Safety Analysis of Autonomous Driving Systems Based on Model Learning

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Abstract—We present a practical verification method for safety analysis of the autonomous driving system (ADS). The main idea is to build a surrogate model that quantitatively depicts the behaviour of an ADS in the specified traffic scenario. The safety properties proved in the resulting surrogate model apply to the original ADS with a probabilistic guarantee. Furthermore, we explore the safe and unsafe parameter space of the traffic scenario for driving hazards. We demonstrate the utility of the proposed approach by evaluating safety properties on the state-of-the-art ADS in literature, with a variety of simulated traffic scenarios.

Index Terms—autonomous driving, verification, AI safety

I. INTRODUCTION

Autonomous driving systems (ADS) are expected to bring forth an efficient and safe road traffic. With the great success of artificial intelligence (AI), such autonomous driving systems are designed and equipped with various components, taking various sensor inputs and performing perception and prediction tasks. Thus, the safety guarantee of such AI enabled autonomous driving systems is a key challenge.

In order to test autonomous vehicles in real-world scenarios, tremendous resources are required to build scenes and simulate real traffic, so it is unacceptable to thoroughly test an ADS in the real world. The development of driving simulators such as CARLA [1] and BeamNG [2] dramatically reduces the testing cost by introducing a virtual simulated environment. Based on the simulator, a variety of testing approaches have been developed to generating test cases and analysing different traffic scenes [3]. However, even that many unsafe testing cases have been found by these approaches, such testing approaches provide almost no safety guarantee to the ADS.

Search-based testing approaches [4]–[11] try to find the parameters that make the ADS misbehave in the corresponding testing scenarios. These approaches often use a fitness function, e.g. time-to-collision [12], to guide the search process. In our work, we adopt this idea of fitness functions to specify safety properties. At the same time, inspired by the previous work on linear model learning from a deep neural network [13], we propose an algorithm to learn a fully connected neural network (FNN) model to approximating the fitness function. Different from testing based approaches, the learned FNN can be proven to be probably approximately correct (PAC), which cannot be achieved by prior ADS testing methods.

In this paper, we focus on the formal verification for the safety properties of the ADS. In contrast to testing, formal verification aims to give a mathematical proof to a given property of the system with the system formally modeled and the property formally specified. An ADS can be modeled as a neural network controlled system (NNCS). The safety verification of NNCS based on reachability analysis has been studied in previous works using activation function reduction [14], abstract interpretation [15] and function approximation [16]–[20]. These white-box methods over-approximate the behaviour of neural networks using Tyler model arithmetic or abstract interpretation, and are too inefficient for large systems like ADS. Unlike the reachability analysis, our approach gives quantified certificate of safety properties instead, in much more efficient way and a black-box manner that is more general.

In particular, in our work we verify the safety property of a given ADS, under various traffic scenarios, with a probabilistic guarantee. For example, with 99.9% confidence, the ADS is collision-free with probability at least 99% in the emergency braking scenario. A traffic scenario can comprise parameters such as vehicle velocity, weather, etc. We are interested in whether the ADS can navigate safely in the traffic scenario with a wide range of parameters.

The idea behind our approach is to learn a surrogate model that approximates the fitness function of the original ADS with a measurable difference gap. If the surrogate model is proved to be safe in a traffic scenario, we can then derive a probabilistic guarantee on the safety property for the ADS in the same scenario. If the surrogate model fails to meet the safety property, we further explore its parameter space, by dividing whole space into cells according to specified parameters and analysing the quantified level of safety in each of these cells. Therefore, our verification framework is quantitative in the formal specification of safety properties, the learned surrogate model with its probabilistic guarantee, and the further analysis of safe/unsafe regions.

In summary, the contributions in this paper are at least three fold.

• We propose a practical verification framework for the
scenario specific safety of an autonomous driving system with probabilistic guarantee, based on surrogate model learning.

