Coverage-based Scene Fuzzing for Virtual Autonomous Driving Testing

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Abstract—

Simulation-based virtual testing has become an essential step to ensure the safety of autonomous driving systems. Testers need to handcraft the virtual driving scenes and configure various environmental settings like surrounding traffic, weather conditions, etc. Due to the huge amount of configuration possibilities, the human efforts are subject to the inefficiency in detecting flaws in industry-class autonomous driving system. This paper proposes a coverage-driven fuzzing technique to automatically generate diverse configuration parameters to form new driving scenes. Experimental results show that our fuzzing method can significantly reduce the cost in deriving new risky scenes from the initial setup designed by testers. We expect automated fuzzing will become a common practice in virtual testing for autonomous driving systems.

I. INTRODUCTION

Autonomous driving, or auto-driving for short, represents the latest advances in AI-powered transportation while safety acts as the major concern to the success of auto-driving. To test an autonomous driving system’s ability of properly handling complicated traffic scenarios, vendors have been running their autonomous driving vehicles with millions of miles of physical road tests [4], [16]. However, despite the gained confidence from the physical world, road testing can hardly trigger many rare and dangerous driving scenarios. For both cost and efficiency reasons, top companies also complement road testing with 3D simulation-based virtual testing [2], [15].

With 3D simulators, developers can build multiple virtual test cases to analyze how well an autonomous driving system responds to abnormal driving scenarios. A virtual test case usually consists of a static driving scene configuration and a set of dynamic configurations. The static configuration often includes map, road, and obstacles while the dynamic configurations can be the surrounding vehicle behaviors, road situations, and weather conditions, etc. A common practice of generating virtual test cases is to setup basic static driving scene and dynamic configurations based on reports of real accident scenes [15]. In practice, however, test designers have to choose the set of dynamic configurations by themselves. Though the 3D simulators provide abundant and configurable choices to tune the close-to-reality simulations, a typical accident report merely contains a static scene description rather than such levels of details. In the simulation, the dynamic environmental information like the speeds and positions of surrounding vehicles, the light intensity, and the weather condition are all left to the test designers’ experiences.

Moreover, we observed that the dynamic configurations for 3D simulation can significantly affect the testing outcome. Similar findings are also reported in recent works [7], [10]. To be specific, we found that behavioral variations of surrounding vehicles or light intensity changes could cause unexpected accidents. That is, replaced with a certain set of dynamic configurations, a benign virtual driving test case can induce remarkable safety challenges to an autonomous driving vehicle. Therefore, simulation-based safety testing needs to address an open question – how to find the effective dynamic configurations that contribute to more challenging test cases?

Driving test case re-construction with more human efforts is by no means the answer. Nowadays, software test automation assemblies essential yet repetitive testing tasks in automatic ways and performs large-scale test generation that are difficult to construct manually. Similar to software testing practice, virtual driving testing also desires automated and practical techniques. Toward this end, we propose ASF, a coverage-driven Autonomous Safety Fuzzing technique. At the high level, ASF adopts the idea of software fuzzing testing for the test case generation in virtual driving testing. Specifically, we design multiple strategies to mutate the changeable content of a simulation input — the dynamic configurations in a driving test case. Given the test cases including static driving scenes and the mutated data, ASF repeatedly executes the simulator with these inputs. Uniquely, we propose trajectory coverage, a metric dedicated for assessing the performance of a driving test case. Once the autonomous driving vehicle delivers a new driving trajectory in the simulation, ASF treats the running test case as a valuable candidate and queues it for subsequent mutation. Also, if the autonomous driving vehicle encounters a collision, ASF treats it as a potential problem and records the running test case for human investigation. Based on the feedback mechanism upon the metric, ASF evaluates the newly mutated test cases in simulation and keeps on mutating chosen candidates to generate more test cases for continuous evaluation, thus forming an evolving loop to search for effective dynamic configurations in virtual test cases.

