RMT: Rule-based Metamorphic Testing for Autonomous Driving Models

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Abstract—Deep neural network models are widely used for perception and control in autonomous driving. Recent work uses metamorphic testing but is limited to using equality-based metamorphic relations and does not provide expressiveness for defining inequality-based metamorphic relations. To encode real-world traffic rules, domain experts must be able to express higher-order relations e.g., a vehicle should decrease speed in a certain ratio, when there is a vehicle x meters ahead and compositionality e.g., a vehicle must have a larger deceleration, when there is a vehicle ahead and when the weather is rainy and proportional compounding effect to the test outcome.

We design RMT, a declarative rule-based metamorphic testing framework. It provides three components that work in concert: (1) a domain specific language that enables an expert to express higher-order, compositional metamorphic relations, (2) pluggable transformation engines built on a variety of image and graphics processing techniques, and (3) automated test generation that translates a human-written rule to a corresponding executable, metamorphic relation and synthesizes meaningful inputs. Our evaluation using three driving models shows that RMT can generate meaningful test cases on which 89% of erroneous predictions are found by enabling higher-order metamorphic relations. Compositionality provides further aids for generating meaningful, synthesized inputs—3012 new images are generated by compositional rules. These detected erroneous predictions are manually examined and confirmed by six human judges as meaningful traffic rule violations. RMT is the first to expand automated testing capability for autonomous vehicles by enabling easy mapping of traffic regulations to executable metamorphic relations and to demonstrate the benefits of expressivity, customization, and pluggability.

Index Terms—metamorphic testing, autonomous driving, deep learning

I. INTRODUCTION

Autonomous driving has attracted wide attention and increasing investment from industry. Waymo launched the first autonomous car service in the Phoenix metropolitan area, making the first step towards commercializing autonomous vehicles [13]. Deep Neural Networks (DNNs) and Convolutional Neural Networks (CNNs) are widely used to solve perception and control problems [3, 43]. These models make real-time predictions of steering angle and speed based on signals from cameras and LiDARs. However, recent accidents involving autonomous vehicles have raised a safety concern. For instance, in a fatal crash caused by Tesla’s autopilot system, the autonomous driving model failed to recognize the white truck against the bright sky and made a wrong decision to run into the truck [4]. Therefore, it is crucial to detect undesired behaviors of autonomous driving models, especially in some complex conditions.

In industry, road test is adopted to test a driving model [6, 46]. However, road test is costly and may not cover various driving scenarios (e.g., different road, weather, or traffic conditions). Simulation-based testing [2, 10, 11, 32, 45, 47] is another testing method that complements road test by mimicking various driving scenarios. Nevertheless, simulation-based testing may miss some real-life scenarios and thus fails to automatically identify when failure occurs. The fidelity of application behaviors in a simulation environment, especially that of images rendered by simulation, is often in question [24, 29, 48].

To improve the robustness of autonomous driving models, recent work leverages metamorphic testing (MT) [7, 24, 37, 45] to generate new test inputs and check the corresponding outputs. Metamorphic testing exploits pre-defined metamorphic relations in a target system to provide both a test case generation strategy and a test result verification mechanism alternative to having a test oracle. However, prior work focuses on equality-based metamorphic relations where metamorphic transformation should produce the same or a similar output. For example, in DeepTest [37] and DeepRoad [45], a simplified equality-based relation was proposed that an updated steering angle should differ from the original angle by at most $\delta$ after image transformation.

However, such equality-based metamorphic relations fall short of expressing complex driving rules in real-world settings. For example, when the driving scene changes from day time to rainy day, the vehicle shall decelerate by 25% according to the Australia New South Wales traffic rule [17]. Such traffic rules are defined by legislation authority in different countries and regions. However, while those are available, no automated technique can easily use the rules to synthesize input images and check the behaviors of driving models for testing purposes. One key challenge is that these traffic rules...
are beyond the scope of equality-based metamorphic relations, as the modified output shall be defined as a higher order function of the original output by domain experts.

We propose a declarative, rule-based metamorphic testing approach called RMT. While existing techniques such as DeepTest [37] and DeepRoad [45] hardcode equality metamorphic relations (MRs), RMT enables domain experts to specify custom rules derived from real-world traffic rules using a domain-specific language. RMT can translate each rule to a corresponding MR. It then injects meaningful input transformation entailed by the custom rule by leveraging pluggable input-transformation engines. RMT currently incorporates three kinds of graphics and image transformation engines: (1) object insertion based on semantic labels, (2) affine transformations in OpenCV, and (3) image-to-image translation based on GANs. Such pluggable transformation engines can be supplied by domain experts to express and test complex compered traffic rules, such as simultaneously changing the driving time to a night time and injecting a pedestrian in front of a vehicle. Furthermore, RMT allows to combine multiple transformations to build composite rules to model complex real-world traffic rules. RMT also supports relations between two transformed test cases instead of just between the original test case and its transformed one.