- When the verification fails, we can further conduct a quantitative analysis on the parameters of interest, and partition the parameter space into safe and potentially unsafe regions for the surrogate model. The analysis results are essential for improving the ADS.
- We apply the developed verification approach and parameter space exploration method to the state-of-the-art ADS with five traffic scenarios in CARLA. The results confirm that the learning-based verification is a promising future direction for ADS.

II. BACKGROUND

A. Autonomous driving systems

An autonomous driving system is designed to assist or even replace the human drivers in real traffic. By the degree of automation, ADS can be categorized into six levels, i.e., from L0 to L5. The desired L5 ADS can perform all actions required for all possible traffic scenarios without any help or human interactions. A modern ADS receives the data from various sensors and generates the control signals using underlying models. A typical ADS we study has an architecture consisting of sensors, perception module, prediction module, planning module, and control module.

The autonomy of a vehicle must not compromise the on-road safety. In Table I there are examples of requirements for guaranteeing that an ADS navigates safely under different traffic scenarios, in which we mainly focus on the collision free property in this paper.

| Safety Properties  | Description                                                                 |
|--------------------|-----------------------------------------------------------------------------|
| Collision Free     | The most critical requirement for ADS is not to collide with other vehicles, etc. This property evaluates the general safety of an ADS by judging whether a collision is occurred. |
| Route Completion   | The functionality of an ADS can be measured with its ability to navigate and control the vehicle moving from one location to another. This property is designed to guarantee the percentage of the route completed by a vehicle with ADS. |
| Traffic Lights     | Running the red light is one of the typical traffic misbehaviour. This property monitors whether the developed ADS can detect and follow the traffic lights correctly under diverse conditions. |
| Vehicle Speed      | There can be speed limits for different roads. This property requires the autonomous vehicle keep its speed in a reasonable range. |
| Lane Keeping       | To maintain the stability of an autonomous driving system, the car should always drive in traffic lanes as long as there is no overtaking or lane changing actions in progress. The ADS fails this property if the car ran over the lane where it should follow. |

![Fig. 1. The simulator $\mathcal{E}$ iteratively generates the next state.](image)

![Fig. 2. In this scenario, the ego vehicle drives along the road while the leading NPC vehicle brakes. Parameters are NPC agent speed $\theta_1$, the deceleration $\theta_2$, and the distance $\theta_3$ between two vehicles. The behaviour model of the ego vehicle is its ADS, and the behaviour model $\psi_{\text{NPC}}$ decelerates the NPC. A function $\omega$ measures the distance between the ego vehicle and the leading NPC. The safety property is to guarantee the safe distance of $\tau = 0.1(m)$ between two vehicles.](image)

B. CARLA & Scenario Runner

We use the high-fidelity simulator CARLA to generate the traffic scenarios. CARLA is based on Unreal Engine 4, and it supports the real-time simulation of sensors, dynamic physics and traffic environments. It also provides an extensive library of traffic blueprints including pedestrians, vehicles and street signs, etc. Many modern autonomous driving systems, e.g., Transfuser [21] and LAV [22], are developed with the CARLA simulator.

In this paper, the Scenario Runner is used to build common traffic scenarios in the simulator. Scenario Runner is a tool provided by CARLA to build traffic scenarios. The logic of a scenario is encoded into a behaviour tree, which is composed of non-leaf control nodes (Select, Sequence and Parallel) and leaf nodes (behaviours). A scenario is then executed following the state of its behaviour tree.

III. SCENARIO DRIVEN SAFETY VERIFICATION

In this section, we first formalize the autonomous driving scenario (Section III-A). Then, we introduce a model learning based verification approach in Section III-B. When the verification cannot conclude the safety property, in Section III-C techniques are also proposed to partition the parameter space into safe/unsafe regions.

A. Formalism of the autonomous driving scenario

An autonomous driving scenario comprises an autonomous driving agent ego and other agents NPC_1, NPC_2, \ldots in the
(simulator) environment. Denote by $\Theta = [0, 1]^m$ the set of the parameter vector $\theta = (\theta_1, \ldots, \theta_m)$, where each $\theta_i$ is a normalized parameter variable of the scenario.

