Analysing Adversarial Threats to Rule-Based Local-Planning Algorithms for Autonomous Driving

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Main idea of our study

- Local-planning is an essential function for navigation and achievement of journey/mission – security of algorithms is a developing space.
- A lack of robustness to adversarial threats in one or many of the local-planning modules can lead to unsafe Autonomous Driving (AD) behaviour.
- What if an attacker directly targeted the algorithm responsible for generating safe trajectories?
- Can the attack be conducted in a stealthy manner?



Figure 1: Local-Planning Algorithm



Figure 2: iseAuto Autonomous Vehicle Shuttle





Trajectory Generation and Evaluation





Figure 3: Local-Planning Trajectory Generation

Figure 4: Cost-Function Algorithm for Local-Planning





Threat Model

Attack Case 1: Position Offset

- Manipulation of Current_Pose Data: Longitudinal and Latitudinal position.
- Deviations range from minimal to 1meter.
- Attack Case 2: Message Time-Delay
 - Delay in the communication of sensed pose data to the cost-function algorithm.







Experimental Setup

- Attack Case 1: Position Offset
 - Test Case 1a 1c Lateral Pose Deviation. (0.16%, 0.33%, 0.5%)
 - Test Cas 1d 1f Longitudinal Pose Deviation. (0.33%, 0.66%, 1.0%)
- Attack Case 2: Message Time-Delay
 - Test Case 2a 2c Time-Delay.
 (0.3sec, 0.6sec. 1.0sec)



Figure 6: Low-Fidelity Simulation of AV Overtaking Manoeuvre





Results



- Small deviations of the Pose data can substantially impact safe AD driving behaviour.
- The higher deviation results in the AV being stuck in the passing lane, this is due the dramatic change in lateral pose.
- Greater Time-Delay of Pose Data impacts Trajectory Generation.



Figure 7: Experiment Test Results



Results



- Small deviations to lateral pose result in a fluctuation of the cost of different rollouts which cause greater lane transitions as the cost function causes the AV to choose a route based on minimum cost.
- The higher deviation results in a higher occurrence of breaking activity and hitting the curb.
- The time-delay of the pose data to the local-planning nodes results in a loss of localisation and the greater delay the greater impact on the cost calculation which in turn causes uncertainty for the behaviour selector/decision-making.



Figure 8: Experiment Test Results Trajectory Behaviour



Discussion

- Minor pose deviation attacks, where the deviation is a range of 20 to 25cm offer a good starting point to mutate adversarial data for further attacks based on this range.
- Delays in sensed-data input flowing to the local-planning modules of greater than 1 second increase the rate of mission failure and safety violations. Given that 1 message is broadcast every 20 milliseconds, 1 second represents around 50 messages, and a delay of this magnitude is also likely to be more observable.





Conclusion

- Local-planning cost-function is sensitive to adversarial data manipulation that introduces deviations to the lateral and longitudinal values.
- Small deviations of the pose data input, which are below the threshold of normal noise, affect AD safe driving behaviour.
- Trajectory Generation was robust against limited delays in message communication.
- It is possible to mutate malicious input to develop greater stealth attacks.
- Future work should focus on monitoring solutions to such attacks.







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