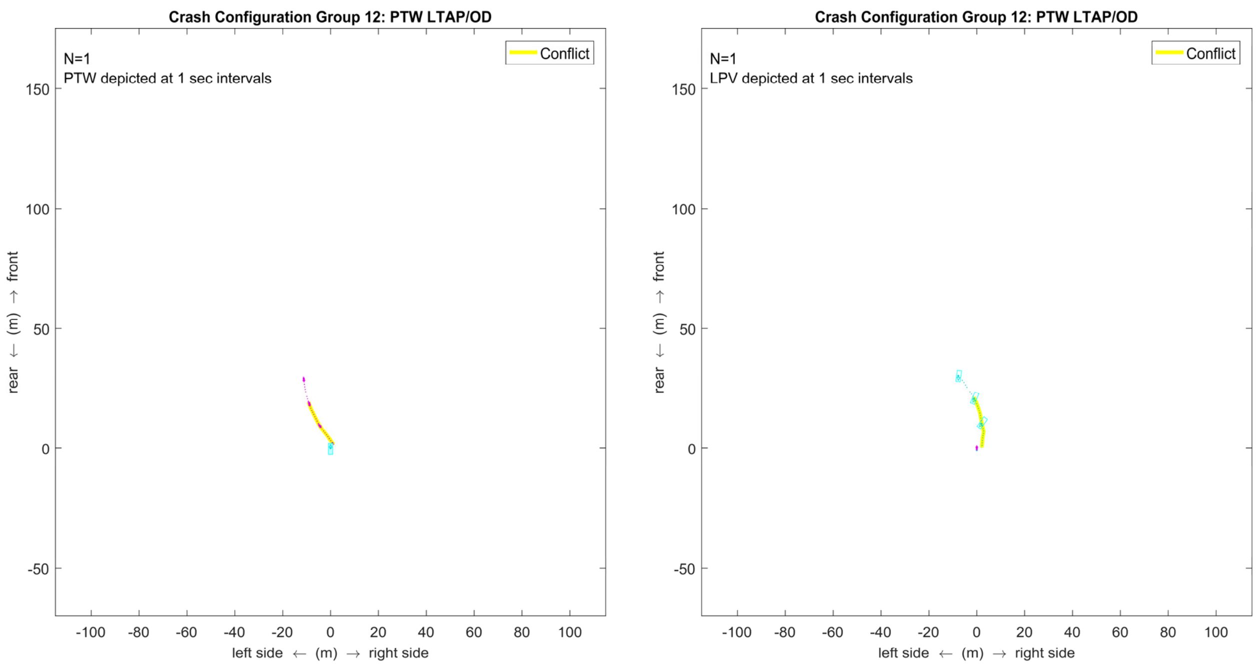


Figure B12. PTW left turn across LPV path/opposite direction

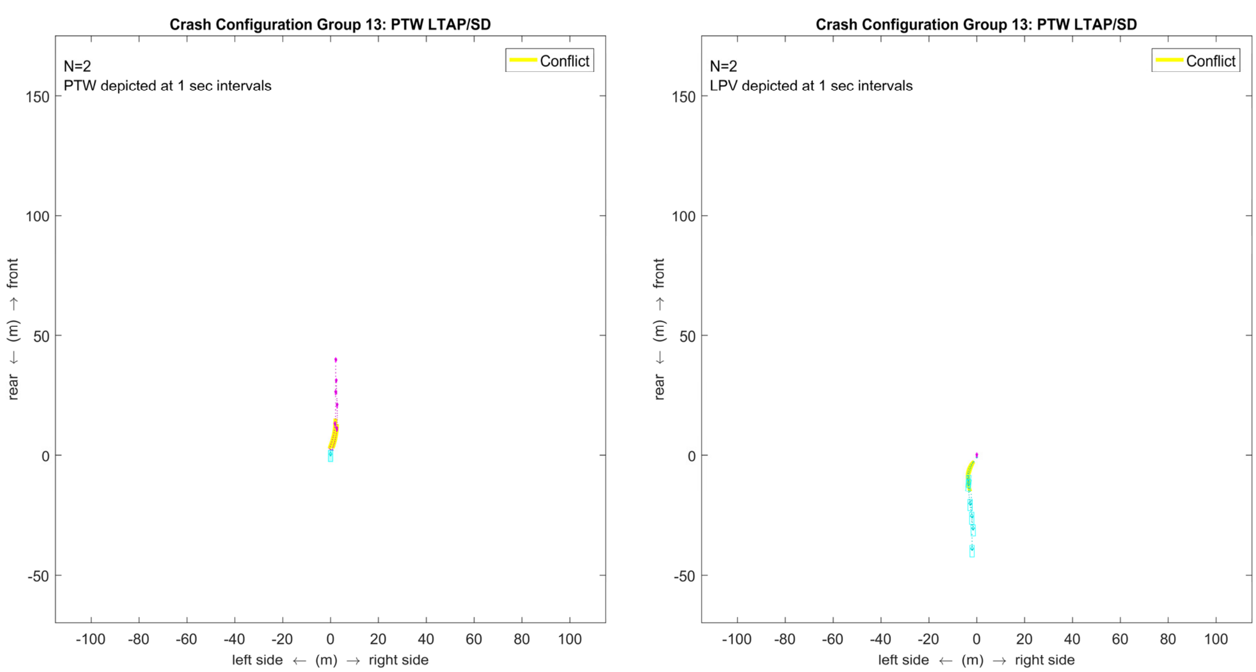


Figure B13. PTW left turn across LPV path/same direction

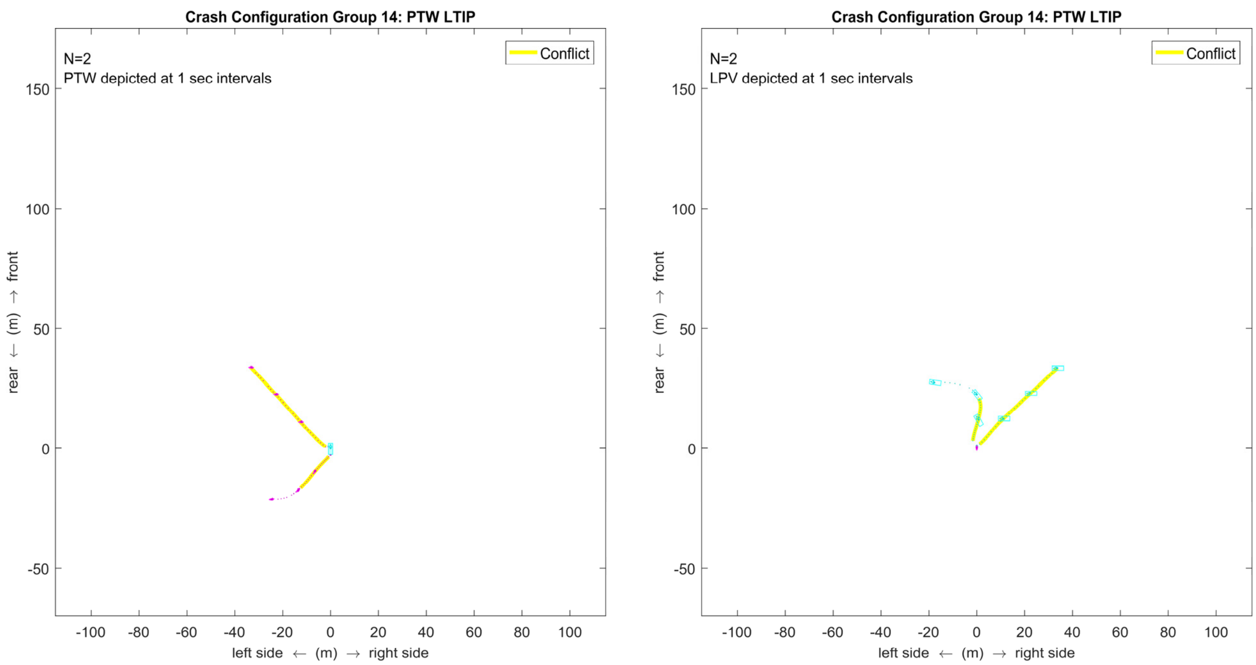


Figure B14. PTW left turn into LPV path

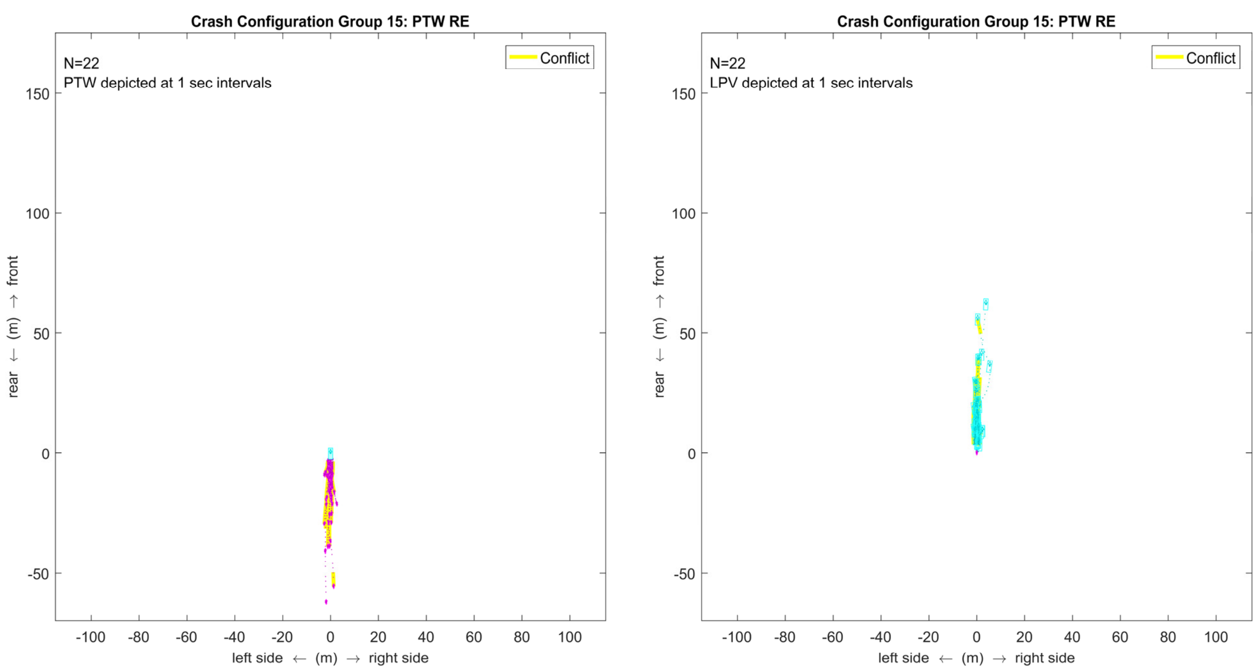


Figure B15. PTW rear-end LPV

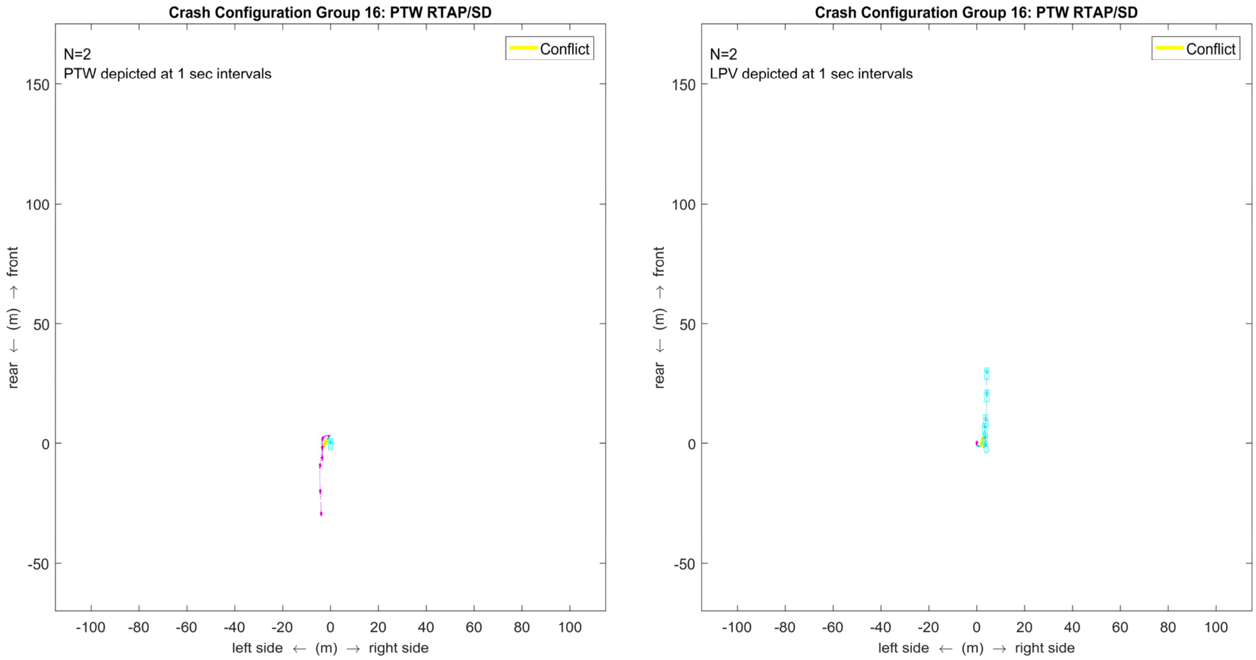


Figure B16. PTW right turn across LPV path/same direction

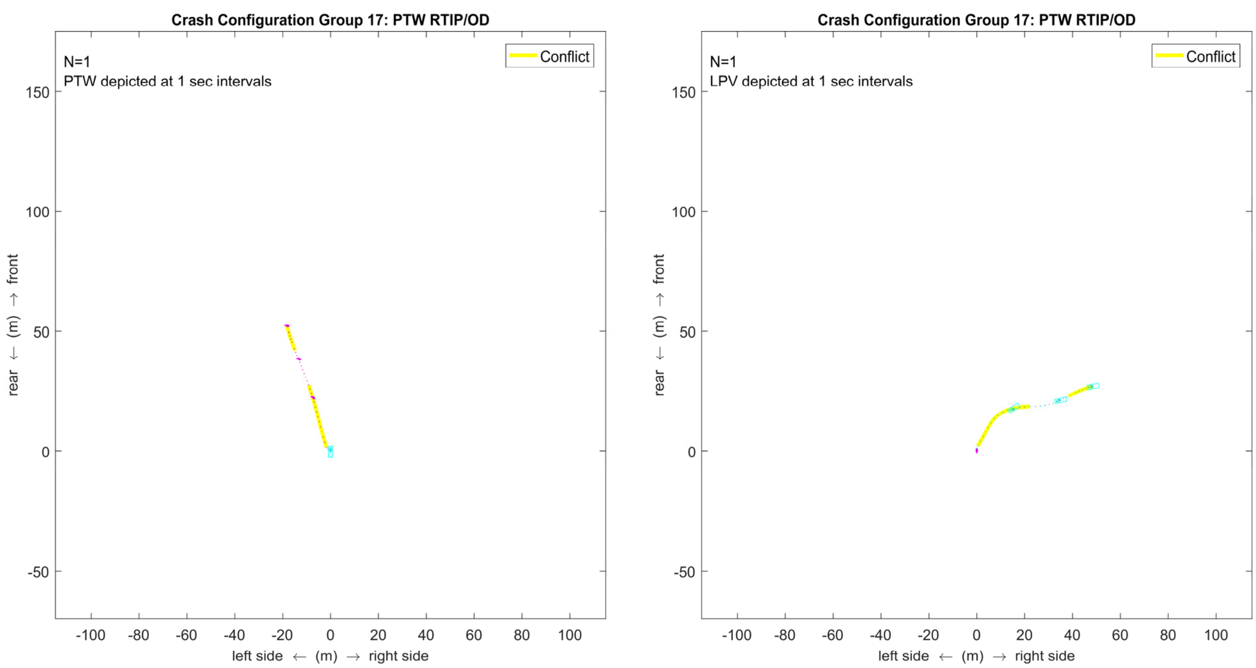


Figure B17. PTW right turn into LPV path/opposite direction

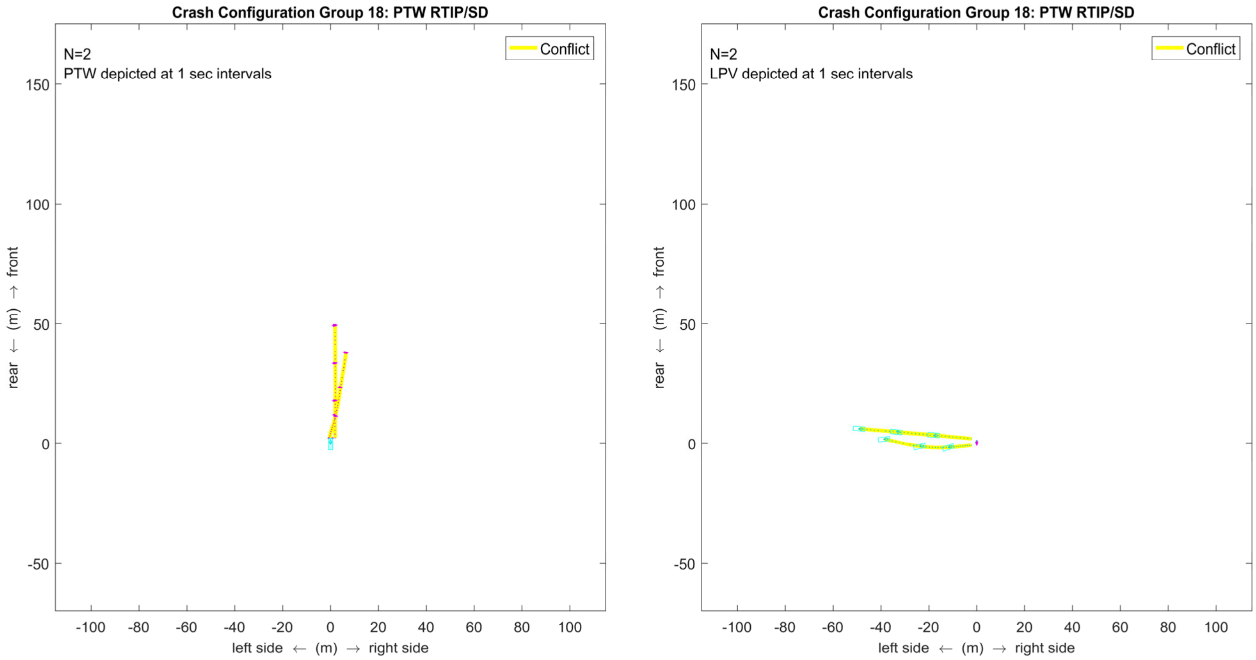


Figure B18. PTW right turn into LPV path/same direction

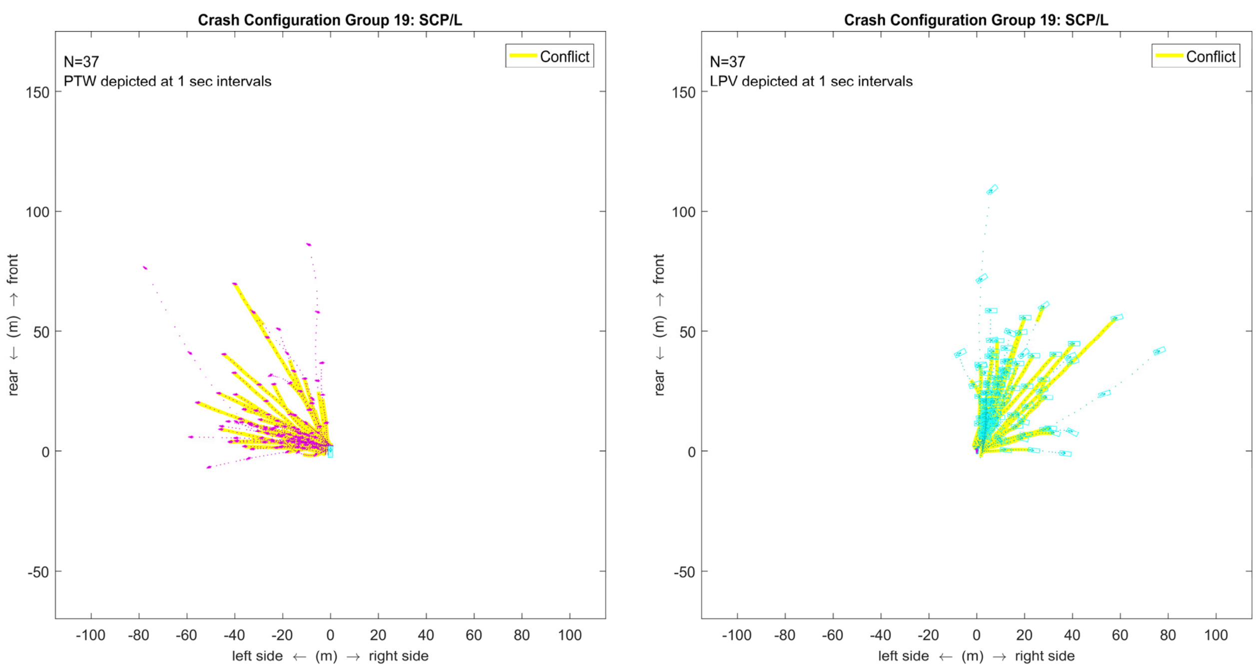


Figure B19. Straight crossing path/PTW on left side of LPV

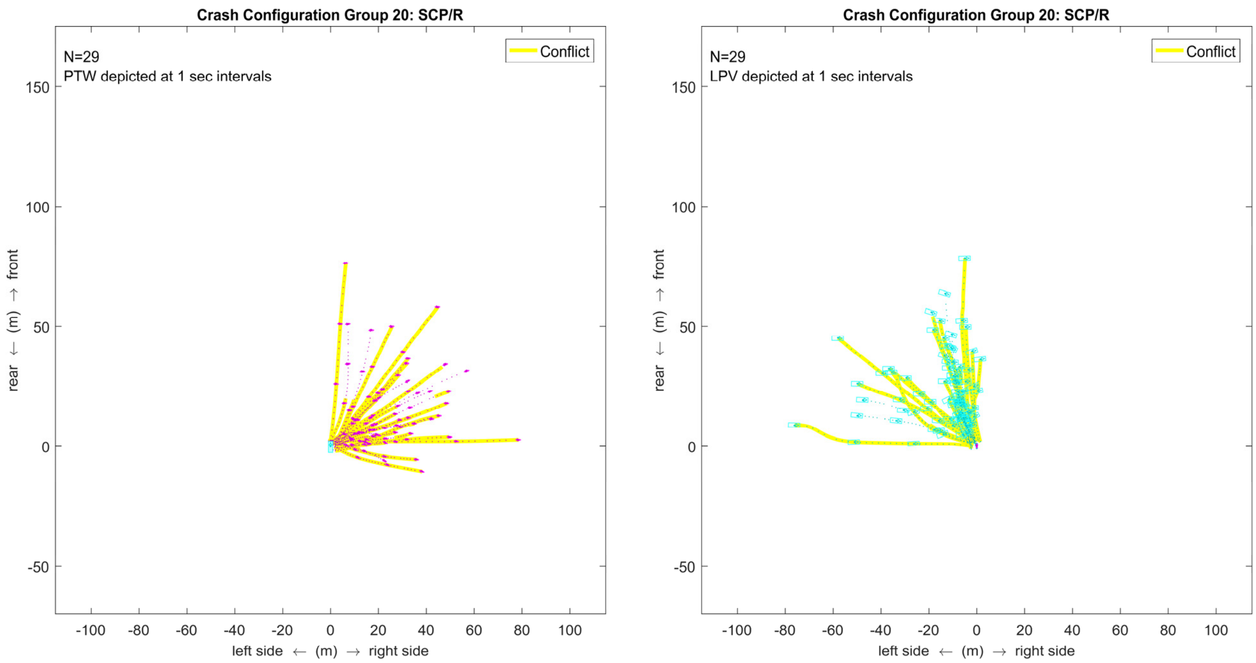


Figure B20. Straight crossing path/PTW on right side of LPV

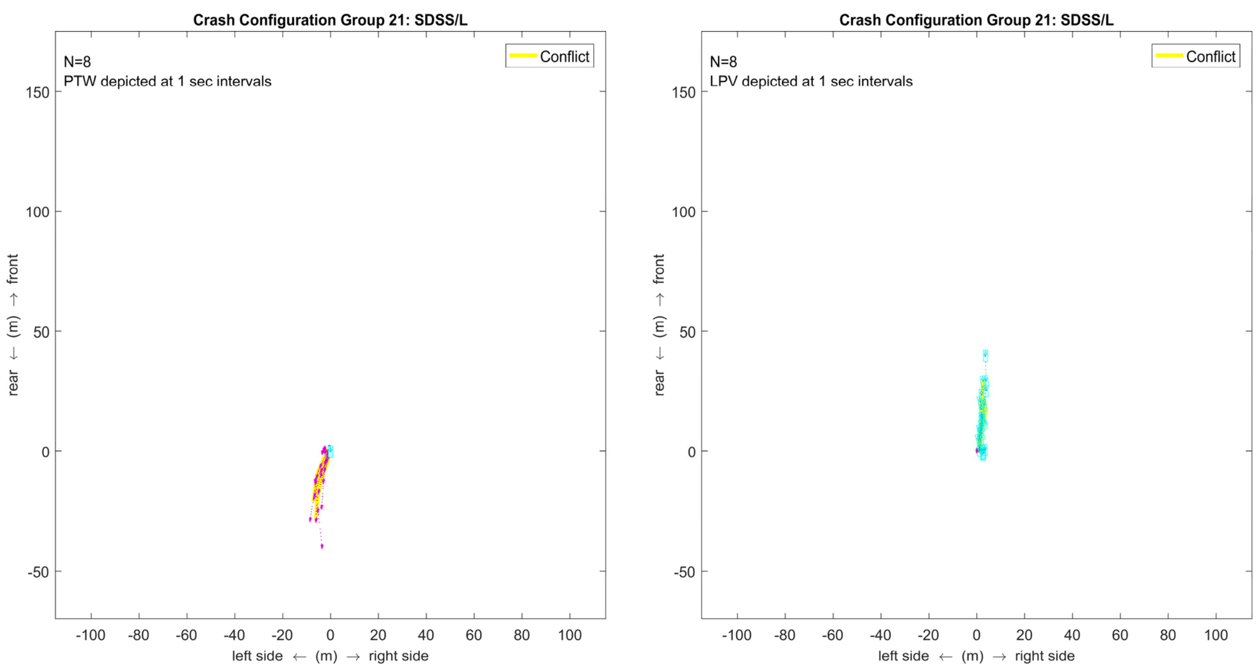


Figure B21. Same direction side swipe/PTW on the left side of LPV

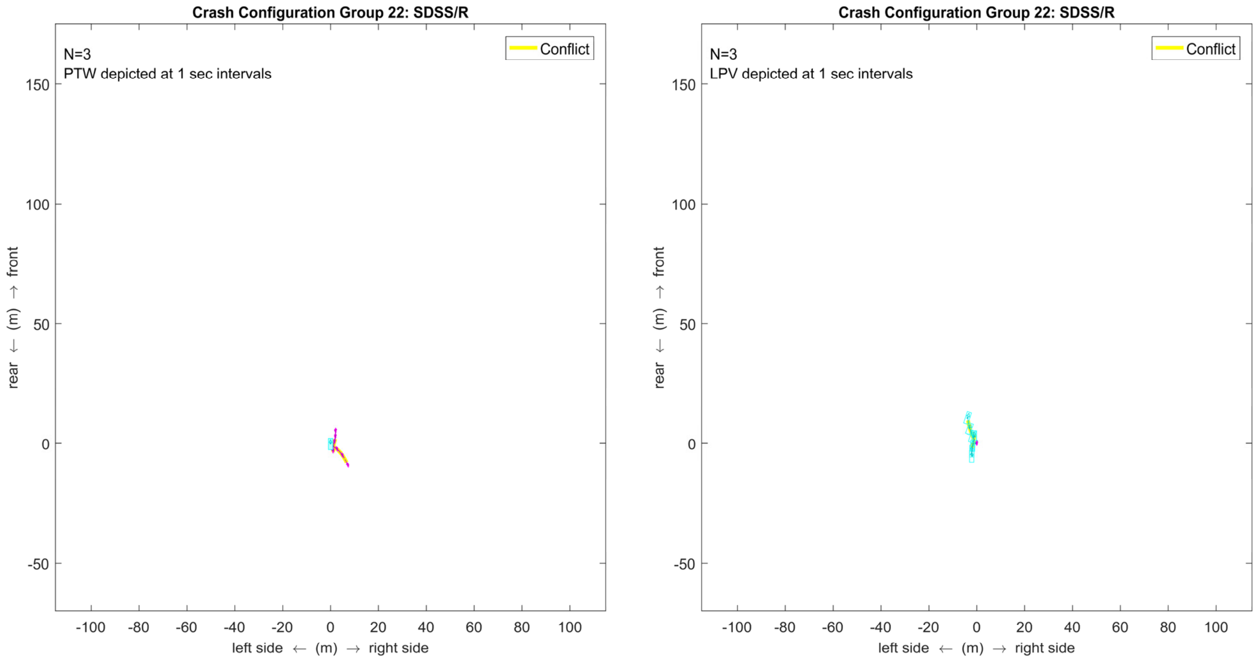


Figure B22. Same direction side swipe/PTW on the right side of LPV

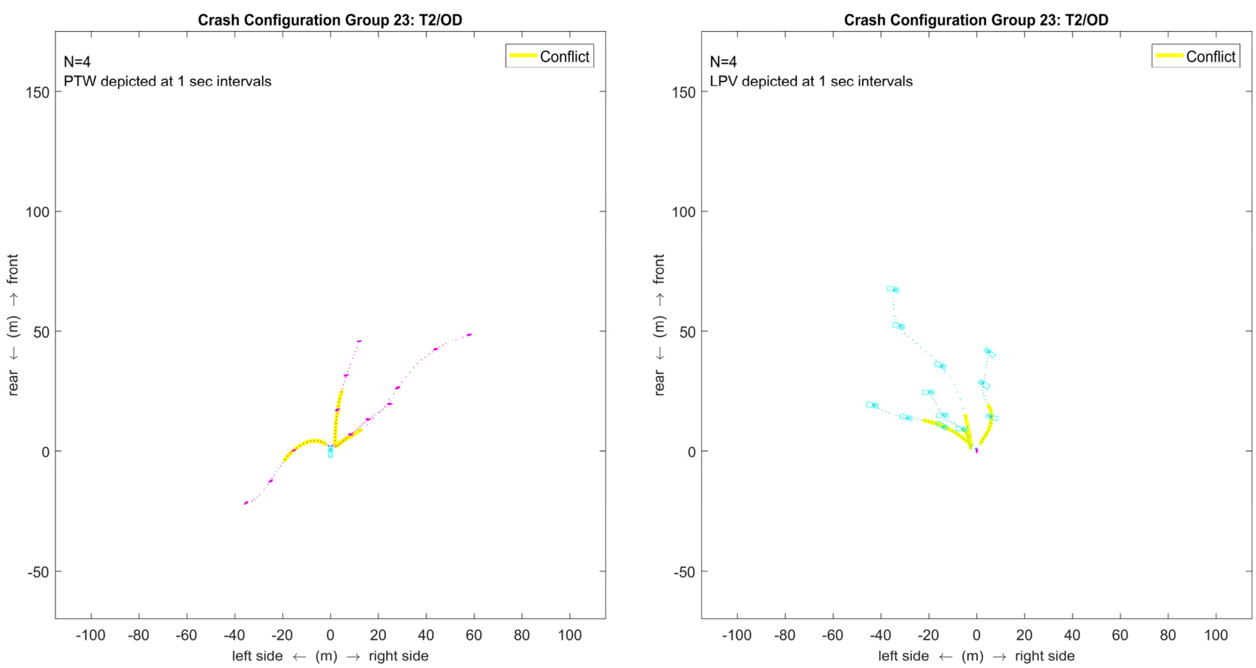


Figure B23. Both vehicles turning/opposite direction

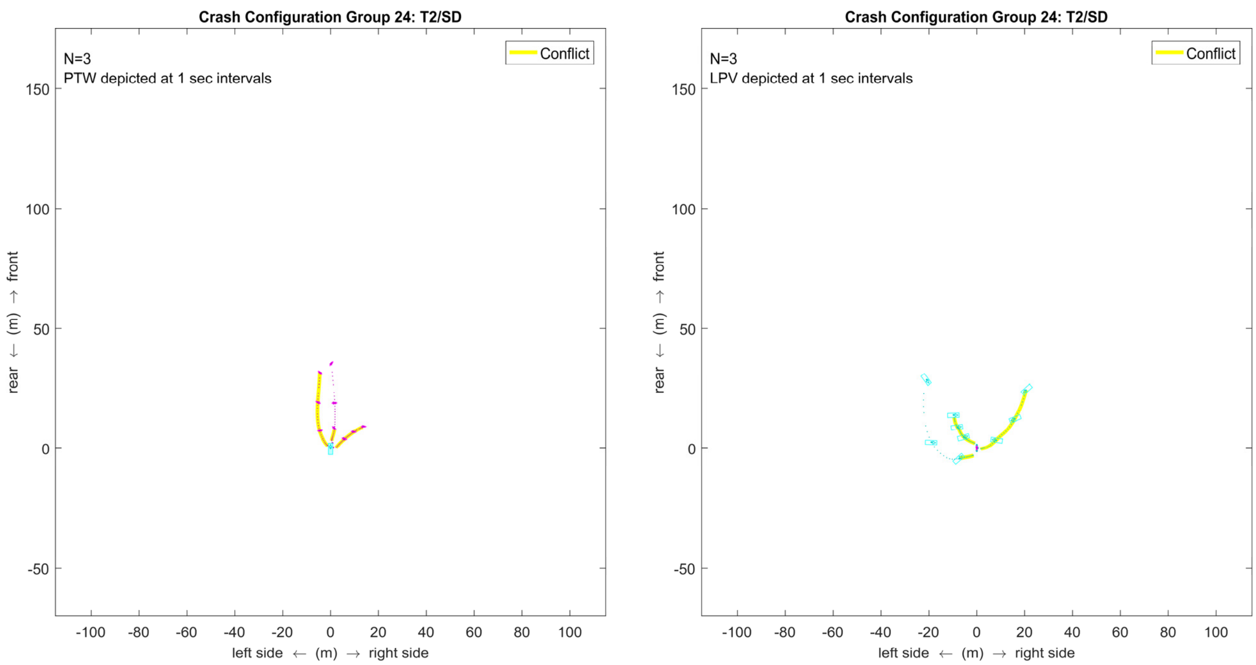


Figure B24. Both vehicles turning/same direction

SIMULATION OF TEST DRIVES BY USING POLICE-RECORDED ACCIDENT DATA AND COMBINING MACROSCOPIC AND MICROSCOPIC ELEMENTS

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Paper Number 19-0098

ABSTRACT

With the development of autonomous driving functions, the evaluation of their functional safety is becoming increasingly important. Current vehicles are tested with separate simulations or test drives. In order to validate future autonomous vehicles by means of test drives, a substantial number of test kilometers are necessary. In