In-Service Monitoring and Assessment of Autonomous Driving Vehicles with AI based Algorithms

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Academy:
M.Tech in Computer science from Indian Institute of technology, Kolkata, India (2005)
Research Assistant at Frankfurt institute of Advance Studies (FIAS), Germany. (2010-2012)
Research Associate at Goethe University, Frankfurt, Germany (2012-2016).

Industry:
2022-2023: AI Engineer (Computer vision and perception), Continental Automotive Technologies, Frankfurt. Germany.
2016-2022: SW Engineer at Continental Teves. Frankfurt, Germany.
2008-2010: Research Associate, Infosys Technology Ltd. Hyderabad, India.
2005-2008: Senior Engineer, Honeywell Technology solution, Bangalore, India.

Core subject area: AI, Machine learning, Computer vision.
Domain: Automotive, Surveillance, Inspection, Power train.
Conference attended- CVPR’18, ICCV’19, ECCV’20, NIPS’21.
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VVMethoden PEGASUS Family – Publicly-funded Projects in Germany

- The PEGASUS Family focuses on development / testing methods and tools for AD systems on highways and in urban environments.

**PEGASUS**

- Scope: Basic methodological framework
- Use-Case: L3/4 on highways
- Partners: 17

**VVM-Methods**

- Scope: Methods, toolchains, specifications for technical assurance
- Use-Case: L4/5 in urban environments
- Partners: 23 partners
- Timeline: 07/2019 – 06/2023

**SET Level 4to5**

- Scope: Simulation platform, toolchains, definitions for simulation-based testing
- Use-Case: L4/5 in urban environments
- Partners: 20 partners
- Timeline: 03/2019 – 08/2022

+ future projects of the PEGASUS Family
VVMethoden – Project Setup

- **Funded by**: Federal Ministry for Economic Affairs and Climate Actions (BMWK)
- **Start - End**: 07/2019 - 12/2023
- **Budget total**: 47M€
- **Objectives**: Development of methods and tools for the testing of highly automated and autonomous vehicles (SAE level 4/5) for homologation in urban environments
- **Partners**

<table>
<thead>
<tr>
<th>Tier</th>
<th>Companies</th>
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<tr>
<td>OEM</td>
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<tr>
<td>Tier-1</td>
<td><img src="image" alt="Bosch, Valeo, Continental, ZF Logos" /></td>
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<td>Tech</td>
<td><img src="image" alt="AVL, Prostep, dSPACE Logos" /></td>
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<td>Science</td>
<td><img src="image" alt="Fraunhofer, Technische Universität Darmstadt, OFFIS, DLR Logos" /></td>
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**Continental Contribution**: Development of a In-Service Monitoring & Assessment System & prototype implementation
In-Service Monitoring - Motivation

How can our AD System react to unexpected changes in such an complex and uncertain environment?

We should be able to monitor continuously rare new events and be able to adapt and improve.

To increase confidence in AD safety we need to drive many millions of kilometers. How can we achieve this challenge in cost efficient way?

We should have an big vehicle fleet monitoring the safety performance + select situations which are needed for the validation.

In-Service Monitoring and Assessment

In-Service Monitoring and Assessment

VALID 2023
# Content

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Objective: Monitoring, Data Collection & Assessment of an AD Vehicle during operation

- **Monitoring**
  - to ensure that all safety risk controls are effective throughout the product life cycle
  - and to identify and evaluate previously unknown unsafe events.

- **Data Collection**
  - for analysis purposes

- **Assessment**
  - to identify new safety risks
  - to modify ineffective safety risk controls
  - ..or to eliminate those that are no longer needed due to changes in the operational environment.
The Approach

Data Acquisition
- In-Service Monitoring
- Trigger Event
- Data Recording

Data Transfer
- Data Analysis Tools
- Visualization

Data Management
- Server / Data Lake
- User Interface

Data Analysis / Reporting
- Report
In-Service Monitoring and Assessment in the Context of DevOps

- Analyse System Operation
- Update Vehicle
- Optimize System
- Model Training
- Data Base
- Simulation
- Data Ingest
- Validation with Test Data
- Record and Upload Data
- In-Service Monitoring
- Vehicle Operation
- Engineering World
- Real World
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Related Work: Smart Monitoring

Smart data monitoring and Safety standards

Data Selection Methods

Uncertainty methods:
- Softmax Entropy
- MC dropout (Gal & Ghahramani 2016)
- MetaSeg (Rottmann et al. 2019)
- ...

Anomaly / novelty detection methods:
- cf. Pang et al. (2020)
- Beghi et al. (2014)
- ...

Temporal methods:
- Temporal aggregation (Huang et al. 2018)
- Temporal consistency (Varghese et al. 2020)
- ...

