Monitoring Safety of Autonomous Vehicles with Crash Prediction Network

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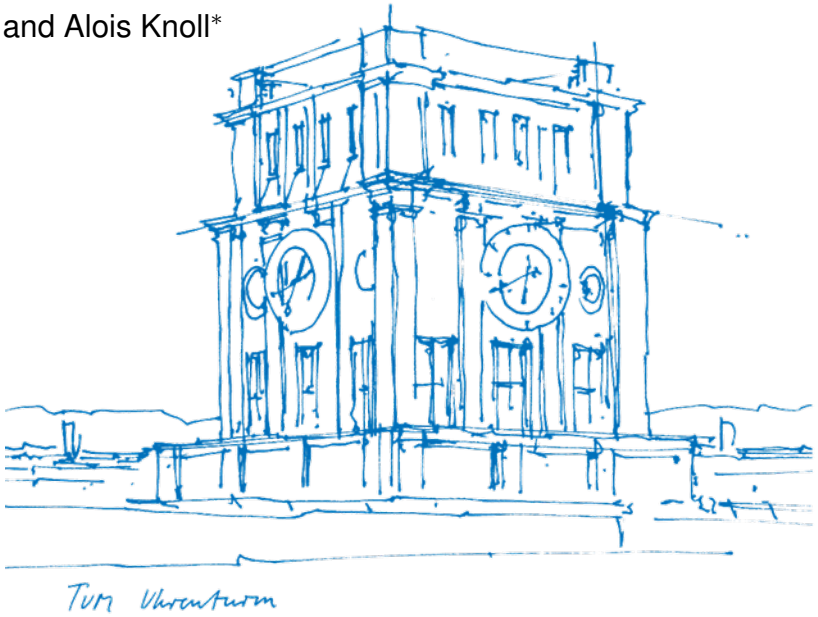
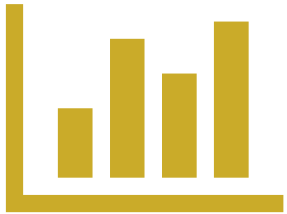


Outline

Introduction

Current strategies

Proposed Approach

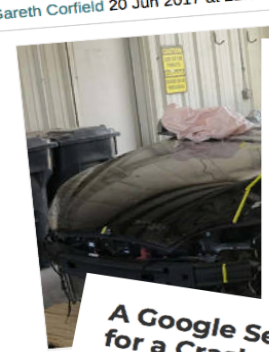


Conclusion

Tesla death smash probe: Neither driver nor autopilot saw the truck

Report shows driver took a hands-off approach to driving

By Gareth Corfield 20 Jun 2017 at 21:58 143 SHARE



Self-driving Uber kills Arizon… first fatal crash involving pedestrian

Tempe police said car was in autonomous mode at the time of the crash and that the vehicle hit a woman who later died at a hospital

REUTERS

TECH

Google Says It Bears "Some Responsibility" after Self-Driving Car Hit Bus

No one was injured in the accident, but it prompted the company to make changes to its software

A Google Self-Driving Car Is at Fault for a Crash

Google's self-driving car has been in an accident. The news is it's the first time one of its autonomous vehicles has been at fault.

Jun 7 6:58p

Tesla Model X sped up in Autopilot mode seconds before fatal crash, according to NTSB

Megan Rose Dickey @meganrosedickey

The National Transportation Safety Board has released a preliminary report detailing the fatal crash involving a Tesla Model X in March. The crash also resulted in a fire and shut down two lanes of Highway 101 near Mountain View, Calif. At this point, the NTSB has yet to determine a probable cause of the crash and is continuing to investigate the accident.

The report says the Model X, while in Autopilot mode, sped up to 71 mph in the seconds leading up to the crash.

"At 3 seconds prior to the crash and up to the time of impact with the crash

ML has problems...

- Large amount of training data required
- Incompleteness of training data
- Differences in training and operational data/platform
- Noise in training data
- Uncertainty about what has been learnt
- Wear-and-tear of hardware/software

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Traditional software testing approaches are not applicable

What has been done till now?

- Rule extraction from Neural Networks, e.g. DeepRed [ZMJ16]
- Visualization of Neural Networks' results
- Train-Test-Validation split of data
- Automated Testing and Test Case Generation, e.g. DeepTest [TPJR18], Sim-ATAV [TFIK18]

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But the focus on testing the trained system before deploying!

How about MONITORING the operational-time performance of the system?

Crash Predication Network

Proposed Approach

Input Features:

- Output of Perception module
- Planned trajectory of the ego vehicle
- Predicted/Intended (via V2V) trajectory of obstacles
- Number/Severity of previous crashes of the ego

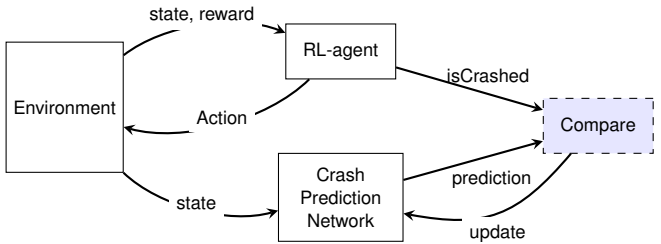

Figure: Block diagram for training for Crash Prediction Network

Crash Predication Network

Proposed Approach

Pros:

- “Informed” decisions - multiple data sources
- Allows smoother transition from human drivers to fully autonomous driving
- Generalizable and scalable

Cons:

- Requires handling data from multiple modalities
- Considerations for sensor failures

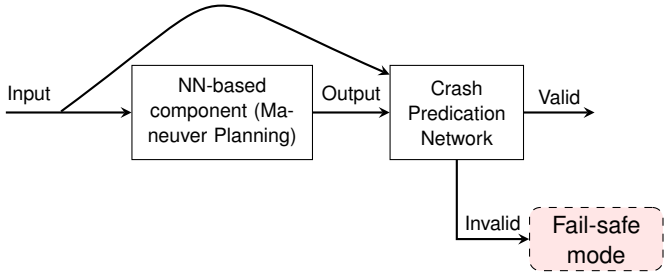

Figure: Block diagram for operation of Crash Prediction Network

Crash Predication Network

Proposed Approach

Research Questions:

- Does Bayesian Deep Learning provide a ‘better’ performance?
- Which different sources of information to use as input to the Crash Prediction Network?
- How to be robust against sensor/component failures or missing data?
- How well can an ML-based solution ‘supervise’ another ML-based solution?

Conclusion

Summary

- Safety is one of the barriers for Autonomous Vehicles
- Traditional Safety Techniques not sufficient
- Monitoring approaches - like Crash Prediction Network - could help

Thank You.

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