We used ASF to generate virtual driving test cases upon the open-source version of autonomous driving system Apollo 5.0.0 [3] and the SVL simulator [14]. Experimental results show that ASF generates a desired number of test cases within a short search time budget. Running these test case makes the autonomous driving vehicle drive significantly diverse trajectories. In our experiments, ASF also revealed several system flaws that are extremely hard to find by random or human crafted test cases. These flaws have all been confirmed and fixed in the latest version of Apollo 6.x.
II. PRACTICES AND CHALLENGES OF VIRTUAL SAFETY TESTING FOR AUTONOMOUS DRIVING

Autonomous driving system senses the environment and plans driving decisions with few or no human intervention. When referring to the safety properties, people usually conduct large-scale road testing to fulfill the safety requirements. However, millions of on-road mileage still rarely covers dangerous corner scenarios. In order to make up for the insufficiency of road testing in cost and coverage, people start virtual safety testing for autonomous driving systems through 3D simulators.

A. Safety testing in virtual simulations

Virtual safety testing. Virtual safety testing supplements physical road testing by creating extensive simulation test cases that mimic interested real-world driving scenarios. It can repeatedly run and exam the safety properties of the targeted autonomous driving system, so as to magnify how well the targeted system responds to the designed cases. To build an effective virtual safety testing technique, the involved simulator should serve as the digital mirror of the physical driving environment. The driving simulation should produce high-fidelity reflection of what the autonomous driving vehicle encounters on the road, especially the abnormal driving scenarios. Next, we will explain how the virtual driving simulation works.

Virtual driving simulation. Fig. 1 illustrates the typical flow of a virtual driving simulation. The simulator utilizes 3D game engines to construct photo-realistic virtual driving scenes that are similar to the ones in the real world. The simulator also provides various sensors, such as LiDAR, camera, IMU, and GPS, to present environment perception in the virtual driving. In addition, the simulator provides a communication bridge that exchanges messages between itself and the targeted autonomous driving system. Then the targeted system is connected to the simulator through the communication bridge to control the simulated vehicle.

In this paper, we leverage the advanced 3D simulator SVL [14] and the popular L4 autonomous driving platform Apollo [3] to demonstrate virtual safety testing. The same behavior logic of Apollo used in the road testing is replicated in the virtual driving simulation: it uses the simulated sensor data provided by SVL to perform the driving task including obstacle prediction, path planning and controlling the vehicle in a given driving scene.

Fig. 1. Driving simulation overview

B. Formalized virtual test case

Fig 2 displays a JSON-format test case of the SVL simulator. This example showcases the compact static and dynamic configurations to start a driving environment simulation:

- **Static configurations**: a set of configurable elements that sets up the skeleton of a driving scene. These elements include the name of the high-definition map, the driving area on the map, and the start and end points of the autonomous driving vehicle.

- **Dynamic configurations**: the set of elements whose values can be altered in dynamic simulation. These elements include multiple surrounding NPC vehicles, controllable objects of traffic lights, and environment factors like light and weather conditions.

The static configurations remain unchanged throughout the entire driving scene simulation. For example, the autonomous driving car Lincoln2017MKZ will operate within the pre-designed drivingArea on the SanFrancisco map.

By contrast, altering the dynamic configurations in simulation can derive more safety-related driving situations against the ego car. For example, changing the number, positions, and maneuvers of surrounding NPC vehicles challenges the obstacle detection and path assessment. Irregularly flipping the controllable Trafficlight tests the signal recognition and error signal resilience. Increasing the light intensity or deteriorating the weather threatens the perception precision.
C. Challenges of selecting the dynamic configurations

Existing virtual safety testing methods heavily rely on the scenario database populated from accidental reports [12], [13]. These databases often serve as the basis for constructing virtual test cases. However, the textual descriptions and limited images from the reports are insufficient for creating a vivid 3D simulation, and the developers have to artificially fill the missing environmental information [15].

Then, choosing appropriate dynamic configuration values from the huge search space becomes the major challenge in creating effective virtual test cases. For example, within the drivingArea of SanFrancisco map, the dynamic configurations, such as the maneuvers of surrounding NPC cars, can easily form thousands of possibilities. The selection among possible choices can significantly affect the resulting outcome. Therefore, finding a practical and automated way to make right selections for virtual safety testing is of essential importance.

