“Simulation: A Must for Autonomous Driving”

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Deep Learning for Autonomous Driving

Requirements (1/4)

• Huge amount of sensor data is necessary to train Neural Networks
  • Resources may be unavailable (e.g. test vehicle, specific sensor set, test drivers...)
  • Current processes are inefficient:
    • Data has to be collected, stored, classified & transferred for labeling
    • Multiple teams/stakeholders are involved
    • Long & expensive cycle time to generate a new data set
    • Only a small percentage of the generated data is relevant for Neural Networks (~80h driving to produce 3min of relevant data)

• Define reusable virtual scenarios & new multi-sensor configurations
• Generate new sensor data sets continuously
• Automate/optimize processes & focus on relevant data
Deep Learning for Autonomous Driving

Requirements (2/4)

• Diversity of the data is the key for a proper training
  • Difficulty to replicate driving scenarios in the real world (e.g. weather conditions, variations in trajectories/positioning of target vehicles...)
  • Specific long & costly test expeditions have to been prepared (e.g. winter/summer testing, day/night driving, multiple test vehicles, highway/country road/city driving)

• Create thousands of virtual scenarios through scripting
  • Integrate new environment & road user models on demand
Deep Learning for Autonomous Driving

Requirements (3/4)

To train the neural network:
• The data needs to be annotated
  • e.g. object classification, bounding box, image segmentation...
  • Expensive & Time consuming to do it manually
  • Ground truth information is missing

Generate labelled sensor data using ground truth information automatically
Deep Learning for Autonomous Driving

Requirements (4/4)

- Different data sets are needed for Training & Validation. Neural Networks should continuously integrate new driving situations.
  - Existing databases may not provide enough quantity and diversity for both
  - Flexibility is reduced to create new data sets
  - Different sources are necessary to validate robustness of Neural Networks
  - Introducing “unpredicted” objects / environments is the key to further train Neural Networks

- Extend Simulation database through scripting and automation
- Combine Real and Simulated data for more robust Training/Validation
- Extend Simulation database with new objects and 3D environments
Safety Ratings

5-Star Safety Ratings
More Stars. Safer Cars.

ADULT OCCUPANT PROTECTION
Considers the level of protection offered by the vehicle to adult occupants seated in the front and second row in the most common types of serious injury crashes.

TESTS, ASSESSMENTS AND MAX. SCORES
- Full Width: 8
- Frontal Offset: 8
- Side Impact: 8
- Pole (Oblique): 8
- Whiplash Protection (Front): 1.5
- Whiplash Protection (Rear): 0.5

Max. score: 38

CHILD OCCUPANT PROTECTION
Evaluates the level of protection offered to child occupants seated in appropriate child restraints in the rear seats. The ability to effectively accommodate a range of child restraints is also assessed.

TESTS, ASSESSMENTS AND MAX. SCORES
- Dynamic (Front): 16
- Dynamic (Slide): 8
- Child Restraint Installation: 12
- On-Board Features: 13

Max. score: 48

PEDESTRIAN PROTECTION
Assesses the design of the front of the vehicle to minimise injury risk to a struck pedestrian. Vehicles are also assessed for their ability to actively avoid or mitigate impacts with pedestrians and cyclists.

TESTS, ASSESSMENTS AND MAX. SCORES
- Head Impact: 24
- Upper Leg Impact: 6
- Lower Leg Impact: 6
- AEB VRU (Pedestrian): 6
- AEB VRU (Cyclist): 6

Max. score: 48

SAFETY ASSIST
Evaluates the presence and effectiveness of active safety technologies fitted to the vehicle which assist the driver in preventing or minimising the effects of a crash.

TESTS, ASSESSMENTS AND MAX. SCORES
- Speed Assistance System: 3
- Seat Belt Reminders: 3
- Lane Support System: 8
- AEB Interurban (2018/19): 3
- AEB Interurban (2020): 4
- Interurban Assist (from 2020): 4

Max. score (2018/19): 15
Max. score (from 2020): 16

Euro NCAP / ANCAP Rating
2018 - 2020
Generating Synthetic Data for Neural Networks

ESI Pro-SiVIC™: Overview
Introduction to Pro-SiVIC™

A platform solution for modeling and simulating multi-frequency environments & multi-technology sensors

- ACC
- AEB
- LDW
- BSD
- FCW/RCW
- IPA
- CTA
- LCA
ESI Pro-SiVIC™: Overview

- **Realistic Environment Models DB**
  - Road environment simulation
    - Highway, country road, urban area
    - Customized marking
    - Different road signs
  - Road users simulation
    - Cars, trucks
    - Pedestrians, bicyclists

- **Traffic Dynamics Generation**
- **Parameters Management**
ESI Pro-SiVIC™: Overview

• Physical Sensors Models / Customization
  • Cameras
    • Physical behavior
  • Radar
    • Radar & Targets characteristics
    • Lidar, Ultrasonic, GPS...