In summary, this work makes the following contributions:

- **DSL for Metamorphic Relation.** We propose a domain specific language to express higher-order and composite metamorphic relations for autonomous driving models instead of constructing MRs in an ad-hoc manner to make it easier to express complex, real-world rules.
- **Extensibility.** We design RMT such that new transformation engines can be easily added to support complex transformations required by a custom MR.
- **Comprehensive Evaluation.** We evaluate RMT using three state-of-the-art driving models for speed prediction on two widely used datasets. We compare its effectiveness using two test adequacy measures: detection of erroneous predictions and neuron boundary coverage.
- **Human Assessment.** We conduct a user study with six human drivers. Participants found generated test cases are meaningful traffic rule violations, reflecting real world driving scenarios that must be avoided.

In the emerging era of ML-based systems, the absence and difficulty of having test oracles is posing a threat to expand automated testing capability. Generally, it is costly to define ground truth data sets apriori, and it is unreasonable to expect that domain experts individually check the validity of test outcomes in a post-hoc manner. While the idea of metamorphic testing has existed for a while, the challenge is that users must manually define metamorphic relations to enable metamorphic testing. Despite the availability of traffic regulations documented by federal governments and state authorities, currently, there is no easy means to easily map these regulations to executable metamorphic relations. RMT is the first to significantly expand automated testing capability for autonomous vehicles by focusing on expressivity, customization, and pluggability.

The rest of the paper is organized as follows. Section II describes the RMT framework and rule-based MR specification. Section III-E demonstrates our tool. Section III explains the experiment settings and Section IV presents the experimental results on RMT. Section V discusses related work. Finally, Section VI concludes our paper.

## II. The RMT Framework

### A. Overview

As shown in Figure 1, RMT contains three components: (1) a MR generator, (2) a metamorphic test generator and (3) a MR evaluator. Initially, a domain expert expresses expected driving rules in a domain specific language similar to Cucumber [42] using the syntax of natural language and formulas. Given those rules, RMT’s rule parser extracts key elements (e.g., Transformation) from and builds a corresponding MR.

Once the MR is created, these key elements will then be passed to the metamorphic test 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 transformed (metamorphic) input.

RMT currently provides two kinds of image transformations: (1) add objects in a specific location, (2) change scenes from day to night or normal to rainy. A simple metamorphic relation may only require a single transformation (e.g., changing weather from normal to rainy to check corresponding speed change) while composite metamorphic relations need to be created either by combining multiple transformations (e.g., adding a vehicle in front and changing to rainy scene to check speed change) or a single transformation with different settings (e.g., adding a vehicle in front close by or far away to check speed change). We define the former, simple metamorphic relation as Simple Rules and the latter composite metamorphic relations as Composite Rules.

If encoding the underlying real-world rules requires new transformation engines (e.g., removing an object), the only thing that a user must do is to update the rule parser and plug-in the corresponding transformation engine. In the MR evaluator, the test pair that contains the original input and the modified, transformed input or two transformed inputs are both fed to the driving model under test, and the model then produces predictions for both. The evaluator will verify whether the predictions violate the underlying MR. We also have implemented a GUI that integrates all three components. A user can easily configure metamorphic relations and inspect test results.

### B. Rule-based metamorphic relation

In real life, drivers should obey local traffic rules for safe driving. In the context of autonomous vehicles, obeying traffic rules is equally, if not more, important for safety. Therefore, autonomous driving models shall be tested against these rules. However, there are no easy ways to leverage such traffic
rules for generating required test images and declaring the corresponding oracle.

Our goal is to automatically create test scenarios based on these rules and validate whether the models violate them. For example, a domain expert can define a rule that if there is a car x meters ahead the autonomous driving vehicle, the vehicle should slow down by t1% to t2%, where thresholds t1% and t2% are set by a domain expert or based on the traffic law. The rule actually describes a MR for the autonomous driving model: transformation of input by adding a car at a specific location in the driving scene should cause an expected change of the prediction proportionally (i.e., speed slows down by t1% to t2%). Inspired by the success of writing specifications in natural language [42], [49] for software testing and verification, we propose a Cucumber-like rule template below:

**RMT: Simple Rules (SR)**

**Rule 1**
**Description:** Adding a vehicle x meters in front of the main vehicle should cause a deceleration to less than t

**Given:** Model under test M, Original input \( X_O \)

**MR:** \( X_{N1} = X_O \) or \( X_{N1} = \text{Transformation}_1(X_O) \),

\( X_{N2} = \text{Transformation}_2(X_O) \)

\( \Rightarrow \) predictions on \( (X_{N1}, X_{N2}) \) as higher order functions

**Rule 2**
**Description:** Adding a speed limit sign at the roadside will cause a deceleration to less than t

**Given:** Model under test M, Original input \( X_O \)

**MR:** \( X_{N1} = X_O \), \( X_{N2} = \text{inject}(X_O, \text{[sign, roadside]}) \)

\( \Rightarrow M(X_{N1}) < t \)

**Rule 3 - 5**
**Description:** Adding a vehicle/bicycle/pedestrian x meters in front of the main vehicle will cause a deceleration by t1% to t2%.

