ADEPT: A Testing Platform for Simulated Autonomous Driving

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ABSTRACT
Effective quality assurance methods for autonomous driving systems ADS have attracted growing interests recently. In this paper, we report a new testing platform ADEPT, aiming to provide practically realistic and comprehensive testing facilities for DNN-based ADS. ADEPT is based on the virtual simulator CARLA and provides numerous testing facilities such as scene construction, ADS importation, test execution and recording, etc. In particular, ADEPT features two distinguished test scenario generation strategies designed for autonomous driving. First, we make use of real-life accident reports from which we leverage natural language processing to fabricate abundant driving scenarios. Second, we synthesize physically-robust adversarial attacks by taking the feedback of ADS into consideration and thus are able to generate closed-loop test scenarios. The experiments confirm the efficacy of the platform.

KEYWORDS
Software testing, Deep Neural networks, Autonomous driving, Test case generation, Testing platform

ACM Reference Format:

1 INTRODUCTION
There has been an increasing concern about the reliability and safety of autonomous driving systems (ADS), especially with the use of deep neural networks (DNN) as their core components. Testing, as one of the most effective quality assurance methods of ADS, is expected to play an indispensable role in ADS development. Testing with physical autonomous vehicles is natural, but clearly is neither cost-effective nor safe. In particular, it is usually challenging to reproduce various types of accidents (e.g., those involving switching between severe weather conditions) and its cost can be financially unaffordable. A realistic alternative and arguably more effective strategy is to test ADS under a simulated environment, where both driving scenes and physical logic (i.e., car dynamics, traffic regulations, and weather conditions) are built in a virtual world.

In this paper, we present a platform ADEPT (Autonomous Driving Test Platform) to provide comprehensive testing for ADS which are akin to real-world scenarios. Several virtual simulators including CARLA [9] and AirSim [25] are available. We base our tool on CARLA in light of its abundant APIs and community support. ADEPT supports various functionalities, including scene construction, ADS importation, test execution and recording, etc. Of paramount importance for testing frameworks is test case generation, which, in our setting, exhibits in the form of building up a specific scene for ADS to react. The inherent complexity of ADS gives rise to a tremendous search space of scenes for which exhaustive search is clearly prohibitive. Moreover, ad-hoc testing case generation methods are prone to yielding impractical and less meaningful scenarios from the physical-world perspective. For example, the scenario that an obstacle suddenly appears in the middle of the road would be meaningless as it rarely happens.

In ADEPT, we introduce two strategies to enable effective generation of more realistic test cases. First, we observe a connection between harmful circumstances and security breaches which we use to direct the search toward a more security-sensitive area. To this end, we extract potential ADS infractions from real-life accident reports by leveraging natural language processing (NLP) techniques, which are then used to fabricate testing scenarios. Second, we adapt adversarial examples of DNNs to generate testing scenario. In view of the central role of DNNs in ADS (e.g., in the decision-making module) and their fragility to imperceptible malicious perturbations known as adversarial examples, it is not difficult to generate test scenarios based on these examples. However, the effectiveness of adversarial examples are usually dependent on physical conditions (e.g., illumination, blur, and angle of view), making the test scenarios unrealistic. Moreover, an individual attack that tricks ADS into making mistakes is usually insufficient as ADS can recover from these one-time, sporadic mistakes. In ADEPT, we instead generate a sequence of robust adversarial examples that takes the feedback of ADS into account and thus form a closed-loop test scenario.

The code is available at https://github.com/shengzh-oOoO/ADEPT and a video demo can be found at https://youtu.be/evMorf0uR_s.

2 THE TOOL ADEPT
Figure 1 depicts the three-layer architecture of ADEPT, i.e., Simulator Kernel, ADS Testing Libraries, and Scenario Engine.

The Simulator Kernel layer includes several key components directly built upon Unreal Engine and Carla to provide specific operations for ADS testing, e.g., interactive camera. Note that all
modules in red boxes are developed by us, while those in blue boxes are essentially from either CARLA or Unreal Engine.