III. APPLY FUZZING FOR VIRTUAL SAFETY TESTING

We observe that the test case generation for virtual driving testing bears a strong similarity with software fuzz testing (fuzzing). For example, the selection of dynamic configuration values can be analogous to the input mutation in fuzzing: the collisions of vehicles or traffic rule violations can be analogous to the program crashes found by fuzzing. In what follows, we first introduce the general flow and the core components of fuzzing, then describe the challenges of adopting fuzzing for test case generation in virtual driving testing.

A. Fuzz Testing

Fuzzing [1], [11], [17] has achieved significant successes in software testing and vulnerability detection, owning to its practicability and scalability in code coverage improvement and test case generation.

![Fuzz testing flow and the core components](image)

Fig. 3. Fuzz testing flow and the core components

Figure 3 shows the workflow of a fuzzing engine (i.e., fuzzer). Without loss of generality, we separate the fuzzer into three core components including the crash signal processing, the feedback mechanism, and the seed mutation, as emphasized by the bold fonts in Figure 3. Given a set of initial seed input files, the fuzzer repeatedly executes the program under testing with the initial seeds and later the mutated test inputs originated from these seeds. If the fuzzer encounters a program crash or halting in dynamic execution, it records the bug-triggering input into a persistent file. We call this action as crash signal processing. If running an input receives an unique runtime feedback like new code coverage rather than a crash, the fuzzer would treat the input as a valuable seed and prioritize it as a candidate for near future mutation. The coverage feedback and the evaluation of this metric form the feedback mechanism. Then, based on a queue of prioritized candidate seeds, the fuzzer performs fast seed mutation through several strategies like bit and byte flipping, arithmetic increment, value replacement, etc. We name this action as seed mutation. On each new input from seed mutation, the fuzzer repeats the program execution, crash signal processing, feedback evaluation, and further mutations, thus forming a non-terminating fuzzing loop.

B. Challenges of virtual safety fuzzing

Applying the fuzzing idea to producing diverse dynamic simulation configurations for virtual safety testing is imaginative yet challenging. In general, mutating structured parameters is close to the intuitions of grammar-based fuzzing [8], [6] and structure-aware fuzzing [5], [18]. The bug symptoms in software fuzzing could correspond to safety issues under virtual safety testing. However, the primary challenge comes from the feedback mechanism that leads the fuzzing progress. Existing fuzzers often utilize low-level code instrumentation to obtain the code coverage of the running seed, which guides subsequent seed mutation hence steering the fuzzing direction. However, the internal code coverage no longer suits virtual safety testing since the latter focuses on the behavioral safety. Using the code coverage may help find implementation bugs rather than detecting safety risks in simulation.

Therefore, virtual safety fuzzing demands a new metric that bridges both the autonomous driving state and the evolving simulation state. With this metric, we can depict the goal and monitor the progress of fuzzing. After running a driving simulation, we evaluate the finished driving state against the metric. Then, upon the evaluation feedback, the fuzzing conducts pertinent mutations on interested configurations to form new test cases for continuous simulations.

IV. A COVERAGE-BASED FUZZING SYSTEM FOR VIRTUAL SAFETY TESTING

We propose ASF, a coverage-based fuzzing system to efficiently generate risky test cases for virtual safety testing.

A. The overall flow

Fig. 4 shows our ASF framework, which consists of four components: the formalized test cases, the fuzzing engine, the 3D simulator, and the autonomous driving system under test.

Briefly speaking, ASF works as follows: given a small set of formalized test cases as the initial seed inputs, the fuzzing engine repeatedly run the simulation. We call running simulation on a mutated test case as an iteration. At each iteration, the simulator loads a mutated case from fuzzing engine to render a virtual driving scenario. Then, the autonomous driving system is bridged into the simulator as the backend controller to drive the specified vehicle in the virtual scenario. After an iteration, ASF evaluates whether the finished run has increased
the trajectory coverage — a new metric defined in Section IV-C dedicated for virtual safety fuzzing. If the feedback reports coverage increase, the executed test case would be kept for further mutation. Meanwhile, if the driving vehicle encounters an accident or a traffic rule violation, ASF records the correlated test case. Then, ASF resumes execution and proceeds to the next iteration. Note that a test case includes static and dynamic configurations in JSON format where we focus on the dynamic part (ref. Section II). For brevity, dynamic configurations and test cases are interchangeable in the rest of the paper.