**Given:** Model under test M, Original input \( X_O \)

**MR:** \( X_{N1} = X_O \),

\( X_{N2} = \text{inject}(X_O, \text{[vehicle/bicycle/pedestrian, front, x]}) \)

\( \Rightarrow t_1 < (M(X_{N1}) - M(X_{N2}))/M(X_{N1}) < t_2 \)

**Rule 6 - 7**
**Description:** Changing the driving scenes to night time or rainy day will cause a deceleration by t1% to t2%.

**Given:** Model under test M, Original input \( X_O \)

**MR:** \( X_{N1} = X_O \),

\( X_{N2} = \text{changeScene}(X_O, \text{[night/rain]}) \)

\( \Rightarrow t_1 < (M(X_{N1}) - M(X_{N2}))/M(X_{N1}) < t_2 \)
apply a single transformation, \(X_{N1}\) is always set to \(X_O\). In the case of composite rules, \(X_{N1}\) could be a result of applying another transformation. A rule’s right side describes how to check the test pair’s prediction using higher-order functions. For example, in Rule 3 \(t_1 < (M(X_O) - M(X_{N1}))/M(X_O)) \times t_2\) dictates a function that the decrease ratio of model predictions should be in the range \((t_1, t_2)\). Compared with prior work [37], [35] that uses a hardcoded equality-based metamorphic relationship, this rule template enables domain experts to more flexibly prescribe the desired property of model predictions, especially in custom test scenarios.

Rules 1 and 2 are derived from traffic laws that give specific oracles (i.e., speed limits) [17], [36]. Because they use a single transformation, \(X_{N1}\) is always set to \(X_O\). Rule 1 tests whether a driving model follows a safe driving distance regulation, when a vehicle appear in the front and close to the main vehicle. This is based on NSW Australia’s traffic law (Figure 2). To keep 3 seconds response time, there should be 50 meter distance from the front vehicle when the speed is above 60 km/h. Therefore, \(M(X_O)\) should be no more than 60 km/h when a vehicle is located in the front less than 50 meters away from the main vehicle. Rule 2 tests scenarios of seeing a speed limit sign.

Rules 3 to 7 are designed based on traffic rules that specify required driving behavior in certain circumstances without specific speed oracles. For example, Texas traffic law requires drivers to “slow down and increase the following distance when the road is wet” [36]. Since the speed oracle is not specified, we quantify the required driving behavior as speed decrease ratio in a range. Rules 3, 4 and 5 test anomalous scenarios where objects suddenly appear in the front and close to the main vehicle, which are similar with Rule 1 but allow the injection of more types of objects. Rules 6 and 7 test the impact of different driving scenes on speed.

Rules 8 and 9 are composite rules that compare the outcome of more than one transformation. Compared with the prior work that test relations between the original input and its modified input, RMT makes it easier to test the compounding, proportional effect of more than one transformation.

### C. Metamorphic transformation engines

To support a diverse set of transformation capability, RMT plugs-in five transformation engines based on three different GANs, and OpenCV.

#### RMT: Composite Rules (CR)

**Rule 8**

**Description:** Adding a vehicle \(x\) meters in front of the main vehicle and changing to rainy day will cause a deceleration by \(t_1\%\) to \(t_2\%\).

**Given:** Model under test \(M\), Original input \(X_O\)

**MR:** \(X_{N1} = X_O\), \(X_{N2} = \text{changeScene}(\text{inject}(X_O, \{\text{vehicle}, \text{front}, x\}), \{\text{rainy}\})\)

\(\Rightarrow t_1 < (M(X_{N1}) - M(X_{N2}))/M(X_{N1}) < t_2\)

**Rule 9**

**Description:** Compared with adding a vehicle \(x_1\) meters in front of the main vehicle, adding a vehicle \(x_2\) meters (\(x_2 < x_1\)) in front of the main vehicle will cause a bigger deceleration.

**Given:** Model under test \(M\), Original input \(X_O\)

**MR:** \(X_{N1} = \text{inject}(X_O, \{\text{vehicle}, x_1\})\), \(X_{N2} = \text{inject}(X_O, \{\text{vehicle}, x_2\})\)

\(\Rightarrow t_1 < (M(X_{N1}) - M(X_{N2}))/M(X_{N1}) < t_2\)

### TABLE I: Transformation functions

| Transformation Function | Description |
|-------------------------|-------------|
| \(\text{inject}(image, [object, orientation, distance])\) | inject object into an image at distance in orientation |
| \(\text{changeScene}(image, [scene])\) | change the driving scene of an image to scene |

1) **Integrating OpenCV:** OpenCV [5] is a powerful open source image processing library that provides many affine transformations (e.g., translation and rotation) and complex filter effects (e.g., making the image become foggy and rainy). DeepTest [37] is one of the first MT tools based on OpenCV and implements nine effects including Scale, Brightness, Contrast, Blur, Rotation, Translation, Shear, Fog, and Rain to test autonomous driving models for steering angle prediction.