addition, these test drives must be repeated for every new release of the system, which increases the expenses for validation. For this reason, programs that can simulate test drives have a high significance. Previous programs do not include the indispensable combination of routing simulation and accident simulation needed to represent a simulated test drive. Therefore, an approach to combining a macroscopic simulation (routing simulation) with a microscopic simulation (accident simulation) is used in this paper.

When the start location and the destination are given, the macroscopic simulation can compute the test route by means of the OSRM (Open Source Routing Machine) routing application. While driving along the test route, the simulated vehicles pass various locations of real accidents. The relevant data is taken from the accident database compiled by the police of Saxony, Germany.

A selection procedure ensures that only relevant accident situations along the test route are later simulated microscopically. Only if the accident situation is similar to the current situation of the simulated vehicle can the accident situation be simulated microscopically. Therefore, various boundary conditions are used to determine whether there are similarities regarding weather, traffic, light conditions and trajectories of the accident vehicles. To study different variations of the selection procedure, three different concepts are developed and evaluated. The first concept is based on a given test route between start location and destination and a realistic calculation of the travel time. The second concept is also based on a given test route but combines this with a time window for the entire route. The third concept combines an unknown test route, which is calculated between relevant accident locations during the simulation, with a realistic calculation of the travel time. After the evaluation of all three concepts, only the third concept is implemented in the simulation.