The ADS Testing Libraries layer includes three key modules.

- the communication module, which is responsible for the interactions between subjects (e.g., driving model or attack algorithm) and objects in simulators (e.g., cars, humans, and electronic billboards). This module is designed to encapsulate the basic CARLA APIs for developing and recording specialized ADS testing scenarios, as data access and transmission between the subjects and the simulator are inefficient via CARLA’s native APIs.

- the model management module, which is responsible for the management of ADS and cars, e.g., connection of ADS to ADEPT and to place the required sensors on the victim car.

- the control management module, which deploys the generated scenario online, e.g., it utilizes virtual camera redirected to platform objects to adjust textures in real-time.

The Scenario Engine layer implements various methods for effectively generating real-world scenarios that may trigger ADS violations. Currently, there are two such methods, as detailed below.

**Generation of Test Scenarios from Accident Reports.** This engine takes a traffic accident report and translates the accident description (in natural language) to an intermediate representation (in a scenario-description language) for which we use Scenic [11]. The Scenic-supplied tools can load the scene and connect to the ADS for testing at the same time.

We leverage natural language processing aiming for automated translation of the accident report. Technically, we utilise a question-and-answer technique based on the question-answering system GPT-3 [5]. We define a set of questions as well as Scenic code templates. The report text and predefined questions are sent to GPT-3. Upon the response, we choose the template that corresponds to the accident report’s description from the predefined templates and fill in the template’s important missing information. Specifically, we inquire about the location of the collision (including whether it occurred at a three-way, four-way, or non-intersection), the time, the weather, and the relative position relationship between the two cars involved (including the left-right relationship of the lane, the front-to-back relationship of the distance, etc.).

**Closed-loop Testing Based on Adversarial Attack.** It is well-known adversarial examples (AEs) reveal the weakness of DNNs which are widely adopted in contemporary ADS, so one can easily utilize them to test ADS. In real-world conditions, however, several physical conditions (such as illumination, blur, angle of vision, etc.) may severely diminish the effectiveness of AEs, especially when the car is in motion. Moreover, sophisticated ADS is able to recover from the past deception, further undermining the effectiveness of a single attack. We propose two strategies to address these issues.

1. We generate AEs more robust in the physical sense. We find, based on the observation of pixel shifts, that the color between the real pixel and the illustrated pixel of an RGB-camera-captured image can be captured by a nonlinear transformation. On the basis of pixel data collected from the testing platform, we employ a lightweight neural network to fit such a nonlinear transformation. Since the car’s perspective does not change significantly during the victim vehicle’s decision-making interval, factors caused by the moving state on our testing platform consist primarily of blur and minor changes in angle of view. Here, we resort to Expectation Over Transformation (EOT) [3], which abstracts various transformations into distributions and embeds the transformations as the parallel preprocess of the input, then regards the expectation over all transformations as the ultimate optimized object, with each step of iteration accepting the input updated in the previous step.

2. We design a sequence of AEs to achieve continuous deception for the vehicle by incorporating the feedback into successive attacks. Figure 2 depicts the “practical AA-based testing” engine of Figure 1 where the feedback refers to the positional and postural changes of the victim vehicle as observed by the Malicious Attacker Module (MAM). MAM leverages the feedback to anchor itself from the view of the victim vehicle in order to conduct tailored attacks. With adversarial attack algorithms, MAM determines what to show in the next frame attempting to fool the victim vehicle.

To this end, MAM considers the dynamic model of the vehicle, i.e., the actual steering radian and traveling distance at one frame. We implement the Pure Pursuit (PP) [8] algorithm to force the victim vehicle to pursue the goal moving point, thereby following the prescribed trajectory. The target curve comprises multiple points, and the PP algorithm calculates the curvature that will move a vehicle from its current position to the goal position specified by the closest point and the lookahead distance. Eventually, the estimated curvature will serve as the attack target.

