Poster: SlowTrack: Increasing the Latency of Camera-Based Perception in Autonomous Driving Using Adversarial Examples

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Abstract

In Autonomous Driving (AD), real-time perception is a critical component responsible for detecting surrounding objects to ensure safe driving. While researchers have extensively explored the integrity of AD perception due to its safety and security implications, the aspect of availability (real-time performance) or latency has received limited attention. Existing works on latency-based attack have focused mainly on object detection, i.e., a component in camera-based AD perception, overlooking the entire camera-based AD perception, which hinders them to achieve effective system-level effects, such as vehicle crashes. In this paper, we propose SlowTrack, a novel framework for generating adversarial attacks to increase the execution time of camera-based AD perception. We propose a novel two-stage attack strategy along with the three new loss function designs. Our evaluation is conducted on four popular camera-based AD perception pipelines, and the results demonstrate that SlowTrack significantly outperforms existing latency-based attacks while maintaining comparable imperceptibility levels. Furthermore, we perform the evaluation on Baidu Apollo, an industry-grade full-stack AD system, and LGSVL, a production-grade AD simulator, with two scenarios to compare the system-level effects of SlowTrack and existing attacks. Our evaluation results show that the system-level effects can be significantly improved, i.e., the vehicle crash rate of SlowTrack is around 95\% on average while existing works only have around 30\%.

I. MAIN CONTENT

This research\textsuperscript{[1]} is recently published in AAAI 2024. The original abstract and author list are shown above. We post the paper links with arXiv version\textsuperscript{[1]}.

II. ACKNOWLEDGMENTS

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REFERENCES


\[\text{https://arxiv.org/abs/2312.09520}\]
### Autonomous Driving (AD) Perception

- **AD visual perception consists of object detection and object tracking.**

  - **Detection Results:**
    - Images captured in sequence
    - bbox, score, class
  - **Existing trackers:**
    - Track ID
  - **Tracking Results:**
    - Images captured in sequence
    - bbox, velocity, track ID

- **Anchor-based Object Detection**

- **Multi-Object Tracking**

- **Data Association**

- **State Prediction**

- **Fusion Planning Control**

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### Problem Formulation & Tracking Analysis

- **Under the constraint of limiting the maximum number of detection boxes, we formulate the SlowTrack Design:**

  \[
  \text{arg max}_{P(z|x)} \quad \text{s.t.} \quad \begin{cases} \text{Detect new objects} & \text{if } \mathcal{D}_{\text{max}} < \mathcal{D} \\ \text{Track existing objects} & \text{if } \mathcal{D} \leq \mathcal{D}_{\text{max}} \end{cases}
  \]

- **Tracking analysis:**

  - **Detection Results:**
    - Detection Filter
    - O(m) + O(\mathcal{D}_{\text{max}})
  - **Existing Trackers:**
    - State Prediction
    - O(m)
  - **New trackers are initiated:**
    - O(m + \mathcal{D}_{\text{max}})
  - **Last tracker is deleted:**
    - O(\mathcal{D}_{\text{max}})

- **Challenge 1:** The maximum number of detection is limited

- **Challenge 2:** Only consecutively appearing objects will be initialized, but hot trackers will be deleted.

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### Attack Effectiveness Evaluation

- **Evaluation dataset:**
  - MOT17DET and BDD
  - Model: SORT (Y5), FairMOT, ByteTrack, and BoT-SORT
  - Baseline: PS [2] and Overload [1]

- **Evaluation metric:**
  - R-Track, R-Lat, and #Track

- **Effectiveness results SlowTrack with two baselines [1] [2] and average L2 norm in different models and hardware. Bold denotes the best results (i.e., highest R-Track, R-Lat, and lowest #Track) in each row.

- **Baidu Apollo and LGSVL simulator**

- **Two scenarios S1 and S2**

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### System-level evaluation (vehicle crash rate)

- **SlowTrack can achieve 95% vehicle crash rate** on average while for other attacks, they can only have around 30%.