Within the microscopic simulation by means of PC-Crash, a relevant accident situation is simulated twice, once without and once with the tested driver assistance system in action. With the help of a collision detection system, a conclusion about the efficiency of the driver assistance system is made. The result is a program that combines completed test kilometers with avoided accident situations to simulate a test drive.

The current program can only be used in Saxony, Germany. For an expansion to all of Europe, comprehensive accident data is necessary. In addition, the selection procedure could be improved by means of georeferenced weather and traffic data. Because of the basic simulation tools, the actual simulation is not designed for quality but rather for quantity. However, high-quality simulation tools can be implemented with little effort. The simulation of test drives is an important challenge, and with the program developed here, an opportunity to solve it is introduced.

OBJECTIVE

In the development process of automated driving functions, the evaluation of their efficiency is unavoidable. Currently, simulations as well as test drives are used for evaluation purposes. With the help of repeated simulations of real accidents, it is possible to estimate whether an accident could have been prevented if the vehicle had been equipped with an Advanced Driver Assistance System (ADAS). Test drives in road traffic or on test tracks, on the other hand, expose the ADAS in question with real or staged situations [1].

In the future, the homologation process for highly automated driving functions and autonomous vehicles will become increasingly important. Currently, the functionality of prototypes is established in long test drives. However, several million test kilometers must be driven in order to obtain proof of safety. This procedure must be repeated after each system modification. This means that the expenses for obtaining proof of safety will increase significantly in the years to come [2].

For this reason, the development of a way to simulate test drives is desirable. In order to state the number of test kilometers driven, it is necessary to specify the route of the simulated vehicle. A suitable simulation solution – from now on called macrosimulation – is used for this purpose. Furthermore, an appropriate selection process for specific accident scenarios is developed within the scope of the macrosimulation. These scenarios are then studied microscopically. This way, it is possible to make a claim about how many of the selected specific accident scenarios could have been prevented by the system under testing. This is achieved with the help of a simulation that maps the interaction of the party who caused the accident and other parties involved in the accident. This simulation will be called microsimulation from now on.

METHODS AND DATA SOURCES

The combination of macroscopic and microscopic simulation elements allows the simulation of a test drive. Using the OSRM navigation application as a macrosimulation tool, the test route can be calculated from given points of origin and destination, and the vehicle's position can be simulated depending on the time. The following elaborations are visualized by the schematic depicted in Figure 1.

