Shape the FUTURE of DRIVING

Jonas Ekmark
Product Area Owner, New Technology
Presentation outline

• What is Zenuity?
• What is most difficult in designing self-driving vehicles?
• How to prove a self-driving vehicle is sufficiently safe?
• Alternative approaches
• Conclusion
19th April 2017

Volvo Cars, the premium car maker, and Autoliv, the worldwide leader in automotive safety systems, have signed a final agreement to establish a new joint venture called Zenuity to develop software for autonomous driving and driver assistance systems.
Zenuity’s technology scope

Cloud
Real-time HD Maps | Connected Safety Functions

Sensor
Sensing | Sensor Fusion | Decision & Control | Vehicle Control

Actuator
Base Tech Software | HW Design | System Design | Technical Safety Concepts

System
Zenuity today
Started April 18th 2017 with 200 employees

Zenuity employees
580
Zenuity’s way to market

Developing automotive driver assistance & autonomous driving software, direction hardware-agnostic

Two customers, no exclusivity

Autoliv markets & sells licenses & adapt to customers
Our Product Roadmap
Combining driver support (ADAS) and autonomous driving

**ROBOTAXI CAPABILITY**
- Driverless
- High availability
- Increased coverage over time (OTA)
- High-performance sensing and compute

**HIGHWAY PILOT & AUTO VALET PARKING**
- On highway (<130 km/h)
- Driverless in park areas
- Increased functionality over time (OTA)
- Additional driver support & NCAP functionality

**CITY PILOT & AUTO VALET PARKING**
- Larger urban roads
- Intersection & Traffic light
- Increased functionality over time (OTA)
- Driverless auto park on public roads

**NEXT GEN DRIVER SUPPORT**
- NCAP 2018 - 2020
- Driver Support
- Connected Cloud
- Connected Road View

**TRAFFIC JAM PILOT**
- Unsupervised
- Boxed-in (<60 km/h)
- Driver monitoring camera
- Redundant architecture

2019  2020  2021  2023  202x
From Driver Support to Autonomous Driving

Fundamental change for safety concepts

Supervised (most ADAS)

Unsupervised (AD)
The Challenge

Driver out of the loop

Self-driving vehicles must be able to handle *all* foreseeable situations of the Operational Design Domain

(and prove that it can!)

This puts unique requirements on the vehicle, its sensor, actuators and electrical architecture.
Unsupervised driving

Safety Case:
“Structured argument, supported by evidence, intended to justify that the AD functionality is acceptably safe for all relevant traffic situations and all relevant environmental conditions.”

Overall safety requirement: Fewer caused accidents (by some margin) than human driver

<table>
<thead>
<tr>
<th>Topic</th>
<th>1/frequency</th>
<th>hours</th>
<th>Market</th>
</tr>
</thead>
<tbody>
<tr>
<td>Road fatalities</td>
<td>150 million km</td>
<td>4 x 10E6 h</td>
<td>U.S.</td>
</tr>
<tr>
<td>Rail fatalities</td>
<td>2.5 billion passenger km</td>
<td>4 x 10E7 h</td>
<td>U.K.</td>
</tr>
<tr>
<td>Air fatalities</td>
<td>50 billion passenger km</td>
<td>1 x 10E8 h</td>
<td>U.K.</td>
</tr>
<tr>
<td>False AEB</td>
<td>0.5 million km</td>
<td>1 x 10E4 h</td>
<td>Global</td>
</tr>
<tr>
<td>Safety Driver interventions</td>
<td>20 thousand km</td>
<td>7 x 10E2 h</td>
<td>CA</td>
</tr>
<tr>
<td>(High Score 2018)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
How to design and prove self-driving to be sufficiently safe?

- **Define** the target. The product should be sufficiently safe when used by real customers in the real world.

- **Divide and conquer**, establish testable requirements for components
  - Use sufficient detail; False Negative performance depends on range, illumination, precipitation etc.
  - Reduce Operational Design Domain if needed
  - **Analyzable** vs non-analyzable components

- Use a combination of field testing, simulation, and selected scenarios at test track for verification

- Show that there is enough redundancy and independence to reach the overall requirement (worst case scenarios occur less than $10^{-8}$/h?)

- Done!
Deep Neural Networks

A DNN consists of many simple functions (neurons) that are arranged in a layered network architecture.

Deep Neural Network

Each neuron has "trainable" parameters. Each connection has a "trainable" weight.
Deep Learning
On the other hand...

- Lidar detections are based on well-known physics and relatively simple algorithms.
- Performance can be predicted also outside of the tested envelope (to some extent).
- When exposed to real life objects different to those used in verification tests, it is likely to detect them as well.
- Similar reasoning can apply to radar and ultrasonic.
Perception, decomposition example

Focusing on **False Negative** performance
Z2  Sensor set-up
Verification & Validation strategy

Safety verification of *All major subsystems for All relevant scenarios*

- Perception
- Decision-Making
- Planned Path
- Vehicle Control

Traffic/Test track with Ground Truth

Resimulation
Augmented/Virtual Data

Formal methods
Closed-loop simulation

Scenario DB
Building complete customer features

Highway Pilot

- Perception
- Decision-Making
- Vehicle Control
Conclusions

- Zenuity develops SW for ADAS and unsupervised AD, approaching AD with its safety heritage from Volvo Cars and Autoliv
- Unsupervised Automated Driving is a huge challenge. Super-human performance needed.
- Safety verification by brute-force driving is not feasible
- Deep learning can be utilized safely by
  - parallel, independent channels with reduced functional safety requirements
  - verification by dedicated testing and various forms of simulation of modules
Zenuity

Make it real.
We are hiring!

Please visit: www.zenuity.com/career/