Given a dataset that contains instance labels, OpenCV [5] can directly extract objects like vehicles and traffic signs from dataset and add them into other images. We integrate OpenCV as a transformation engine to implement injecting objects (in Rule 1-5, and Rule 8-9). To add an object in a specific distance (e.g., 50 meters), we first transform such a real-world distance into a pixel-level distance (e.g., 466 pixels). Using the pinhole imaging model [11], we calculate this pixel distance, knowing the focal distance, the height of the camera, and the physical distance because the ratio of such distance to the focal distance should be equivalent to the height of the camera to the physical distance. Similarly, we calculate the pixel size for the added object. Finally, we inject the object with the calculated pixel size at the specified location.

2) **Integrating Pix2pixHD:** Pix2pixHD [40] is an image-to-image translation technique proposed by Nvidia for generating images from semantic label maps. Given a semantic label map of a driving scene image, Pix2pixHD can synthesize a new

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**Fig. 2:** Traffic law of safe distance and speed in NSW, Australia [17]

### The three second gap will change depending on your speed.

The following table shows the crash avoidance space needed for these speeds:

| Speed     | Crash avoidance space |
|-----------|-----------------------|
| 60 km/h   | 50 metres             |
| 80 km/h   | 67 metres             |
| 100 km/h  | 84 metres             |
| 110 km/h  | 92 metres             |

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driving scene image. Therefore, by modifying the semantic label map to have a vehicle label, Pix2pixHD can synthesize a new transformed image where a car is added. We integrated Pix2pixHD to support the transformation of adding a vehicle, bicycle, or pedestrian to a road image (i.e., Rules 3-5).

To add a pedestrian to a road image, RMT first extracts the semantic label maps of all road images in the data set and extracts the coordinates of all existing pedestrians. If the coordinates of an extracted pedestrian object do not collide with any semantic labels in the road image, RMT adds the pedestrian to the semantic label map of the image and generates a metamorphic test image that is identical to the original one except the new, injected pedestrian transplanted from another image. In Pix2pixHD, we use the same pinhole imaging model as in OpenCV to calculate the distance to inject an object.

3) Integrating UNIT and UGATIT: UNIT [25] is a technique for image-to-image translation using Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs). Specifically, UNIT can transfer an image from one domain to another such as changing a tiger to a lion and changing a real driving scene to a synthetic driving scene (e.g., artistic or cartoon style). RMT leverages UNIT to transform day-time driving scenes to night-time (in Rule 6). UGATIT is another GAN for image-to-image translation [22]. Compared with UNIT, UGATIT has better performance in generating high-fidelity driving scenes, which is used for day-to-night and sunny-to-rainy transformations in Rules 6 and 7.

4) Extending RMT to support more transformations: RMT can be extended to integrate other transformation engines. Using an XML configuration file, a user can bind a transformation engine with a new rule in the DSL and configure its storage directory, parameters, and execution command.

D. Filter and MR evaluator

To ensure high fidelity of transformed images, a filtering mechanism is implemented for each transformation engine to check whether the input image meets the prerequisites for the given transformation, e.g., there is a space in front of the main vehicle to add a vehicle. For Pix2pixHD, the built-in filter identifies whether an original image is feasible to add or remove the desired object in the corresponding location. If there is a conflict, the original image is not used to generate transformed images. When using OpenCV to add objects, original images containing conflict are also filtered out. For the change scene transformation, the built-in filter only considers input images without the target scene (e.g., rain, night) already.

When a transformation engine and its built-in filter are executed, a set of test case pairs \( (X_{N1}, X_{N2}) \) are constructed. The MR evaluator runs the driving model under test (M) on both images and checks the violations based on metamorphic relations, where a violation implies a potential erroneous behavior.

E. Prototype

To ease rule construction, we implemented a GUI for RMT as shown in Figure 3 and 5. A user can choose a transformation and its corresponding transformation engine, and configure parameters. The user configurations in the GUI are then translated to a traffic rule in the DSL.

Figure 3 demonstrates how domain expert can set Rule 7 using RMT. The user could set \( X_{N1} \) as the original image \( X_O \) and set \( X_{N2} \) by applying changeScene to transform the original image \( X_O \) to rainy scene. Then the user could type in the value for the MR’s higher-order function. When the button “Generate test” is clicked, \( x \) number of violations found out of \( y \) number of test cases will be displayed as the test result (Figure 4).

Figure 5 presents how domain expert can set Rule 9 using RMT. Separate transformations, either simple one or composite one (multiple simple ones but nested), can be applied on \( X_O \) to generate \( X_{N1} \) and \( X_{N2} \). Then the user can type in the required higher-order function for the underlying MR.