During the test drive, the simulated vehicle will be faced with several accident scenarios. The database of police-recorded accident data in Saxony provides the basis for all possible specific scenarios. An integrated, three-level selection process ensures that not only accident scenarios relevant in terms of time and location are considered for microsimulation, but also those that show similarities to the simulated vehicle in terms of traffic situation, weather and lighting conditions, as well as trajectories of the involved parties. The similarities are determined and guaranteed by applying several framework conditions. One example of a framework condition is the limitation of the time of the specific accident scenario to the arrival of the simulated vehicle at the accident location. The smaller the time difference to the specific accident, the greater the similarity of the oscillating traffic volume and the lighting is believed to be.

Three different concepts for the integration of the macrosimulation and the corresponding selection process will be developed and compared.

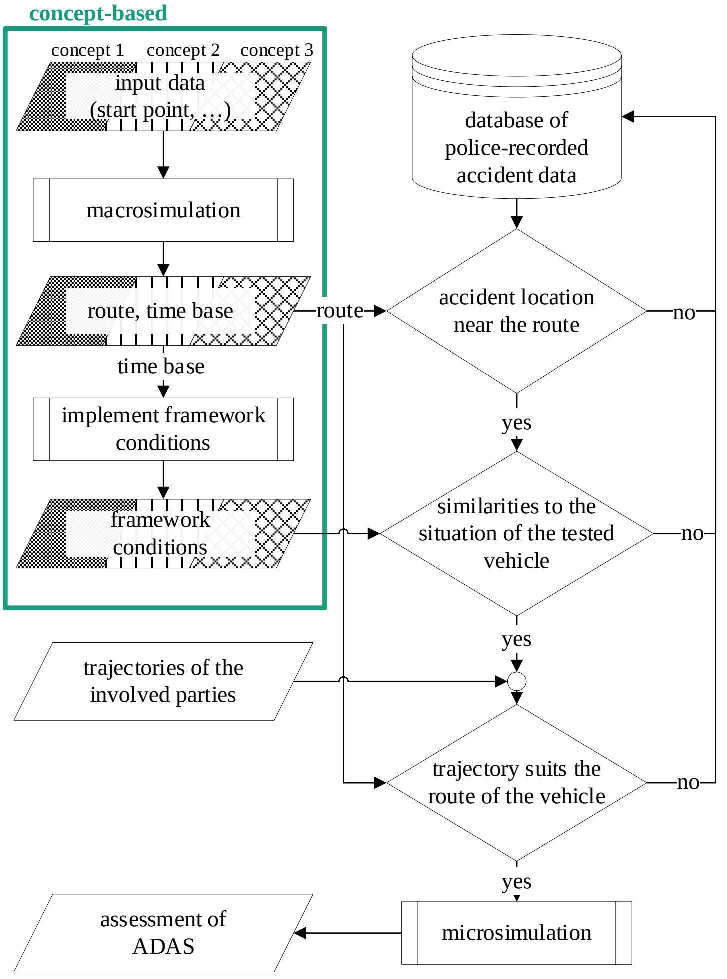

Figure 1: schematic of the selection process

The third and last step of the selection process is based on the intended trajectories of the involved parties. These, as well as the real trajectories, are generated at the Fraunhofer IVI on the basis of the accident data. In order for a certain accident scenario to be selected, one of the intended trajectories needs to correspond with the simulated course of the test vehicle. It is only possible under these circumstances that a vehicle at the same precise location and under similar framework conditions will be involved in an accident similar to the existing concrete accident scenario. If, for example, the simulated vehicle makes a right turn at an intersection where a left-turn accident has occurred, this accident simulation cannot be submitted to the microsimulation.