Ensemble methods:
- Deep ensembles (Lakshminarayanan et al. 2017)
- Ensemble deep learning (Cao et al. 2020)
Related Work: Smart Monitoring

Smart data monitoring and Safety standards
Related Work: Testing approaches

Major testing approaches motivates this work

› Virtual Assessment of Automation in Field Operation (VAAFO)[10]

› Shadow mode testing[7]

› Scenario based testing[6]
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# Smart Monitoring: Rule Based Approach

## Pedestrian detection within defined ROI

<table>
<thead>
<tr>
<th>Sensor</th>
<th>AI Modules</th>
<th>o/p to next stage</th>
</tr>
</thead>
<tbody>
<tr>
<td>I/p video stream</td>
<td>Pedestrian Det</td>
<td>Input to Trigger Generation</td>
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<tr>
<td></td>
<td>Bounding Boxes</td>
<td>Visualization</td>
</tr>
</tbody>
</table>

## Trigger with predicted trajectory

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<th>Sensor Set</th>
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<td>I/p video stream</td>
<td>Object Tracking</td>
<td>Visualization</td>
</tr>
<tr>
<td>CAN Data</td>
<td>Ego vehicle speed</td>
<td>Future path</td>
</tr>
</tbody>
</table>
# Smart Monitoring: Data Driven Approach

## Event Classification and Discovery [23, 19]

<table>
<thead>
<tr>
<th>Normal Driving</th>
<th>Sudden breaking event</th>
<th>Left turn Event: Camera view</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1" alt="Normal Driving" /></td>
<td><img src="image2" alt="Sudden breaking event" /></td>
<td><img src="image3" alt="Left turn Event" /></td>
</tr>
</tbody>
</table>

<table>
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<tr>
<th>Anomaly - Camera jittering</th>
<th>Anomaly – Camera falling</th>
<th>Low visibility</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image4" alt="Anomaly - Camera jittering" /></td>
<td><img src="image5" alt="Anomaly – Camera falling" /></td>
<td><img src="image6" alt="Low visibility" /></td>
</tr>
</tbody>
</table>
Data Preparation:
Event class definitions (Weakly supervised approach) [23]

**Stop:** Speed below 2 m/s and stay for more than 5 sec

**Sudden Break:** Speed drops suddenly
Event Detection

- I/P - 16 frames/sample
- The original BDD100k dataset is grouped based on usecase using the sensor data - **Weakly Supervised Approach**
- Available sensor data - GPS, accelerometer, gyroscope
- 3D ResNet-34 trained on BDD100k dataset for **Event Detection**
- 5 classes - Stop, Sudden Brake, Turn, Normal & Anomaly

**Fig 1:** Training pipeline for Event Detection

**Fig 2:** Inference pipeline for Event Detection [23]
Results on Event Detection:
BDD100k dataset

• Event Detection accuracy on the BDD100k val set 79.85%
• Weakly Supervised approach are less reliable
Results on Event Detection:
ADAS (Conti) data

- Event Detection accuracy on the ADAS val set **77.79%**
- The real-world samples where the instances can have multiple class labels
- Model recognized few anomaly events such as, vibrations due to the unevenness of the road, low visibility, and blockage in the camera view

![Confusion Matrix](image)

**Fig 7:** Confusion Matrix for Event Detection evaluated on ADAS data

![RGB frames](image)

**Fig 8:** RGB frame in four video samples predicted as Anomaly event class in ADAS data
Event Detection – Results comparison
Generalized Category Discovery (GCD) [19]

• Given a **labelled** and **unlabelled** set of images, the task is to **categorize all images in the unlabelled set**.
• The **unlabelled** images may come from **labelled classes** or **novel ones**.

![Fig 11: GCD setting. Black data points represent unlabelled instances. Coloured data points represent labelled instances.](image-url)
Event Discovery Pipeline

Class ID
(Labeled Data)
&
Clustering Parameter

Feature Vector

K-Means ++
Clustering Algorithm

Cluster Indices
Results on Data for Event Discovery (BDD100k dataset)

Fig 18: RGB frames from video samples predicted as group index 2 and group index 5
Results on Data for Event Discovery (BDD100k dataset)

Fig 19. Video Sample:
Group Index-2
Stop event

Fig 20. Video Sample:
Group Index-5
Stop at traffic signal

Fig 21. Video Sample:
Group Index-2
Finer Normal event
Conclusion and Future works

• The approach of In-Service Monitoring and Assessment is presented as a new method for safety validation of highly automated driving.

• State of the art works on verification and validation, different approaches for monitoring of HAD Systems during operation is covered and that motivates the presented exemplary trigger development.

• Results are shown with both rule based, and data driven approach of triggers for Smart Monitoring to filter out anomaly & unknown events for self adaptive systems like HAD.

Our future works includes:

• Exploration of appropriate set of triggers, define suitable metrics for their evaluation and context specific trigger subset selection for improving validation systems during operation.

• Use of safety critical data for continuous learning and model improvement is also a topic needs further study.
Thank you!

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References

References

[24] WWC22 - Finding the unknown unknowns: intelligent data collection for autonomous driving development - YouTube