SMET: Scenario-based Metamorphic Testing for Autonomous Driving Models

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Abstract—To improve the security and robustness of autonomous driving models, this paper presents SMET, a scenario-based metamorphic testing tool for autonomous driving models. The metamorphic relationship is divided into three dimensions (time, space, and event) and demonstrates its effectiveness through case studies in two types of autonomous driving models with different outputs. Experimental results show that this tool can well detect potential defects of the autonomous driving model, and complex scenes are more effective than simple scenes.

Index Terms—metamorphic testing, autonomous driving, metamorphic relation, driving scenarios

I. INTRODUCTION

To improve the robustness of autonomous driving models (ADM), researchers have applied Metamorphic Testing (MT) [1], [2], [3] to generate new test inputs and check the corresponding outputs. MT exploits pre-defined metamorphic relation (MR) in a target system to provide a test case generation strategy and a test result verification mechanism alternative to have a test oracle.

Nevertheless, prior work focuses on the simple scenario, may miss some real-life scenarios, and thus fails to automatically identify when a failure occurs. For example, in DeepTest [2] and DeepRoad [3], a simple scenario was proposed that the weather was changed. The actual driving scenes are far more complex (extreme weather, various obstacles, poor illumination at night, etc.), but a variety of realistic driving scenes are not covered by the existing testing methods.

In this research, therefore, we ask the following research questions. RQ1: Can we develop a generic, domain-independent automated metamorphic testing framework to allow developers and testers of ADM to identify and implement their own complex scenarios and metamorphic relations (MRs)? RQ2: What is the applicability and effectiveness of our solution? To address RQ1, we have developed an automated scenario-based metamorphic testing tool for autonomous driving models named SMET, which allows the users to describe the scene from three dimensions of time, space and event, and it can translate each scene to a corresponding MR. It then injects meaningful input transformation, which is entailed by the custom scene by leveraging pluggable input-transformation engines. We have also conducted preliminary case studies to investigate RQ2.

II. SMET: A MT TOOL FOR ADM

A. Structure of SMET

As shown in Figure 1, SMET contains three components: 1) Metamorphic Relation generator; 2) Metamorphic Testing generator; 3) Metamorphic Relation evaluator. Initially, a tester expresses expected driving complex scenarios for using the syntax of natural language and formulas. Given those scenarios, SMET builds a corresponding MR. Once the MR is created, these key elements will be passed to the metamorphic testing generator, which has an extensible toolkit. Various transformation engines can be plugged into the toolkit and the transformation engines manipulate the original input (image) into the follow-up metamorphic input.

Fig. 1. Structure of SMET

SMET currently provides three-dimensional image transformations, which include: 1) Time: changing scenes for day to night or night to day (simulate real-world time changes in the whole day); 2) Space: changing the static environment in the scene, such as alter roadside traffic signs or buildings; 3) Event: changing weather or traffic participants (pedestrian, motorized, non-motorized, others). A simple scene may only require a single transformation (e.g., change weather from sunny to snowy). While a composite scene needs to be created by combining multiple transformations (e.g., adding a pedestrian in front and changing to night scene).

To support a diverse set of transformation capabilities and to ensure the quality of compositing scenarios, Metamorphic Testing generator is realized with four transformation engine plugs-ins based on Opencv, Pix2pixSC [4], UNIT [5] and Other GANs [6]. In the Metamorphic Relation evaluator, the test pair that contains the original input and the transformed input or two transformed inputs are fed to the driving model.
under test. Then the model produces predictions for them. The evaluator will verify whether the predictions violate the underlying MR.

B. GUI of SMET

We also have implemented a GUI that integrates all three components, as shown in Figure 2. A user can easily configure metamorphic relations and inspect test results. The prototype and more screenshots are available at https://osf.io/nrfh8/.

III. TWO CASE STUDIES WITH SMET

We study two types of autonomous driving models, one is the output of steering wheel angle (referred to as Angle ADMs), the other is the output of driving speed (referred to as Speed ADMs).

A. Angle ADMs

This case study uses top performing self-driving models, which are released in Udacity challenge that includes Autumn [7], Rombo [8] and Nvidia DAVE self-driving systems DAVE-dropout [9] as the test ADMs. It uses the Udacity self-driving car challenge dataset [10] as source test dataset. The dataset has 101,396 training and 5,614 testing samples. We trained all three implementations with the Udacity self-driving car challenge dataset mentioned above. To test the first type ADMs, we first define MR1 as follows: Change the time from day to night should not affect steering angle. We then define MR2 as follows: Change weather from sunny to rainy and time from day to night should not affect steering angle. Not affect the steering angle means that the difference between the ADMs’ prediction of the steering angle of the images which are transformed before and after is less than the threshold. In this experiment, the threshold is $5^\circ$.

The experimental results are shown in Table I. It is interesting to find that, out of 1,000 experiments (hence 1,000 pairs of source and follow-up accuracy scores), at least 135 have violated MR1. It means Change time from day to night should not affect steering angle. Not affect the steering angle means that the difference between the ADMs’ prediction of the steering angle of the images which are transformed before and after is less than the threshold. In this experiment, the threshold is $5^\circ$.

Table II shows the experimental results, however, is surprising. The results of 1200 MT experiments show that for adding pedestrian all driving models, the average violation ratios are 74.17%, 76.92%, 77.58%. Modify the buildings for all driving models, the average violation ratios are 19.33%, 14.42%, 19.92%.

These case studies show that our defined MR and the developed tool SMET can help discover the defects of the autonomous driving models.

C. Threats to Validity

SMET generates realistic synthetic images by applying different image transformations on the source images. While, our transformations like rain and night effects are designed to be realistic, the generated pictures may not be exactly reproducible in reality due to a large number of unpredictable factors. Furthermore, Prior work such as DeepTest [2] and DeepRoad [3] focus on steering angle prediction rather than speed prediction, our work research on Speed ADMs can not directly comparing against them. In our work, a fault is considered to be detected when an MR is violated. However, in the context of autonomous driving, the violation of an MR only implies a potential erroneous behavior. In other words, a detected fault could be a “suspicious” one.

### Table I

|          | Autumn   | Krightman | DAVE-dropout |
|----------|----------|-----------|--------------|
| MR1      | 135 (13.5%) | 168 (16.8%) | 173 (17.3%)  |
| MR2      | 455 (45.5%) | 471 (47.1%) | 469 (46.9%)  |

### Table II

|          | Epoch  | ResNet101 | VGG16 |
|----------|--------|-----------|-------|
| MR3      | 890 (74.17%) | 923 (76.92%) | 931 (77.58%) |
| MR4      | 232 (19.33%) | 173 (14.42%) | 239 (19.92%) |
IV. CONCLUSIONS AND FUTURE WORK

We have presented the design of SMET, a metamorphic testing tool for autonomous driving models, and demonstrated its applicability and problem-detection effectiveness through case studies in two types of autonomous driving models with different outputs. We have shown that the composition of MRs can greatly improve the problem-detection effectiveness of individual MRs. We will add more scene composition methods to ensure the authenticity and usability of scene composition.

Future research will further extensions and larger-scale case studies of the framework that include proposing a more general approach to generate real-world scenarios as well as opening an investigation of the time cost associated with the learning curve for a novice tester to use the tool. Per open science policy, we have made code and data for this submission available at https://osf.io/nrfh8/.

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