Within the microsimulation, a statement is made about whether there is a collision between the parties involved. By executing separate simulations with and without a system under testing, it is possible to assess whether the system is able to prevent an accident. In combination with the length of the test route, a claim can be made about test kilometers driven, simulated accidents as well as prevented accidents.

Development of three concepts for the integration of the macrosimulation

Each of the three concepts is based on the macroscopic calculation of a test route between points of origin and destination. The concepts differ in the integration of the macrosimulation and the establishment of framework conditions for the selection process.

Concept 1 adapts a real test drive. The route is known prior to the start of the simulation, meaning that the points of origin and destination are also known. A route is generated between these two points under consideration of any desired number of intermediate points.

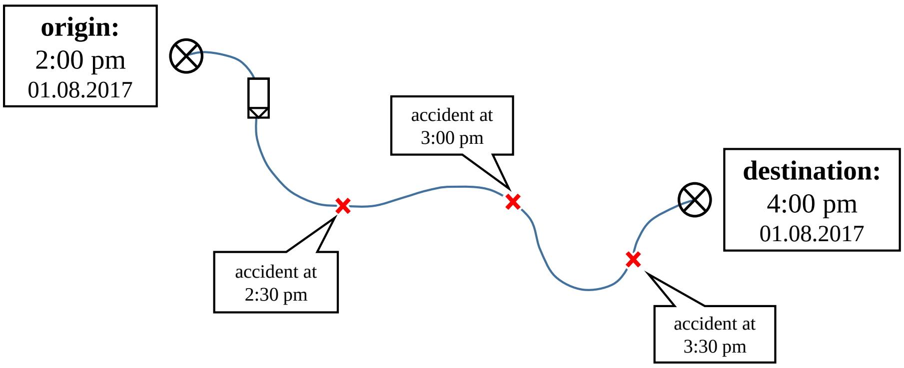

Figure 2: schematic of the first concept

Figure 2 shows the schematic structure of the first concept. The blue line depicts the route from point of origin to point of destination. In concept 1, all accidents along this route with a maximum distance of 15 m to the middle of the road are extracted from the database. The red crosses depict these accident locations along the route. Concept 1 also requires a start date and time, henceforth called the start time stamp. With the help of the start time stamp, it is possible to calculate the position of the test vehicle along the route. The result of this calculation is one arrival time stamp for the point of destination and arrival time stamps for each of the accidents extracted. In addition, each accident also has an accident time stamp describing the date and time at which the accident occurred. The accident time stamp can be extracted from the database of police-recorded accident data. If a simulated vehicle reaches the accident location close to the accident time stamp, the vehicle's situation is similar to the situation. If a simulated vehicle reaches the accident location close to the time of the accident time stamp, its situation is similar to the situation causing the accident. A higher proximity between arrival time stamp and accident time stamp means a higher similarity.

Concept 2 is based on concept 1. Just as in concept 1, a route is generated between the points of origin and destination. This route is shown as blue line in Figure 3.

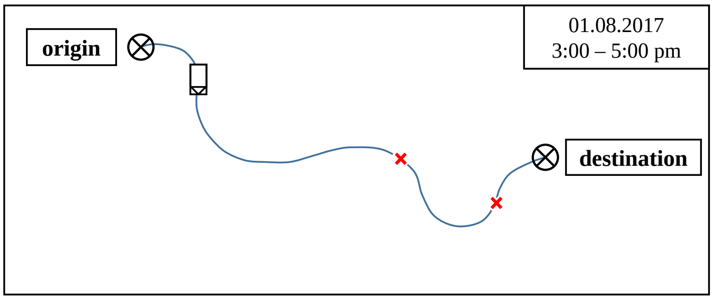

Figure 3: schematic of the second concept

Then, all accidents along the route that are close to the road are looked up. Similar to concept 1, each accident has a time stamp. However, concept 2 does not calculate when a simulated vehicle reaches the accident location. Instead, accidents are selected on the basis of a freely configurable time window. For the example shown in Figure 3, this means that every accident between 3:00 pm and 5:00 pm is selected (red crosses). It is irrelevant in this case whether the simulated vehicle would be able to reach the accident locations in the given time or whether the accidents are depicted in a chronological order. The result of this abstraction is the simulation's loss of direct comparability with real test drives.

Concept 3 is comparable to a real test drive because the calculation of its duration is realistic. However, the drivers do not know their final destination at the start of the test drive. Instead, they receive a new destination after they have reached a given intermediate destination. At the start of the simulation, only the point of origin, the start time stamp and the minimum distance of the test route are known.

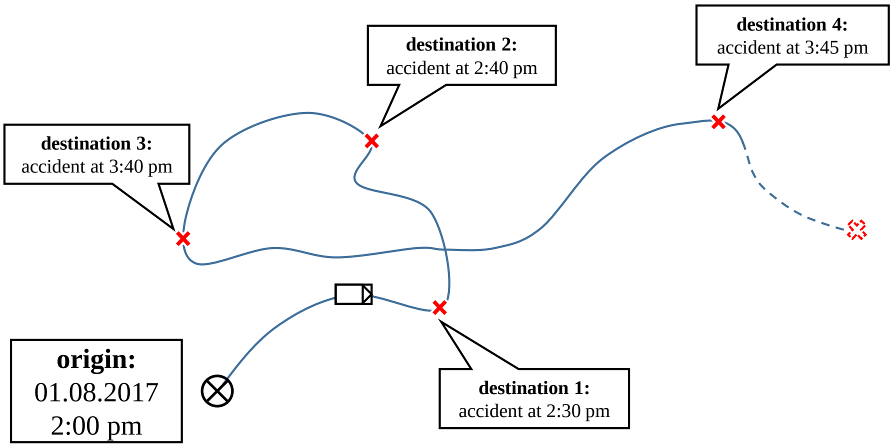

Figure 4: schematic of the third concept

Figure 4 shows the schematic structure of the third concept. The point of origin and the start time stamp are visualized by a black circle with a cross. A pre-defined route, however, needs a destination. To determine a destination, all relevant records are filtered out of the database of police-recorded accidents in Saxony. Then, the distances between the point of origin and all extracted accident location is calculated. The accident location closest to the point of origin becomes the destination of the first route segment (red cross in Figure 4).

An arrival time stamp is calculated for the selected accident location. Based on the arrival time stamp there is an assessment of whether the lighting conditions at the time of arrival are similar and whether the difference between the time of arrival and the time of accident is tolerable. If, considering all framework conditions, the accident scenario is still valid at the simulated vehicle's arrival at the accident location, the scenario can be submitted to the selection process and simulated microscopically.

After this, a destination for the following route segment is determined. The new point of origin is the location of the current accident scenario and the arrival time at the accident location becomes the new start time. As described above, all relevant records are extracted from the database and the distances to potential points of destination is calculated. Again, the closest accident is defined as destination of the current route segment. This loop is continued until the test vehicle has exceeded a predefined number of test kilometers. At this point, the simulation according to the third concept is terminated.

Evaluation of the three concepts

Before the three concepts can be compared to each other, each concept needs to be defined rigidly. For this, each concept is assessed in terms of its possible framework conditions for the selection process so that in the end, each concept is defined by a special combination of rigidly implemented framework conditions. The following three criteria are considered in the specification of the framework conditions.