• Ground Truth Data

• Scenario Scripting

• Testing Automation
Training and Validation of Neural Networks using Camera Sensor Data
New process including introduction of Simulation
Training and Validation of Neural Networks using camera sensor data

Current Process

- Camera videos are recorded from real test campaigns
- Videos are sequenced and annotated to create useable database with scenario characteristics
- Raw & annotated images are used to train Deep Learning algorithms (e.g. lane detection)
- The rest of the raw images is sent as input to previously trained algorithms
- Output of trained algorithms is finally compared to annotated images for validation

HD videos (>FullHD)
TB of stored data
Manual intervention required for processing

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Training and Validation of Neural Networks using camera sensor data

Step 1: Introduction of Simulation to Replace Real Driving

1. Camera videos are recorded from real test campaigns
2. Videos are sequenced and annotated to create useable database with scenario characteristics
3. Raw & annotated images are used to train Deep Learning algorithms (e.g. lane detection)
4. The rest of the raw images is sent as input to previously trained algorithms
5. Output of trained algorithms is finally compared to annotated images for validation

3D Models of scenes of high quality replace real driving environments

Create Virtual scenarios with custom characteristics, and capture high quality simulated videos

ESI Pro-SiVIC™ Libraries

In ESI Pro-SiVIC™
Training and Validation of Neural Networks using camera sensor data

Step 2: Introduction of Simulation to Replace Physical Camera

- **Camera videos are recorded from real test campaigns**

- **Videos are sequenced and annotated to create useable database with scenario characteristics**

- **Raw & annotated images are used to train Deep Learning algorithms (e.g. lane detection)**

- **The rest of the raw images is sent as input to previously trained algorithms**

- **Output of trained algorithms is finally compared to annotated images for validation**

- **3D Models of scenes of high quality replace real driving environments**
  - In ESI Pro-SiVIC™ Libraries

- **Create Virtual scenarios with custom characteristics, and capture high quality simulated videos**
  - In ESI Pro-SiVIC™

- **Simulated camera model is used rather than physical camera to create raw & segmented images**
  - In ESI Pro-SiVIC™

- **DL algorithms are trained on a dedicated platform using one subset of the simulated images (could be completed by real data)**
  - On Linux machine

- **Trained DL algorithms run on NVIDIA PX2 and receive the other subset of the simulated data through co-simulation interface for validation purposes (could be completed by real data)**
  - On NVIDIA PX2
Training & Validating Neural Network Using Synthetic Camera Images
Concept & Application example
Part 1: Training Neural Network Using Synthetic Camera Images

Process

- Synthetic Images Generation
  - Automatically Labeled
- One Color/Category
  - Cars, Motorcycles, Roads, Lane Markings
- ~ 5000 images to validate concept
  - Highway & City Environments
  - Cars & Motorcycles
  - Color Variations
  - Images captured at different positions in the scene using multiple sensors
- Fit Images in Random to avoid overfitting
Part1: Training Neural Network Using Synthetic Camera Images

Results

• Tested on Synthetic and Real World Data
  • Road & Car detected on both
  • Concept Validated
  • Object Detection could be refined

• Next steps:
  • More Image Quantity
  • More Image Diversity
  • Various Image Sources
  • New Objects
  • Tradeoff Resolution vs Speed
  • ...

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Part 2: Validating Neural Network Using Synthetic Camera Images

Process: Using Synthetic Data to Validate Algorithm
Part 2: Validating Neural Network Using Synthetic Camera Images

Results
Conclusion

The Simulation is opening new perspectives to enhance AI for Autonomous Driving:

• Optimize Current Algorithm Training and Validation Processes
  → faster & cheaper, earlier validation, better accessibility

• Introduce more flexibility in generating training and validation data
  → higher fidelity of Neural Networks

• Generate Multi-Sensor data automatically with Ground Truth Information
  → higher data quality, reduced lead time

• Use Automation to extend databases
  → higher test/scenario coverage, increased data sources, improved parallel processing
Thank you!

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