Domain experts can also inspect the original and transformed images generated by RMT, as shown in Figure 4. The prototype and more screenshots are available at https://github.com/JW9MjwnpdRLFw/RMT.
We use a violation ratio to quantify the capability of revealing erroneous predictions. We use the nine rules prescribed in Section II-B. To investigate the effectiveness of using higher-order relations (simple rules) and composite transformations (composite rules) deeper, we assess (1) how many erroneous predictions are found by higher-order metamorphic relations and (2) how many additional erroneous model predictions are found by enabling composite rules. We also quantify the generated test suite in terms of neuron boundary coverage [27], [30]. We are not necessarily arguing that neuron coverage measure is a legit way of assessing a generated test suite, but rather, given the emerging interest in designing neuron-network specific test criteria that resemble the notion of code coverage in traditional software testing, we simply report another metric to quantify RMT’s results.

| Rule   | Parameters                      |
|--------|---------------------------------|
| Rule 1 | $x: 50; [t_1, t_2]: [0, 60 km/h]$ |
| Rule 2 | sign: speed limit 30; $[t_1, t_2]: [0, 30 km/h]$ |
| Rule 3 | $x: 50; [t_1\% , t_2\% ]: [30\%, 40\% ]$ |
| Rule 4 | $x: 50; [t_1\% , t_2\% ]: [40\%, 50\% ]$ |
| Rule 5 | $x: 50; [t_1\% , t_2\% ]: [60\%, 70\% ]$ |
| Rule 6 | $[t_1\% , t_2\% ]: [0\%, 10\% ]$ |
| Rule 7 | $[t_1\% , t_2\% ]: [10\%, 20\% ]$ |
| Rule 8 | $x: 50; [t_1, t_2]: [0, 45 km/h]$ |
| Rule 9 | $x_1: 50, x_2: 30; [t_1, t_2]: [\infty, 0]$ |

RQ2 investigates whether a detected MR violation is considered as a traffic rule violation by humans. We emailed the graduate student mailing list in the CS department of a research university and recruited six students as human raters. Participants have five years of driving experience on average. Each participant was presented with a random sample of RMT’s results where speed prediction violates a metamorphic relation. They were given the original image, the transformed image, and corresponding speed predictions (km/h). Participants were then asked to assess whether the speed prediction on a transformed image seems a realistic traffic rule violation. Then they rated in a 7-point likert scale, where 1 means the speed prediction looks absolutely faulty, while 7 means not faulty. To ensure 95% confidence level with 5% confidence interval, we randomly sampled 147, 126, 168, 217, and 217 test case pairs for Rules 3 to 7. To conservatively assess the benefit of RMT, we did not include the results of (Rules 1, 2, 8, 9), because detected violations were unambiguously clear violations, as they directly encode unequivocal traffic laws that leave no doubt. Participants took on average 3 hours to inspect all the sampled images. Participants were compensated with $25/hr.

B. Evaluation Dataset

(1) Cityscapes [9]. It contains real-world driving road images with cruising speed labels. The dataset is used in several autonomous driving vision tasks. We experimented Rules 3-7 only, because the data is collected from the urban area and speed labels are in general lower than 45 km/h, thus the dataset is not suitable for applying Rule 1, 8. Also urban driving scenes are too crowded to add object both 30 and 50 meters in front of the main vehicle on the same source images as required by Rule 9, thus Rule 9 is not applied on Cityscapes neither. For each road image, Cityscapes provides a semantic label map for objects like vehicles and pedestrians. Because the data lacked sufficient semantic labels of traffic signs needed for Rule 2, we did not apply Rule 2. The semantic label map provided with the data was directly used to generate metamorphic test images for Rules 3, 4, and 5. We trained UNIT using 1000 day scenes from Cityscapes and 1000 night
TABLE II: Driving model implemented

| A2D2       | Cityscapes    |
|------------|---------------|
| Model      | MAE           | Model       | MAE    |
| Resnet101  | 1.2311        | Resnet101   | 2.257  |
| Epoch      | 2.1960        | Epoch       | 2.258  |
| Vgg16      | 2.1788        | Vgg16       | 2.22   |

TABLE III: Number of test cases used in each rule on Cityscapes

| Rule | R3 | R4 | R5 | R6 | R7 |
|------|----|----|----|----|----|
|      | 237| 186| 299| 500| 500|

TABLE IV: Number of test cases used in each rule on A2D2

| Rule | R1 | R2 | R3 | R4 | R5 | R6 | R7 | R8 | R9 |
|------|----|----|----|----|----|----|----|----|----|
|      | 1506| 1648| 1506| 1443| 1894| 2211| 2211| 1506| 1506|

We also trained the same three models on A2D2 with same network architectures as on CityScapes. The input images are cropped from the original size of 1902 x 1280 and then resized to 224 x 224. The MAEs of the three driving models were 1.2311, 2.1960, and 2.1788 respectively.

IV. Evaluation Results

Section [LV-A] presents how well our higher-order and composite rules reveal erroneous model predictions and Section [IV-B] presents how meaningful the revealed erroneous predictions are as rated by experienced human drivers. A sample of original road images and transformed images are shown in Figure 6.