The first criterion is the number of selected accidents per 1,000 km distance. To determine this figure, the absolute number of selected accidents is divided by the test kilometers driven. According to the statistics on road traffic accidents in the year 2016 compiled by the German Federal Statistical Office (Statistisches Bundesamt, Destatis) [3], about 3,375 accidents per 1 billion kilometers driven occurred in 2016. Or, to put it differently: On average, there was one accident every 296,296 kilometers. This corresponds to 0.003375 accidents per 1,000 km. However, it is not practical to use this figure as an evaluation standard for the first criterion. In order to test a system, a much higher number of accidents per kilometer should be simulated. In order to achieve a compromise between higher accident numbers and the highest possible comparability of vehicle and accident situations, a range of 50 to 100 accidents per 1,000 km is desirable.

The second criterion is the representativeness of the selected accidents within the context of all available police-recorded accident data. The database of accident data recorded by the Saxon police includes, among others, all police-recorded accidents between 2010 and 2016. Each of these accidents is described by characteristic features such as accident category, kind of accident, type of accident and area (urban, rural). This means that the distribution of these features within the Saxon database reflect the general accident situation in Saxony in the past years. It is therefore desirable to achieve an approximation of this distribution within the planned simulated test drive.

The third criterion is the logical comparability of vehicle situation and accident scenario. The repeated simulation of a past accident becomes more comprehensible if the situation of the simulated vehicle and the situation that caused the accident are as similar as possible. Different framework conditions may decrease or increase the similarities between the two situations. Therefore, the framework conditions must be studied in terms of their effects.

After the analysis and subsequent definition of the concepts framework conditions, they can be compared. This process takes into account seven criteria that are weighted differently. After the evaluation of all concepts, it is possible to identify the best one.

Trajectory-based analysis of selected accident scenarios

The selection process for the microsimulation is carried out partly based on concepts (within the concepts) and partly independent from concepts (outside of the concepts). Trajectory-based selection is the part of the selection process that is independent from concepts.

Upon the arrival at a selected accident location, the simulation program examines whether the course of the simulated test vehicle corresponds with the intended course of a party involved in an accident. If the courses correspond, the test vehicle is allowed to simulate the specific accident scenario in the role of this specific party only. Figure 5 shows the schematic of a potential accident scenarios along the test route. The party causing the accident (red) collides with the injured party (blue) while making a left turn. The course of the simulated test vehicle (green), however, does not correspond with either of the two intended courses. In this case, the specific accident scenario was selected within the concept on the basis of framework conditions, but it may not be used within the microsimulation because the course and the trajectories do not correspond. This is the reason why it is important to establish a method for assessing the courses and trajectories of the parties involved in an accident.

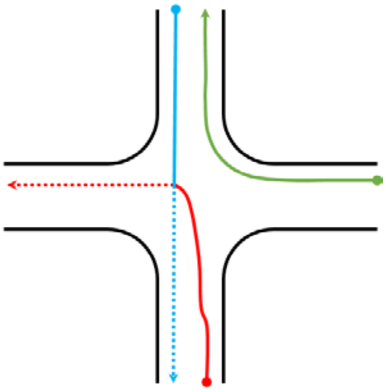

Figure 5: Necessity of the trajectory-based selection

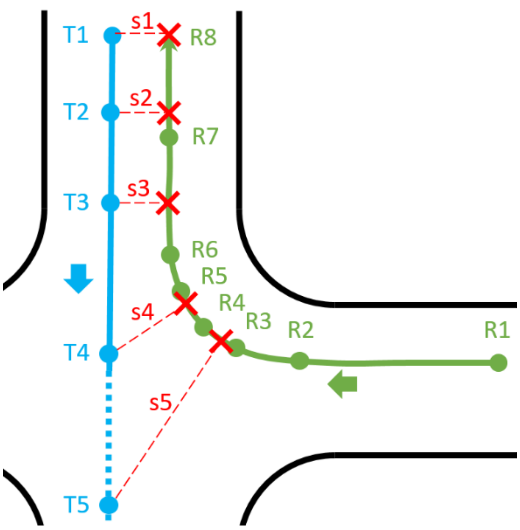

Figure 6: sketch of the solution approach of the trajectory-based selection

The solution of this problem is a method that combines the evaluation of the distance between course and trajectory with the evaluation of the direction of travel. The course and the trajectories are defined by any given number of points represented by geographic coordinates (from now on called supporting points). In Figure 6, these are visualized by the round dots. For each supporting point of the trajectory (blue), the shortest perpendicular distance to the course (green) is calculated (see s_1 to s_5). The resulting vector of shortest distances $\bar{s}$ can be studied in terms of various parameters such as mean value and standard deviation.

In order to compare the directions of travel, it is necessary to analyze the order of the trajectories supporting points (T1 to T5) and their corresponding closest course supporting points (R1 to R8). For this, each trajectory supporting point Tx is matched with the route supporting point Rx that is closest to the point depicted by the red cross in Figure 6. For example, T1 is matched with R8, T2 is matched with R7 and T3 is matched with R6. This way, two vectors are formed that conatin the figures of the matching points (for example: $\bar{T} = [1; 2; 3; 4; 5]$ and $\bar{R} = [8; 7; 6; 5; 3]$).

After that, it is possible to estimate the strength of the linear relation of the two vectors $\bar{T}$ and $\bar{R}$ by using the Pearson correlation ρ according to the Equation 1.

$$\rho = \frac{cov(\bar{T}, \bar{R})}{\sigma_{\bar{T}} * \sigma_{\bar{R}}}, with\ cov(\,) - covariance\ und\ \sigma - standard\ deviation \quad \text{(Equation 1)}$$

In order to test which parameters (mean value, standard deviation, … , ρ) allow the identification of suitable trajectories, a test data set is compiled. The basis of this are 18 different random accidents with known trajectories. For each of the accident locations, all courses in all possible directions are established. Then, a manual assessment is carried out for each of the 256 route-trajectory-pairs of whether they are approximately parallel. If this is the case, a distinction is made between "right direction" and "wrong direction". With the help of several graphic representation methods, it is then possible to determine which parameters allow the identification and selection of suitable trajectories (along the course, right direction).

Microsimulation

The selected accidents are automatically transferred to the microsimulation via an interface and then analyzed. Because the PC-Crash software can easily be integrated by external applications and also supports trajectory-based collision detection, it is used as microsimulation software.

Input data such as the real trajectories of the parties involved in the accident, their speeds and initial locations provide the basis for microsimulation. The maximum allowed speeds of the involved parties can be found in the police-recorded accident data, an uniform movement is assumed. The initial locations of both parties are deduced on the following assumption: the vehicles of both parties collide at the end points of their real trajectories. Based on this assumption, possible initial locations for each party can be established with the help of a reverse simulation along their trajectories that starts at the end points.

The result of the microsimulation consists of two return values. The first return value stores the information whether a collision has occurred without the system under testing, thus error-proofing the process. The second return value gives information about whether the vehicles collide while the system under testing is active. If the first return value is negative (no collision), then no claims can be made about the effect of the system under testing on the basis of this specific accident scenario. If the first return value is positive, a second step describes whether a collision was prevented by the system or not. The system's effects can then be evaluated based on the accidents prevented.

RESULTS

The results of the comparison of the three concepts are depicted in Table 1.

Table 1.
Comparison of the three concepts with the help of a weighted decision matrix

Criterion	Weighting	Concept 1	Concept 2	Concept 3
Comparable with reality	**5**	9	4	9
Accident numbers along the test route	**2**	5	5	9
Options of test route manipulation	**3**	2	2	8
Functionality of long test routes	**5**	3	2	10
Options of influencing the testing environment	**2**	5	9	0
Functionality in case of missing accident data	**4**	10	10	9
Option of expanding the simulation to further regions	**5**	9	9	7
Result [Percentage of maximum points attainable]		**66 %**	**57 %**	**80 %**

Table 1 shows that each of the concepts has its advantages and disadvantages. However, for the simulation of a test drive under the given requirements, the third concept is the most suitable one.

Results of the trajectory-based selection process

The analysis of the parameters for the identification of suitable route-trajectory pairs had the result that no single parameter offers a finite solution. Instead, a combination of the standard deviation and the Pearson correlation coefficient is used. Figure 7 shows which threshold values need to be defined.

