A CarMaker-Based Validation Framework to Virtually Reconstruct and Evaluate Collision Scenarios for Automated Driving

APPLY & INNOVATE, 12.09.2018
Karlsruhe, Germany

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EVOLUTION

2020+
Fully autonomous vehicles
Source: Mercedes-Benz

2010-2020
Traffic jam assist
Highway autopilot
Parked garage pilot
Source: Continental

1990-2010
ESC, ACC, AEB etc.
Parked assist
Source: BMW

Pre 1990
Anti-lock brakes
Cruise control
Source: Mercedes-Benz

REVOLUTION

Source: Google
Source: NAVTEFWay project
Source: RUM group
Examples of Safety Challenges for Automated Vehicles

Roadworks, temporary lane markings, complex intersections and roundabouts, sunglare, adverse weather conditions such as snow, fog or heavy rain, road surface defects such as ruts, cracks or potholes, vulnerable road users, misinterpretation of vision sensors etc.
It would take a few hundred years to prove safety.

11 billion miles or ~500 years needed to demonstrate with 95% confidence that there will be a 20% improvement over human drivers in terms of road fatalities (Kalra and Paddock, 2016)
Functional Scenarios

Use Cases for Automated Driving

Logical Scenarios

Parameters for Virtual Testing
Road Environment
Vehicle and Sensors
Driving Behaviour

Concrete Scenarios

Random Sampling Techniques

Low Level of Abstraction

SCENARIO DATA MINING

Crash Data Clustering
Driving Data Events
Pilot Test Results
Traffic Observations
Risk&Threat Assessment

High Level of Abstraction
In general, the idea is to initially partition historical crash data (involving human drivers) by a **clustering** technique and then apply the **association rule method** on the data subsets (left-hand side).

The derived scenarios are then transferred to a **sub-microscopic simulation** environment for examining the safety performance (right-hand side) based on a combination of numerical indicators.

Risks that could negatively influence the safety performance of automated vehicles are specified as “**criticalities**”. Hence, criticality factors are added to the simulation parameters derived from the association rule analysis.
**k-medoids**

- Algorithm: “PAM“ (Partitioning around Medoids)
- Capable to cluster categorical data
- Robust against outliers
- Dissimilarity measure: “Hamming”
- Validity index: Silhouette value
**Cluster T-C10:** “The car hits another car with its front, while going straight over a T-junction with a minor road joining from the left.”

<table>
<thead>
<tr>
<th>Level-1 Attributes</th>
<th>T- C1</th>
<th>T- C2</th>
<th>T- C3</th>
<th>T- C4</th>
<th>T- C5</th>
<th>T- C6</th>
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<th>T- C8</th>
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<th>T- C10</th>
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</table>
Association rule mining is a method to discover associations between attributes, also called “frequent itemset mining”.

A popular example of association rules is the **market basket analysis**. Retailers can get insights into which items are frequently purchased together, so that marketing strategies and product shelving can be optimized. For example, if a customer buys “beer”, then he/she also buys “crisps”.

<table>
<thead>
<tr>
<th>rhs</th>
<th>lhs</th>
<th>support</th>
<th>confidence</th>
<th>lift</th>
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<td>bottled beer</td>
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<td>0.0016268429</td>
<td>0.9411765</td>
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<td>0.5000000</td>
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<td>0.5454545</td>
<td>67.06</td>
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</table>
High injury scenarios