A. RQ1: Erroneous Prediction Detection Capability

TABLE V: Simple rules: # violations (ratio %) on A2D2

| Rule  | Epoch | Vgg16 | Resnet101 |
|-------|-------|-------|-----------|
|       | 1413  | 1418  | 1424      |
|       | (93.82%) | (94.16%) | (94.55%) |
| Rule 2| 1598  | 1598  | 1596      |
|       | (96.97%) | (96.97%) | (96.84%) |
| Rule 3| 1503  | 1505  | 1505      |
|       | (99.80%) | (99.93%) | (99.93%) |
| Rule 4| 1443  | 1443  | 1443      |
|       | (100%) | (100%) | (100%)    |
| Rule 5| 1894  | 1894  | 1894      |
|       | (100%) | (100%) | (100%)    |
| Rule 6| 215   | 658   | 1221      |
|       | (9.72%) | (29.76%) | (55.22%) |
| Rule 7| 2210  | 2185  | 2199      |
|       | (99.95%) | (98.82%) | (99.45%) |

Table V shows the error detection ratio of the seven simple rules described in Section [II-B] on A2D2. Across all driving models, the average violation ratios are 94.17%, 96.93%, 99.89%, 100%, 100%, 31.57%, and 99.40% for Rules 1-7, respectively. The overall average violation ratio is 89%. Rules 1 and 2 are derived from real-world traffic rules and their violation ratios are from 93% to 97% in three driving models. Rules 3, 4, 5 and 7 achieve near 100% violation ratios. These results substantiate that higher order MRs indeed help generate new test cases that detect erroneous predictions. The exception was Rule 6 that transforms day scenes to night scenes. It seems all driving models are more robust towards night scene change compared to other changes. The deceleration range is set relatively low (0-10%) as well, but we think it is reasonable as proved in our user study.

TABLE VI: Simple rules: # violations (ratio %) on Cityscapes

| Rule | Epoch | Vgg16 | Resnet101 |
|------|-------|-------|-----------|
| Rule 3| 197   | 207   | 217       |
|       | (83.12%) | (83.43%) | (91.56%) |
| Rule 4| 146   | 146   | 156       |
|       | (78.49%) | (78.49%) | (83.87%) |
| Rule 5| 500   | 500   | 490       |
|       | (100%) | (95.2%) | (98%)     |
| Rule 6| 490   | 490   | 483       |
|       | (98.0%) | (98.0%) | (96.6%)   |

Table VI shows the results of Rules 3-7 on detecting erroneous predictions on Cityscapes. For the Epoch model, the violation ratios can be as high as 100% and the lowest is 78% for Rule 4. For other two models, violation ratios for all five rules vary from 83% to 98%.
Result 1: Higher-order metamorphic relations are effective in detecting erroneous model predictions and this capability can be consistently observed across different datasets.

**TABLE VII: Composite rules: # violation (ratio %) on A2D2**

| Rule  | Epoch | VGG16     | Resnet101 |
|-------|-------|-----------|-----------|
| Rule 8 | 1467 (97.41%) | 1459 (96.88%) | 1463 (97.14%) |
| Rule 9 | 274 (18.19%) | 37 (2.47%) | 460 (30.55%) |

Table VII presents the result of composite rules on detecting erroneous predictions on A2D2. **Rule 8** describes a more complex version of **Rule 1** and it finds additional 1467, 1459, and 1463 violations on the three models, respectively. Compared to **Rule 1**, **Rule 8** achieves higher violation ratios, 3.6% more on Epoch, 2.7% more on VGG16, and 2.6% more on Resnet101. While this improvement seems small, the results show that the composite rule could indeed find additional bugs reliably by generating complex, meaningful scenarios. **Rule 9** tests a traffic rule that, when the vehicle in the front is closer, the speed deceleration should be proportionally larger. We are not necessarily arguing that the more images are generated, the better a testing technique is. While the number of detected violations is not as high as that for **Rule 8**, it is essential that these synthesized images involve composition of multiple traffic laws, and errors involving such scenarios are hard to detect. RMT automates synthesizing such images by enabling composite rules.

Result 2: Composite rules can detect additional errors by synthesizing more complex yet realistic driving scenarios.

Table VIII shows the results of neuron boundary coverage (NBC) [27] of the original test suite, the original augmented with simple rules (**Rules 1-7**), and the original augmented with both simple and composite rules (**Rules 1-9**). For the original set, NBC is 0.16%, 1.65%, and 3.38% respectively for the three models. With simple rules, NBC increases impressively on all of three models, achieving 18.49%, 9.70%, and 38.28% respectively. This means that generated test cases contain a large number of corner cases that do not overlap with the previous suite in terms of neuron activation. With composite rules, NBC increases slightly for the three models. Though recent work has shown that neuron coverage based metric may not be adequate for DNN [18], we indeed observe that NBC values are amplified, when the test suite is augmented using higher order and composite metamorphic relations.