B. The fuzzing algorithm

Algorithm 1 formalizes the workflow of ASF’s fuzzing engine. The algorithm starts with some randomly generated test cases by placing them into the priority queue \( Q \) as the initial seeds. Then, it enters the first for loop and performs certain mutations on the highest-priority test case \( c \) taken from \( Q \), shown at lines 1-2. The mutation forms a set of new test cases \( M_c \). Next, at lines 3-4, our algorithm starts the simulation by calling function \( \text{SimRun}(c') \) on each element \( c' \) in \( M_c \). It also retrieves the safety issue report \( \text{isCrash}(c') \), the trajectory coverage result \( \text{drivingTraj}(c') \), and the liability decision \( \text{atFault}(c') \), respectively. If the \( \text{drivingTraj}(c') \) reveals that the autonomous driving vehicle reaches new road locations compared to historical data, our algorithm treats \( c' \) as a valuable candidate and puts it into the priority queue \( Q \), shown at lines 5-6. Otherwise, at lines 7-8, our algorithm examines if the autonomous driving vehicle encounters a safety issue and is not at-fault by checking the results of \( \text{isCrash}(c') \) and \( \text{atFault}(c') \). If both conditions satisfy, our fuzzing technique detects a potentially risky case and stores \( c' \) for investigation.

Note that Algorithm 1 compliments Fig. 4 with the formal descriptions. However, for the brevity reason, we omit the details of the functions in the algorithm. We leave the technical explanations of these functions in Section IV-C.

Algorithm 1: Trajectory coverage-driven fuzzing

**Initialization:**

1. Priority queue \( Q \): initial random test cases;
2. for highest priority case \( c \in Q \) do
3. \( M_c = \text{mutate}(c) \);
4. for mutated case \( c' \in M_c \) do
5. \( \text{isCrash}(c'), \text{drivingTraj}(c'), \text{atFault}(c') = \text{SimRun}(c') \);
6. if \( \text{drivingTraj}(c') \) contains new locations then
7. \( Q.\text{insert}(c') \);
8. if \( \text{isCrash}(c') \land \text{atFault}(c') \) then
9. Store risky case \( c' \);

C. Core techniques in the fuzzing engine

**Trajectory coverage-based feedback mechanism.** As analyzed in Section III-B, the primary challenge of virtual safety fuzzing stems from the feedback mechanism and the measuring metric that drive the fuzzing progress. However, quantifying safety issues remains an open question and there is no standard way to make a general quantification. Alternatively, we propose a novel trajectory coverage as the structural metric for virtual safety fuzzing. The trajectory refers to the waypoints that the autonomous driving vehicle has driven on the road in a simulation scene. The intuition is that by covering more areas on the map, we hope the self-driving car could reach some corner cases, so as to increase the probability of triggering safety issues eventually. Therefore, if ASF receives the feedback that the simulated vehicle in the virtual scenario drives a new road trajectory under a specific test case, ASF will give priority to this case for further mutations.

**Crash signal processing** Program execution crash, e.g., segmentation fault, presents a explicit crash signal to the
software fuzzer (ref. Fig. 4). Analogously, we can consider all collisions as the "crash" signals for virtual safety fuzzing. However, accident reports showed that the autonomous driving vehicle may not always be at fault in the collisions or accidents it involved. Reckless driving from nearby vehicles can cause unavoidable accidents despite the autonomous driving system behaves correctly. Thus those collisions should not be categorized into safety violations from the autonomous driving system. ASF tackles this problem by a liability judgement against captured collisions. Specifically, ASF invokes a callback mechanism to decide the party at fault once agents like vehicles and stationary objects controlled by the simulator collide. For example, Listing 1 shows a callback function in SVL simulator on a collision. The function arguments include involved parties and collision location. Once ASF monitors the signal in simulation, it analyzes both the callback data and navigation history data before the collision to compute the at-fault parties, and makes decisions accordingly.