obtained for T-junctions

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Count</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>T-4.1 (coll. type L)</td>
<td>39</td>
<td>Car A turns into a minor road and is hit by a PTW B on its nearside, which is going straight in the opposing direction. This happens on a single carriageway with 40-50 mph speed limit without active or static yield instruction and is caused by A failing to give way or to manoeuvre inappropriately.</td>
</tr>
<tr>
<td>T-10.1 (coll. type L)</td>
<td>13</td>
<td>Car A goes straight on a major road and hits another car B with its front, which is coming from the opposing direction and is turning right into a minor road. This happens on a single carriageway with a speed limit of 40 mph or 50 mph at an unsignalised junction, and is caused by B failing to give way. The surface is dry and B suffers serious or fatal injury.</td>
</tr>
<tr>
<td>T-10.2 (coll. type J)</td>
<td>11</td>
<td>Car A goes straight on a major road and hits another car B, which is emerging from a minor road on the left with the intention to turn right. This happens on a single carriageway in a rural area with a speed limit of 40 mph or 50 mph at an unsignalised junction, and is caused by B failing to give way. The surface is wet and A suffers serious injury.</td>
</tr>
<tr>
<td>T-12.1 (coll. type J)</td>
<td>20</td>
<td>Car A turns right into a major road and is hit by a PTW B on the offside, which is going straight on the crossing path. This happens on a rural single carriageway controlled by a static give-way sign and is caused by A failing to give way. The surface is wet and B suffers serious or fatal injury.</td>
</tr>
<tr>
<td>T-12.2 (coll. type G)</td>
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<td>Car A turns right into a minor road and is hit on the offside by a PTW B, which is overtaking. This happens on an urban single carriageway with 30 mph speed limit without active or static yield instruction and is caused by an inappropriate overtake from B.</td>
</tr>
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<td>T-12.3 (coll. type M)</td>
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<td>Car A turns left into a major road and is hit by a PTW B on its offside, which is going straight on the major road from the right. This happens on an urban single carriageway with 30 mph speed limit controlled by give-way signs and is caused by A failing to give way. B suffers serious or fatal injury.</td>
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<tr>
<td>T-13.1 (coll. type L)</td>
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<td>Car A turns into a minor road and hits a PTW B with its front, which is going straight in the opposing direction. This happens on a rural single carriageway with 30 to 50 mph speed limit without active or static yield instruction and is caused by A failing to give way or to manoeuvre inappropriately. The surface is wet and B suffers serious or fatal injury.</td>
</tr>
</tbody>
</table>
The identified pre-crash scenarios are modified and simulated until the point of impact, by implementing models for the road scenery, vehicle and sensors as well as driving behaviour and control. The Monte Carlo sampling method, in particular the Latin Hypercube Sampling (LHS), was applied to randomly select samples among the value range of the varying parameters. The resulted safety performance indicator values are then used to compute a collision and near-miss probability for each scenario variation to derive findings. The findings are discussed against the hypotheses stated for each experiment.
Latin Hypercube Sampling (LHS) divides the cumulative probability curve into equal intervals on the cumulative probability scale and samples a random value from each interval of the input distribution.

It takes even unlikely extremities into account as it is desired for vehicle tests.

The sampling approach ensures that the input probability distributions are maintained and that the resulting simulation outputs are considered representative in this respect.
The input for the simulations, are specified by an XML-structured configuration file (1). This allows the script file for the simulation automation to be kept slim without changing the code for each new test run.

The automation script (2) is implemented in MATLAB and sets up the simulation environment, interprets the input XML-file and communicates with the CarMaker-Simulation instance.

The CarMaker GUI (3) is then executed to perform the simulation runs and to deliver the specified output quantities for each run. Those output files are stored in the simulation database and are post-processed to compute the safety indicators (4), stored in the results database (5).
When a collision is detected, the aim is to estimate the severity in terms of injury risk. To do this, the impact velocities and the impact angle are calculated to obtain the Delta of Velocity, which is used for estimating the injury severity.

In case there is no collision detected, the aim is to find out whether the scenario is a critical conflict or an undisturbed situation. There are two decision points to answer this: First, did one of the vehicles perform an evasion maneuver, i.e. an emergency braking? Second, did the vehicles come close to each other, even if there was no braking involved.
Demonstration Experiment

Example of a near-miss conflict situation

- v-approach-B: 15.3 m/s
- Collision: no
- Conflict: yes
- PET = 0.3 s
- TTA-A = n/a
- TTA-B = 2.1 s

Summary of run #3633

- Actual exit point B
- Actual exit point A
- Actual entry point B
- Actual entry point A
- PET

Perspective of the opponent vehicle B (human driver)

Perspective of the ego vehicle A (automated)
Demonstration Experiment
Example of a collision situation

Perspective of the opponent vehicle B (human)

Perspective of the ego vehicle A (automated)

Collision: yes
bullet veh: B
impact-angle: 49.1 deg
v-impact-A: 4.4 m/s
v-impact-B: 5.8 m/s
delta-v-A: 4.0 m/s
delta-v-B: 4.6 m/s
P(MAIS0,A): 48.1%
P(MAIS0,B): 43.7%
P(MAIS1,A): 36.9%
P(MAIS1,B): 41.4%
P(MAIS3+,A): 1.3%
P(MAIS3+,B): 1.5%
P(MAIS6,A): 0.1%
P(MAIS6,B): 0.1%
Simulation Results
from 16,000 runs

- 75% Kollisionen
- 55% Beinahe-Kollisionen

- 96% Kollisionen
- 75% Beinahe-Kollisionen
IMPROVED ENGINEERING DESIGN
Faster development cycles for automotive and supply industry through reduction of test variations and systematic safety performance assessment.

VEHICLE APPROVAL CRITERIA
Important step towards certification and approval of automated vehicles through pre-defined scenarios and safety metrics, which can be transferred to pass/fail criteria.

HIGHER SAFETY AND ACCEPTANCE
Improved public acceptance and accelerated penetration of automated driving, which leads to higher overall traffic safety.
Thank you!

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