**TABLE VIII: Neuron boundary coverage comparison**

|                | Epoch | VGG16 | Resnet101 |
|----------------|-------|-------|-----------|
| Original test set | 0.16% | 1.65% | 3.38%     |
| Original + SRs   | 18.49%| 9.70% | 38.28%    |
| Original + SRs + CRs | 18.91% | 10.72% | 39.42%    |

Result 3: Both higher-order relations and composite rules help diversify neuron activation behavior.

**B. RQ2: Qualitative Analysis**

Figure 7 shows the scores given by the six human raters about to what extent a faulty speed prediction detected by RMT looks like a real violation of traffic rules to them. 1 means a detected fault is indeed a real violation, while 7 means the detected fault is absolutely not a violation. Despite individual differences across six participants, the majority of faulty predictions are deemed as real traffic rule violations with an average rating of 2.7. The ratings are consistent across all three models and all five metamorphic relations (corresponding to **Rules 3-7**). The average rating for Epoch, VGG16, and
ResNet is 2.7, 2.7, 2.8 respectively. The average of rating of the five MRs is 2.9, 2.2, 2.3, 3.0, and 2.6 respectively. The number of 1s is 2691 out of 15750.

Participants made the assessment at their own discretion, e.g., based on their own driving experience and their understanding of traffic rules and driving scenes. For example, P1’s ratings are mostly between 1 and 3, while P5’s ratings are mostly between 4 to 6. We use Fleiss Kappa score to measure the agreement among raters. The score is 0.279, which means fairly in agreement. Since the user study is conducted with participants from different countries and with different personalities, such difference is expected. The difference in agreement indeed points out that traffic rules need to be customized (e.g., speeding violation in California and Autobahn are different). RMT allows a domain expert to experiment with rule customization, which highlights RMT’s strengths in terms of expressivity, customization, and pluggability.

Result 4: Most erroneous predictions revealed by RMT are considered to be realistic traffic violations by human subjects.

C. Threats to Validity

RMT currently plugs-in OpenCV, UNIT, UGATIT, and Pix2pixHD. RMT as its image transformation engines. With more datasets to train GANS or with a more powerful GAN, we can replace or extend the current engines to achieve better results. For example, Pix2pixHD used for Rules 3-5 could only add, move, or delete existing items (one of the instances in the semantic label maps) based on semantic label maps without the capabilities of adding new items. This restriction can be removed by finding a more powerful alternative for the transformation engine. We chose Cityscapes as our dataset because it has built-in semantic label map for each road image. A highly accurate semantic label map is essential for Pix2pixHD we used for Rule 3-5 to generate a truthful road image. We do not implement all rules on Cityscapes due to limitations of the data described in Section III. We find another more comprehensive dataset A2D2 and implement all rules to evaluate RMT.

RMT is not just an integration of better and more transformation engines. We design a principled approach to allow experts to declaratively specify higher-order and composite metamorphic rules. Prior work such as DeepRoad [45] and DeepTest [26] hardcodes equality-based metamorphic rules, which can also be expressed by the rule template in RMT. The traffic rules and metamorphic relations in this work are all inequality-based, which does not constitute a head-to-head comparison with the rules in DeepRoad and DeepTest. Furthermore, DeepTest and DeepRoad focus on steering angle prediction rather than speed prediction. Compared with speed, there are less specifications about steering angles in traffic law. This is why we choose to focus on speed prediction instead of steer angle prediction in this work. Instead of directly comparing against DeepRoad and DeepTest, we choose to conduct a careful experimentation to assess the power afforded by RMT’s expressivity, as discussed in Section III.

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 behaviour. In other words, a detected fault could be a “suspicious” one. We used the qualitative user study to mitigate this validity issue. Out of 7-point likert scale, participants consider a detected MR violation to be highly likely to reflect a real-world traffic violation.

V. RELATED WORK

Testing and verification of deep learning models. The quality of a deep learning model is typically evaluated based on its prediction accuracy by checking the model against a test dataset. However, the common metrics used for testing (e.g., MAE and MSE) are not good enough to provide safety-guarantee for mission-critical systems. Recently, various testing techniques on deep learning models have been proposed in the software engineering community. Pei et al. [30] developed a white-box testing framework called DeepXplore, which uses neuron coverage metric to evaluate deep learning systems. Based on this metric, DeepXplore leverages multiple DNNs with similar functionality to automatically select test inputs that are able to cause incorrect behaviors. Lei et al. [28] proposed DeepMutation, a framework for measuring the quality of the test data set based on mutation testing. More
recently, a tool called DeepConcolic [35] was developed to implement concolic testing on DNNs, which is able to generate adversarial examples for safety-critical systems. Based on the detection of DNN’s inner states, DeepGauge [27] performs multi-granularity testing for deep learning systems, which could be adapted to fit complex DNN models.