Listing 1. SVL collision callback function

```python
def on_collision(agent1, agent2, contact):
    print("{} collided with {} at {}".format(name1, name2, contact))
    ego.on_collision(on_collision)
```

**Mutation strategies.** The mutation strategies in ASF focus on mutating the content of dynamic configurations of a test case. Intuitively, fuzzing the JSON test case is close to the existing software fuzzing works on well formatted files like PDF, XML, YAML, etc. However, these existing works primarily concentrate on finding the implementation bugs in file interpreter or parser. By contrast, ASF needs to provide diverse yet valid test case files to set up simulation environments, so as to test behavioral differences of autonomous driving vehicles. Note that each dynamic configuration element may correspond to a specific object in simulation. Fuzzing the element content has to take its semantics into consideration to produce meaningful mutants. Thus, we cannot simply adopt the AFL strategies or the structure-aware fuzzing strategies. To accommodate the virtual safety fuzzing nature, we design a set of mutation strategies in ASF as follows:

- **Arithmetic.** To derive more trajectories on the map in a deterministic way, we attempt to subtly increment or decrement numerical parameters in the configuration. An example is to add or subtract \(x\) coordinate and \(y\) coordinate values of an agent’s position.
- **Flip.** Flip strategy alters the state of a controllable object (e.g., traffic light color). Flip action also applies to numerical parameters. For example, we design position flip that reflects the position of an agent with respect to the center point of the driving area.
- **Random.** Random strategy randomly replaces the numerical parameters or states with the values within a certain working range.
- **Insert.** Insert strategy specifically works for the set of observable agents. It adds specific agents along with the routing path.

Fig. 5 demonstrates the visual effects of the above mutation strategies. More workable mutation strategies will be tested and added to our strategy repository.

![Fig. 5. Examples of mutation strategies](image)

**Figure 5.** Examples of mutation strategies

V. CASE STUDY

To show the benefit of applying fuzzing on virtual test case generation, we use a concrete case study to demonstrate how ASF works. Through this case study, we will show how the coverage-driven feedback mechanism in ASF can help find potential risky test cases. We first demonstrate the trajectory coverage efficiency of ASF, then present some risky cases found by ASF.

A. Case study setup

We make two definitions to depict the trajectory coverage.  

**Definition 1:** Driving area. The driving area on the map is a rectangle bounded by the specified geographic Universal Transverse Mercator (UTM) coordinates in the static configurations of a test case.

**Definition 2:** Trajectory coverage. We divide the driving area into \(1m\times1m\) blocks. The trajectory coverage presents the set of blocks covered by the autonomous driving vehicle trajectory in a simulation.

In this study, we set the block granularity of the driving area as \(1m\times1m\) for simplicity. Note that the vehicle may never reach certain areas within the driving area and the choice of block granularity might affect the search cost and experimental result. We leave the granularity reasoning as future work.

Fig. 6 shows the basic driving scene in our study. The autonomous driving vehicle goes from the start point at the leftmost lane to the end point marked by the green arrows. The driving scene skeleton is formalized by the static configurations shown in Fig. 2(a). The driving area in this case is the green translucent rectangle in Fig. 6, bounded by point \(A = \text{(easting} = 553029.90, \text{northing} = 4181687.30)\) and point \(B = \text{easting} = 553153.89, \text{northing} = 4181749.28)\) in the UTM coordinate system. In the middle there is also an intersection with traffic lights. We conduct all the experiments on a Ubuntu Desktop with an AMD Ryzen 7 3700X CPU, 16GB memory, and an NVIDIA GTX1080 Ti.
B. Coverage efficiency

We use Fig. 7 to visualize the concept of trajectory coverage. It shows the planar graph of the driving area, divided by the red $1m \times 1m$ blocks. There are four driving trajectories generated by running an initial test case (case 1) and three mutated test cases (cases 2-4). We observe that case 2 and case 3 contribute to new trajectory coverage since both of them have covered new map blocks. By comparison, case 4 covers no new blocks compared to other three, hence it would be discarded without further mutation in ASF.

In this study, the mutating content is the positions of the surrounding NPC agents (e.g., the brown sedan in Fig. 7). Now, we compare ASF with two other fuzzers regarding the ability of covering more driving area blocks. The first one is a random fuzzer that generates random positions of the NPC agents within the driving area. The second fuzzer is the state-of-the-art autonomous vehicle safety fuzzing tool AV-Fuzzer [10]. AV-Fuzzer developed a genetic algorithm driven by a fitness function, i.e., the maximum distance the vehicle can move without colliding with any obstacle or vehicles.

