Machine Learning & Active Safety Using Autonomous Driving and NVIDIA DRIVE PX

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Agenda

1. Open vehicle research platform
2. Machine Learning & Active Safety
3. Austrian Test & Validation Region
4. Fully digital tool chain

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Open vehicle platform

Automated Driving Demonstrator
Open vehicle platform: Roadmap

**NVIDIA DRIVE PX 2**

- **Electrified vehicle with internal access:** steer, brake, drive by wire, dual energy storage
- **Demonstrator Vehicle**

**ADAS Sensor Integration**
- Radar, Camera, GPS, IMU, Ultrasonic, Lidar, Interior Camera, C2X, Battery-monitoring
- **Sensor-Fusion**

**HW-Platform**
- **Nvidia**, Infineon Aurix, dSPACE
- Data logging & measurement equipment, self-diagnostics

**Deep learning**
- Scene interpretation, Advanced HMI augmented reality, ...

- **Optimization and Validation**
  - HW-SW co-simulation, Distributed vehicle-Testing, Testdrives, Function optimization
  - Vehicle in the loop tests

**ADAS Functions Implementation**
- Advanced control (LKA, ACC, LCA, Motorway Assistant, EBA), Online Driver Monitoring, Collision detection, Traffic-Light-Assistant, Infrastructure interaction, sensor self-diagnostics ...

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Open vehicle platform: Components

- **1 x Mobileye 630** (Full Extended Log Data)
- **4 x Continental Short Range Radar SRR208**
- **2 x Continental Long Range Radar ARS 408**
- **4 x Sekonix SF3323 Automotive Camera** (100° aperture angle for 360° surround vision)
- **2 x Sekonix SF3322 Automotive Camera** (60° aperture angle for long range vision)
- **1 x Infineon ToF Camera prototype** (evaluation for park assistance)
- **2 x Sekonix SF3322 Automotive Camera** (60° aperture angle for long range vision)
- **2 x ScaLa LIDAR sensor**
- **2 x Continental Long Range Radar ARS 408**

*planned in Future
Open vehicle platform: Data Rate

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Data Rate (per second)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cameras</td>
<td>~20-40 MB</td>
</tr>
<tr>
<td>Radar</td>
<td>~10-100 KB</td>
</tr>
<tr>
<td>Sonar</td>
<td>~10-100 KB</td>
</tr>
<tr>
<td>GPRS</td>
<td>~50 KB</td>
</tr>
<tr>
<td>LIDAR</td>
<td>~10-70 MB</td>
</tr>
</tbody>
</table>

Autonomous Vehicles: 4,000 GB per day

Source: Intel
Machine Learning & Active Safety
Motivation.
Active Safety vs. Automated Driving

HAF technologies offers the possibility to optimize active safety systems in lower automation levels!

- **Driver only**: No intervening vehicle system active.
- **Assisted**: Vehicle assisted longitudinal and lateral control.
- **Partially automated**: Vehicle assisted longitudinal and lateral control (for a period of time and/or in specific use case).
- **Highly automated**: System has longitudinal and lateral control in a specific use case. Recognizes its performance limits and requests driver to resume control with sufficient time margin.
- **Fully automated**: System can cope with all situations automatically during the entire journey. Driver doesn't monitor the system.

Automation level / Technological effort: Driver only, Assisted, Partially automated, Highly automated, Fully automated.

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Problem: Complexity and high variation of accidents

- Thinking of safety functions for every combination of accident **type** and **cause**

  ![Graph showing coverage type vs. cause of accident combination](image)

  - Function design based on **quantitative** (e.g. DESTATIS) and **qualitative** accident databases (e.g. GIDAS Pre-Crash-Matrix)

- Exponentially growing effort → tiny increase in accident coverage
  How to cover wide range of variations?

First 50%: 26 types and causes of accidents
Last 50%: 5287 types and causes of accidents

Type: Speeding, slippery road, etc
Required Technologies for Highly Automated Driving:

- Redundant 360° environment recognition
- High-precision digital maps incl. localization
- Driver monitoring
- Automated driving until the high dynamic limits
- Backend communication
Vision. Optimization based on real world traffic data.

- 360° sensors
- High-precision maps
- Driver monitoring
- Backend

Collecting accident and traffic data

- Accident data
- Effectiveness Assessment

Offline optimization

- Data Mining / Machine Learning
- High number of accidents with detailed information
- Optimization risk assessment algorithm
- Validation new system behaviour

Release to fleet

- Active Safety System
- Release new system behaviour to fleet
- Advanced system performance
- Increasing effectiveness with new accidents

Our use case: Crossing pedestrian (75% of all pedestrian accidents)

- Generated pedestrian scenarios from the Effectiveness analysis

Crossing scenarios

<table>
<thead>
<tr>
<th>Training data</th>
<th>Test data</th>
</tr>
</thead>
<tbody>
<tr>
<td>1840</td>
<td>1829</td>
</tr>
<tr>
<td>242</td>
<td>243</td>
</tr>
</tbody>
</table>
Machine Learning.  
What are we going to learn?

**Point of No Return** – Learning of the brake time based on the accident data, when the emergency brake assistance needs to brake. The *brake time* is a result of the *system limitations* of the Active Safety System. The *uncertainties* of the pedestrian and the driver behavior will be considered by the variation of the accident data.