### 3 Evaluation

In this section, we evaluate ADEPT with the two scenario engines.

**Generation of Test Scenarios based on Accident Reports.** To select the adequate subject for evaluation, we choose the end-to-end ADS, which is the winner of the Camera-Only track of the CARLA
This crash occurred on a straight ... street ... Vehicle 1, a 1989 Jeep Wagoneer... V2, an 2003 Chevrolet Tahoe ... parked at the leftroad edge ...

4 RELATED WORK

Abrecht et al. [1] classify all ADSs testing into four levels, i.e., directly test individual deep learning models (L1); hardware sensors to the scope of co-testing (L2); continue to consider external environmental factors on the basis of L2 (L3); and test ADS in the closed-loop environment (L4). Our testing platform achieves L4 testing capabilities.

AC3R [12] is the first approach for testing ADS via automatically reconstructed car crashes from accident reports. AC3R builds the scene from an empty world and ignores the construction of background entities, such as buildings, greenbelt, etc. It may not be realistic for testing. Moreover, it cannot process long reports.

Besides generating test scenarios from accident report text, Nguyen et al.[20] generated test scenarios from accident sketches, and Xinxin et al.[28] generated test scenarios from accident videos. In addition to generating 3D test scenarios, Holland et al.[15] and Goss et al.[14] also generated 2D plane scenarios from accident reports or data for testing the decision-and-control module of ADS.

Due to the complexity and unpredictability of autonomous driving, defining and finding critical scenarios becomes the key challenge [29]. Gladisch et al. [13] formulate the problem as a Search-based Testing problem. To optimize the search process, Klischat et al. [16] use evolutionary algorithms; Althoff et al. [2] reduce search space by analyzing the reachability of scenarios; SAMOTA [27] combines surrogate-assisted optimization and many-objective search to generate test scenarios effectively and efficiently; SALVO [21] reduces search space by generating test scenarios from existing maps. In SBST Tool Competition 2021 [23], competitors competed on how to search for road layouts that could lead to a vehicle accident. Gambi et al. [12] try to generate scenarios based on accident databases. Scenic [11] and Paracosm [19] provide languages and tools to define and build critical scenarios manually.

Adversarial examples of DNNs have been extensively studied in literature. Typical generation algorithms include CW [6], PGD [18], etc. Simple application of AEs for testing can be classified as L1...

5 CONCLUSION

We present a new testing platform ADEPT for ADS, which conducts testing based on a virtual environment and provides numerous facilities. Distinguished features of ADEPT include deriving realistic scenarios from accident reports and crafting physically-meaningful closed-loop testing scenarios via adversarial examples of DNNs.

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REFERENCES


Table 1: Results of ADS in test scenarios generated based on accident reports.

<table>
<thead>
<tr>
<th>Type of accident location</th>
<th>Reports</th>
<th>Scenic codes</th>
<th>Scenarios</th>
<th>Safety</th>
<th>Risk</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Light Risk</td>
<td>Serious Risk</td>
</tr>
<tr>
<td>Non-Crossroads</td>
<td>11</td>
<td>46</td>
<td>230</td>
<td>153/66.52%</td>
<td>48/20.87%</td>
</tr>
<tr>
<td>V1&amp;V2 in same direction</td>
<td>8</td>
<td>40</td>
<td>200</td>
<td>130/65.00%</td>
<td>43/21.50%</td>
</tr>
<tr>
<td>V1&amp;V2 in opposite directions</td>
<td>3</td>
<td>6</td>
<td>30</td>
<td>23/76.67%</td>
<td>5/16.67%</td>
</tr>
<tr>
<td>Crossroads</td>
<td>9</td>
<td>27</td>
<td>135</td>
<td>79/58.52%</td>
<td>31/22.96%</td>
</tr>
<tr>
<td>Total</td>
<td>20</td>
<td>73</td>
<td>365</td>
<td>232/63.56%</td>
<td>79/21.64%</td>
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</tbody>
</table>