There are also a large body of verification techniques for deep learning models. Pulina et al. [31] proposed an abstraction-refinement approach to examine the safety of a neurons network. Moreover, an SMT solver, namely Reluplex [21], was proposed to verify the robustness of DNNs with ReLU activation function. Based on Reluplex, DeepSafe [16] was developed to identify safe regions where the neural network is able to defend against adversarial examples. Huang et al. [20] proposed a framework to find adversarial examples using SMT and exhaustive search.

Compared with the above testing and verification techniques, our main focus is to provide a generic yet easy-to-use testing framework for DNN-based autonomous driving. We investigated a variety of traffic regulations written by federal and state authorities and converted them into intuitive MRs, which in turn generate follow-up test sets to detect subtle faults inside autonomous driving models. Compared with traditional program analysis, deep learning-based autonomous driving models cannot explain their behaviors and thus cause concerns on reliability and interpretability. Using metamorphic testing, deep learning based driving models can be tested on whether they are robust against input changes by detecting those important features which might not be obvious. For example, when a vehicle appears in the front of the main vehicle, the closer it is to the vehicle, the slower the speed should be. By exploring such distance-speed relation, we can test whether the driving model is robust to such input changes reflected from real-world rules.

**Testing in autonomous driving systems.** Wicker et al. [41] proposed a black-box approach that can be applied to evaluate the robustness of DNN-based autonomous driving, especially against adversarial examples. DeepTest [37] and Deep-Road [45] were proposed to test autonomous driving models for steering angle predictions using equality metamorphic relations. Zhou et al. [50] proposed DeepBillboard to generate adversarial billboards to construct real-world adversarial images. Those adversarial images could be used to test the robustness of autonomous driving models for adversarial examples [15]. Dreossi et al. [12] proposed an image generation tool to detect the blind corner in the autonomous driving scenario. This tool generates synthetic images by adding a car into the original image, which is similar to one of our rules but the texture and the light and shadow effect of generated images are not realistic as ours. Their task focused on object classification and detection, which is different from our focus on metamorphic testing. Uesato et al. [39] proposed an adversarial evaluation method based on the estimation of rare event probability to detect potential failures for reinforce learning-based models. The test on TORCS simulator shows that this method is reliable and efficient. Zhou et al. [51] tested the LiDAR module, used for obstacle detection task in the real-life autonomous driving cars, leveraging fuzzing test and MT.

Compared with these studies, RMT focuses on expressivity, pluggability, and customization to enhance the current capability of metamorphic testing in autonomous driving by enabling easy encoding of real-world traffic rules. The aforementioned studies are complementary to ours in that their goal is to improve the robustness of driving models. Some of these could be integrated into RMT as new traffic rules and different underlying transformation engines (e.g., defining adversarial noise as one specific kind of MR for [41], [50]).

**VI. Conclusion**

Though AI and ML show much promise in enabling the next generation of intelligent software systems, lack of test oracles make it difficult to fully unleash automated testing potentials. It is costly to define ground truth data sets apriori and it is also unreasonable to expect that domain experts check test outcomes individually in a post-hoc manner. Though the idea of metamorphic testing has existed for a while, currently, there are no easy means to map real-world traffic regulations to executable metamorphic relations.

To our knowledge, RMT is the first to enable experts to specify custom traffic rules and in turn automatically derive metamorphic relations to test autonomous driving models. More expressive higher-order relations and composite scenes can be explored to reveal more unexpected behavior of deep learning models under test. Moreover, the rule template in RMT can be extended from metamorphic testing pairs to metamorphic testing tuples with more than two test inputs. Since RMT already allows customized transformation on each test input, we can allow customized transformation on more than two test inputs. Hence more complex metamorphic relations reflecting real-world traffic rules can be evaluated. For instance, we can evaluate the decreasing speed metamorphic relation for the testing tuple—adding a car, a bicycle, a pedestrian 50 meters in front of the main vehicle. In general, the main vehicle should decelerate to a greater extent when a bicyclist appears in front compared to another vehicle appearing in front, since a bicyclist moves slower than a vehicle. And the main vehicle may have to even make a full stop when a pedestrian appears in front. With metamorphic testing tuples, this scenario can be written as the following rule:

| MR: | $X_{N1} = inject(X_O, \text{[vehicle, 50]})$ |
|-----|---------------------------------------------|
|     | $X_{N2} = inject(X_O, \text{[bicycle, 50]})$ |
|     | $X_{N3} = inject(X_O, \text{[pedestrian, 50]})$ |
|     | $\Rightarrow M(X_{N1}) < M(X_{N2}) < M(X_{N3})$ |

This expressiveness and customization is unparalleled compared to the state-of-the-art in MT testing in general where metamorphic relation can be only used for testing pairs. RMT should generalize to a wider range of deep learning models.
(e.g., models trained on time series data), as its extensible framework allows easy addition of new metamorphic relations and new transformation engines. Per open science policy, we have made code and data for this submission available at https://github.com/JW9MsjwjnpdRfW/RMT

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