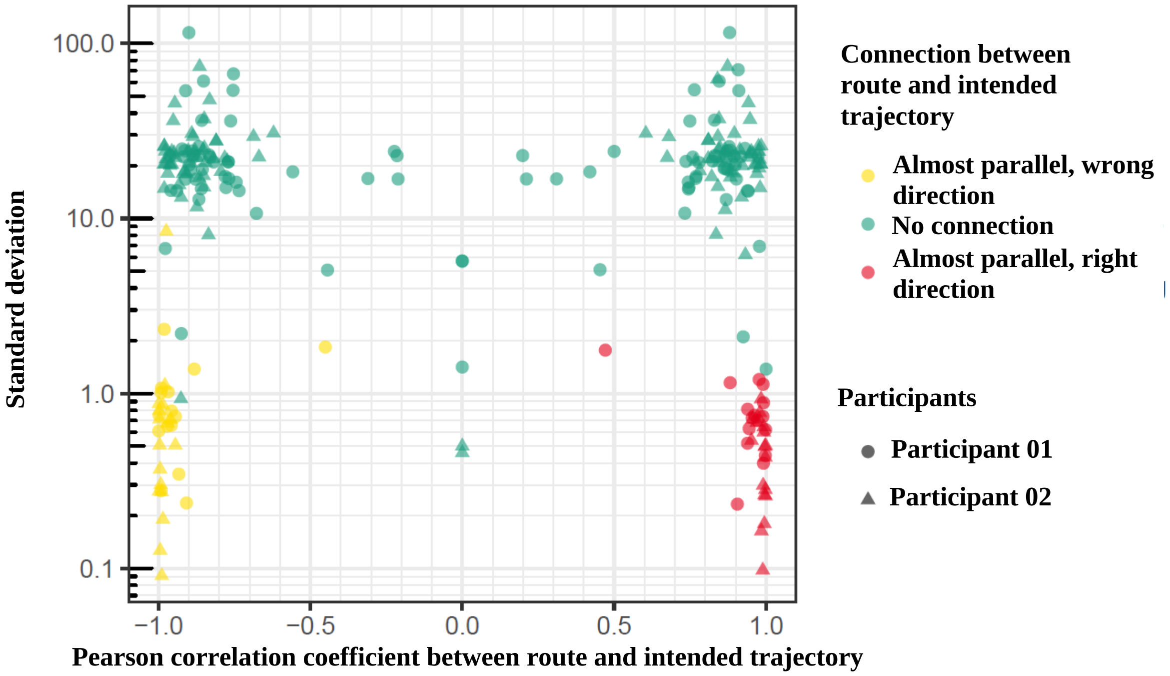

Figure 7: standard deviation and correlation coefficient (256 route-trajectory pairs)

Based on the above image, the trajectory-based scenario selection procedure is implemented as follows: For the examination, the type of road use of the trajectories taken into account is limited to the class of "passenger car". For example, pedestrian trajectories are not allowed. The remaining intended trajectories can be examined with the help of the standard deviation and the correlation coefficient. In 97% of cases, trajectories with a standard deviation $\sigma \leq 3$ and a correlation coefficient $\rho \geq 0{,}8$ are suitable for the current route and go in the right direction.

Example application of the program

The example application demonstrates the entire process of the developed program using a vehicle equipped with an advanced emergency braking system (AEBS). At the beginning of the example application, the input data is defined. The test drive begins on August 1, 2017 at the Fraunhofer IVI in Dresden and covers a distance of 100 km or more. The system under testing is mapped in PC-Crash with the help of a proximity sensor with a range of 80 m, an opening angle of 5 degrees and a cycle time of 100 ms, as well as with an active TTC time to collision monitoring system. If the TTC falls below 1 second, an emergency braking process is initiated.

Within 11 minutes, the program carries out the construction of the route, the selection process and the microsimulation. The resulting test route of 109 km length is visualized in Figure 8 by a transparent green line. It passes through Dresden's urban center as well as through surrounding areas. Along this route, the test vehicle is confronted with 18 selected accident scenarios. 14 of these pass the trajectory-based selection process and are then simulated microscopically. The results are summarized in Figure 9.

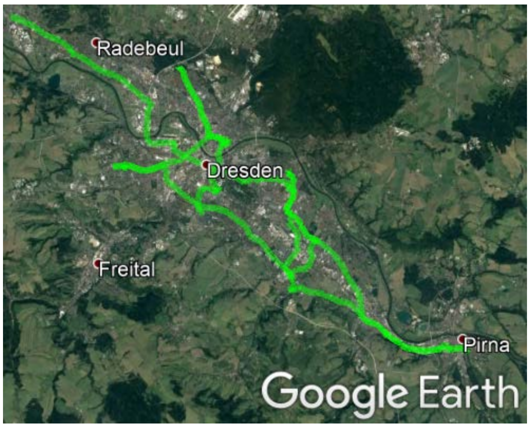

Figure 8: test route of the example application

The 14 simulated accident situations are plotted according to their types of accident and distinguished by color. Only those accident situations that were prevented by the AEBS are marked green. Thus, the efficacy of the AEBS becomes evident with respect to the different types of accident.

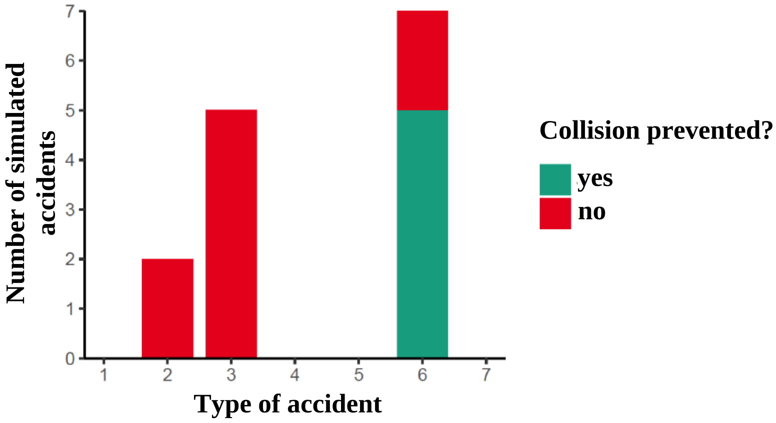

Figure 9: results of the example application, broken down by type of accident

According to Figure 9, the AEBS is able to prevent over 70 % of accidents in parallel traffic (accident type 6) within the simulation. However, no accidents are prevented during turning and during turning/crossing accidents (types of accident 2 and 3). This leads to the conclusion that the AEBS in use is mainly effective in rear-end collisions. Further examination of the simulation files created by the microsimulation confirms this conclusion. Only in the situation of a rear-end collision on a straight road is the injured party detected in time, so that an emergency braking process can prevent the collision. In rear-end collisions in turns and in all other accident situations included in the simulation, the injured party is not detected or not detected early enough.

DISCUSSION

The integration of traffic and weather data would be very beneficial for the area of the macrosimulation. The implementation of other external macrosimulation applications is also conceivable to and the modular design of the program supports this.

The selected variant of microsimulation is able to draw a conclusion about prevented collisions. However, a more detailed realization of sensors and advanced driver assistance system would improve the plausibility of results. Also, no exact input parameter exist for the microsimulation, which is why they need to be deduced with the help of assumptions. Thus, there is a potential for an expansion of the microsimulation. Due to the modular design of the program, the microsimulation could also be realized through the implementation of other simulation programs.

In order to evaluate the simulation of an entire route, the accident selection is studied in terms of representativeness by comparing it to a reference data set. For this, the distribution of the double-digit types of accident of the selected accidents is examined in the context of the distribution of the double-digit accident types of the reference data set. The result of the comparison provides the basis for a two-level score, which is calculated automatically. This score first examines how many of the types of accident are reflected in the accident selection. Subsequently, it evaluates how well the reflected types of accident are represented. The score has values between 0 and 1, where 1 symbolizes a perfect reflection of the overall data set.

The score of the example application was calculated to be 0.38, which means an inadequate representativeness. Although 5 of 14 collisions were prevented, the statement “The AEBS is able to prevent 5 in 14 (35%) accidents” is a misinterpretation. A longer test route with an increased number of simulated accidents would improve chances of a higher score and a more well-founded statement.

CONCLUSION

Due to the necessity mapping test drives in a simulation environment, a method was developed that allows a statement about test kilometers driven and accidents prevented. To achieve this, a simple macroscopic simulation of a test vehicle was combined with a selection process for specific accident scenarios with the objective of transferring selected scenarios from the macroscopic simulation to the microscopic simulation. On the basis of multiple simulation, the latter allows to draw a conclusion about the collision prevention potential of the system tested.

The reduction of effort and expenses for real test drives will be possible with the help of the described method. If comprehensive accident data is available, the expansion of the simulation to additional regions will be possible.

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