**FEATUES**

1. Velocity Vehicle*
2. Acceleration Vehicle*
3. x/y-position Pedestrian*
4. Rel. velocity x/y-direction Pedestrian*
5. Brake pedal position
6. Angle Vehicle – Pedestrian*
7. Distance Vehicle – Pedestrian*
8. Velocity Pedestrian*
9. Orientation Pedestrian*
10. Time-To-Collision*
11. Predicted pedestrian position at TTC=0*

### Simplified labeling datasets:

a = 10; % Acceleration vehicle \[m/s^2\]  
td = 0.2; % Delay brake \[s\]  
ts = 0.2; % Delay max. brake pressure \[s\]  
SAFETY_GAP_SIDE = 0.7; \[m\]

```
ttb = (ego.v - a/2*ts)/a + ts + td;  
if (ttb > ttc) && abs(object.y_pred) < ego.width/2)  
    avoidable_aeb = 0;  
else  
    avoidable_aeb = 1;  
```
Example – VRU Safety

Animation made by Virtual Vehicle Competence Center

Vehicle Dynamics Simulation

MBS Head Positioning Simulation

FEA Crash Simulation
Concept.
Function Development Active Safety System.

**DEVELOPMENT**

1. Accident Database
   - Data Preprocessing

   - Training Data
   - Test Data

   Machine Learning
   - Neural Network
     - Network

   Evaluation System Performance
     - Effectiveness Analysis
     - System behaviour

**VEHICLE**

4. Sensors
   - Environment Model
     - Preprocessing
     - Network

   Actuators
     - Driver Warning
     - Brake Request

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Simulation Results. False positives vs. speed reduction

Variation by the algorithm evaluation:
1) Feature set (feature variation)
2) Training data (reduced speed range pedestrian)
Simulation Results. Distribution speed reduction

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Speed reduction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reference Implementation</td>
<td>73.7%</td>
</tr>
<tr>
<td>Random Forest</td>
<td>83.4%</td>
</tr>
<tr>
<td>Neural Network</td>
<td>92.0%</td>
</tr>
</tbody>
</table>

*Operating point algorithms:* equal amount of false positives (10)
Summary. Active Safety uses Machine Learning

Limitations in our consideration:
- Theoretical analysis of the method, without the consideration of legal aspects. Proof-of-concept.
- Series application only based on real world data.

Results:
- Machine Learning offers the potential to improve Active Safety Systems. But the verification of the system raises new challenges.
- Required system behavior is reachable, technical design for defined effectiveness or FP/FN is possible.
- Neural Networks handle the missing excluded speed range of the pedestrian and a standard feature set without a performance drop compared to the Random Forest.

Challenges:
- Required real world data: amount, quality and more complex scenarios.
- Verification of the system behavior
Fully digital tool chain
Initiative: Open Connected Testbed
Real-Time Co-Simulation

System Simulation / RT capability
- Combine simulation models from very different tools
- Seamlessly from MiL from SiL to HiL

Key technology
Energy preserving algorithms for stability (patented)
VIR-REAL Environment

Real Environment

Real Sensor Actuator (Vehicle) → Sensor Aktuator Models → Virtual Dev. Env.

Computing Platforms (NVIDIA, Aurix) → ADAS Function (Control, Data Fusion) → MiL/SiL

HiL

Virtual Environment
AGENDA

ALP.Lab

Austrian Light Vehicle Proving Region for Automated Driving
ALP.Lab: testing possibilities

**Private**

- **Magna & AVL proving grounds**, Graz/ Styria
- **Research@ZaB**, Eisenerz/ Styria (tunnel)
- **Lungau proving grounds**, Salzburg (tunnel, toll station, snow)
- **The Red Bull Ring, Formula 1** Spielberg/ Styria

**Public**

- **Motorway A2**, Graz-Ost – Laßnitzhöhe Mooskirchen – Graz-Ost (planned)
- **Motorway A9, A2** St. Michael – Graz-Ost (tunnel, toll station)
- **Motorway S6, S36, A9** Leoben – SLO (border crossing)
- **City of Graz public roads**, Graz/ Styria

*…with more testing grounds that will follow*
Full digitally integrated test chain

1. **MiL / SiL (Simulation):** Testing of ADAS/ADV software functions
2. **HiL:** Driving simulator (test of human interactions)
   Sensor validation and qualification
3. **ViL (Driving Cube):** ADAS/ADV vehicle qualification prior road test
4. **Proving Ground:** Reproducible test of dangerous scenarios
5. **Public Road Testing:** Test in regional-specific real-world scenarios

The 5 testing stages are embedded in a system of comprehensive tools and models, for data management, processing and reporting.
ALP.Lab at a glance

C-ITS cloud (from OEM or from Test field operator)

Data acquisition

- 3D maps
- Ground truth static
- Vehicle data
- Ground truth dynamic

Test support Cloud

- Test evaluation
- Rate Safety and comfort

Tool chain

- Data exchange
- Scenario extraction

Tool chain

- Ground truth

Development data backbone

V2I data backbone

ALP.Lab Operating company

ALP.Lab at a glance

ALP.Lab Infrastructure at partner companies

Model-in-the-Loop
Software-in-the-Loop

Hardware-in-the-Loop

Driving Cube
Powertrain Test Bed

Proving Ground Test

Public Road Test (Test Field)
ALP.Lab – Examples of point cloud and image data

Graz West A9/ A2

Dense 3D LiDAR point cloud
Color represent Elevation
ALP.Lab – Examples of point cloud and image data

Graz Webling

Dense 3D LiDAR point cloud
Color from UltraCam Panoramic Image Data
ALP.Lab – Examples of point cloud and image data

A2 between Graz West and Graz Airport

Dense LiDAR Point Cloud and Image Data

Color Code of the Point Cloud: Elevation

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SUMMARY

Proof of Concept: Machine Learning can improve active safety systems

Flexible Research Platform for Autonomous Driving is available

Austrian Test & Proving Ground including a full digitally integrated test chain is build starting in June 2017

Combined virtual & real simulation environment prepares future virtual homologation of complex systems.
Thank you

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