Fig. 8 compares the aggregate number of covered blocks by ASF, random fuzzer, and AV-Fuzzer in a 40-iteration simulation. The overall comparison shows that ASF covers obviously more drive area blocks than the other two approaches, resulting in a higher trajectory coverage. Moreover, in ASF, the coverage growth rate at the early stage is significantly ahead of the other two methods, which indicates the superior fuzzing efficiency in ASF with the testing budget.

The reason that ASF outperforms both AV-Fuzzer and random fuzzer is two-sided. First, ASF’s feedback mechanism favors seeds that always contribute new trajectories. Second, ASF also conducts a preferential search near the seeds through the dedicated mutation strategies for virtual safety fuzzing.

C. Risky cases

Table I lists the statistics of the risky cases found by random fuzzer, AV-Fuzzer, and ASF, in the 40-iteration simulation. The entries highlighted by red color are severe cases that lead to collisions. The orange-colored entries represent the near-collision cases. As seen, within the 40-iteration simulation, ASF found one near-collision case and two risky cases that directly lead to collisions that hit a traffic cone and a sedan vehicle. In comparison, AV-Fuzzer only found one near-collision case and the random fuzzer found no risky case.

For better understanding of the collision found by ASF, we visualize the traffic cone accident in Fig. 9. In the left-side simulation snapshot, the autonomous driving vehicle hit a traffic cone on the solid double-yellow line. In the right-
side Dreamview UI snapshot, we can see that the autonomous driving car controlled by Apollo planned a trajectory that goes across the double-yellow line and points to the reverse lane on the left. After analyzing the Apollo source code, we believe that the root cause of the planning error works as follows. When there are surrounding stopping obstacles, i.e., the front NPC vehicle and the right-side NPC vehicle, Apollo makes a decision to borrow the lane on the left. However, at this time, Apollo actually does not check the boundary type of the lane to be borrowed. As a result, it plans a trajectory across the middle double-yellow line, which forms a severe traffic violation and causes a collision in this case. This example shows that ASF can help to find subtle logical flaws in autonomous driving system that would be hard to detect if only using random or handcrafted test cases.

![simulation planned trajectory]

**Fig. 9.** Collision with traffic cone

### D. Discussion

Experimental results have shown that the coverage-driven feedback mechanism in ASF identifies more risky cases under the same driving scenario. We propose speculative explanations for the results. One point is that when the trajectory of an autonomous driving vehicle covers more driving area, there would be more possibilities to trigger dangerous corner cases, such as the above traffic cone accident. The fitness-driven AV-Fuzzer searches for the high potential seeds that might lead to collision. However, it can be trapped in the local optimum like the near-collision case. Though the restart mechanism can help AV-Fuzzer get out of the local optimum, its efficiency of finding new trajectory is close to that of a random fuzzer. On the other hand, coverage-driven ASF explores different trajectories as much as possible. Though these trajectories may not necessarily lead to collisions, they help ASF to filter the benign cases thus approaching the severe cases.

### VI. Conclusion and Future Work

Just as software testing cannot primarily rely on human efforts to find bugs, virtual safety testing also desires automated test case generation due to the huge configuration search space. Toward this end, we propose a coverage-driven fuzzing method ASF to generate high-quality test cases for the virtual safety testing of autonomous driving system. ASF can automatically mutate dynamic configurations to form new test cases for detecting risky autonomous driving scenes in simulation. Comparisons among ASF, the state-of-the-art AV-Fuzzer, and the random fuzzer show that ASF can find more severe safety issues. With ASF, we have found few flaws in a popular open-source autonomous driving system in a short time.

To systematically study virtual safety testing, we plan to explore the following points in the future:

- How to improve the feedback mechanism to make the autonomous driving car be more prone to collisions?
- How to design appropriate environmental settings for virtual safety fuzzing, such as driving area and block granularity, in order to balance the search space and the fuzzing cost?
- How to optimize the combination of various mutation strategies to improve the fuzzing efficiency?

We are actively conducting research to answer these questions and pursuing approaches to generate more efficient virtual drive test solutions.

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