We use $\mathcal{S}$ to denote the set of states. A state $s_t \in \mathcal{S}$ describes the status of all agents in the virtual world at step $t$, including locations, speeds, accelerations, etc. The behaviour of ego and NPC$_i$ is modeled by the function $\psi_{\text{ego}}(s_t)$ and $\psi_{\text{NPC}_i}(s_t)$, which generate the action $a_{\text{ego},t}$ and $a_{\text{NPC}_i,t}$ at step $t$, respectively.

The simulator $\mathcal{E}$ generates the next state $s_{t+1}$ according to the ego action $a_{\text{ego},t}$, the NPC actions $a_{\text{NPC}_i,t}$, and the current state $s_t$ (see Figure 1). A simulation is a sequence of states $s_0, s_1, \ldots, s_{t\perp}$ generated by simulator $\mathcal{E}$, where $s_0$ is the initial state and $s_{t\perp}$ is the final state satisfying some terminating conditions. Note that the initial state $s_0$ and the behaviour functions $\psi_{\text{ego}}$ and $\psi_{\text{NPC}_i}$ are all instantiated and fixed by the parameter $\theta$. Therefore, the state sequence $s_0, s_1, \ldots, s_{t\perp}$ is uniquely determined by the parameter $\theta$. Namely, each state $s_t$ at step $t$ can be considered as a function $s_t(\theta)$.

Safety properties: We are interested in the safety requirement of critical scenarios. In traffic scenarios, many safety properties can be described as a physical quantity (such as velocity, distance, angle, etc) always satisfying a certain threshold during the entire driving process. In autonomous driving scenarios, we define a function $\omega$ to measure such physical quantity at a given state, and the safety properties can be defined as follows.

Definition 1 (Safety Property): For a given parameter $\theta \in \Theta$, a quantitative measure $\omega: \mathcal{S} \to \mathbb{R}$ and a threshold $\tau \in \mathbb{R}$, the state sequence $s_0, s_1, \ldots, s_{t\perp}$ is safe if:

$$\forall t \in \{0, 1, \ldots, t\perp\} \omega(s_t(\theta)) \geq \tau.$$  \hspace{1cm} (1)

For simplicity, we introduce a fitness function $\rho(\theta) = \min_{0 \leq t \leq t\perp} \omega(s_t(\theta))$, and the property can be equivalently rewritten as $\rho(\theta) \geq \tau$. For instance, we can use the distance between two vehicles as the quantitative measure $\omega$, and the collision free property requires that the distance is no smaller than a safe threshold $\tau > 0$.

The example in Figure 2 maps these notations above to a driving scenario. The question then is how to verify that an ADS meets the safe requirement in Equation (1), as a scenario can be initialised with all possible parameter values.

B. Surrogate model based verification

In general, it is intractable to check the safety property since the fitness function $\rho(\theta)$ depends on the behaviour models and the simulator, which cannot be expressed by explicit functions. Moreover, the simulator and the ADS often act in a black-box manner, which will further complicate the analysis. For verification purpose, we use a surrogate model $f$ (FNN with ReLU activate function in this paper) to approximate the original fitness function. An illustrative example is in Figure 3 for assisting the following discussion.

Solving the absolute distance $\lambda$ between the surrogate model $f$ and the original fitness function $\rho$ can be encoded into an optimization problem:

$$\min_{\lambda \in \mathbb{R}} \lambda$$

$$s.t. \|f(\theta) - \rho(\theta)\| \leq \lambda, \forall \theta \in \Theta$$  \hspace{1cm} (2)

Based on the scenario optimization technique [23], we reduce the infinite parameter set $\Theta$ to a finite subset $\Theta_{\text{sample}}$ containing $K$ samples.

$$\min_{\lambda \in \mathbb{R}} \lambda$$

$$s.t. \|f(\theta) - \rho(\theta)\| \leq \lambda, \forall \theta \in \Theta_{\text{sample}}$$  \hspace{1cm} (3)

As a result, the absolute distance given by Equation (3) can be guaranteed with an error rate $\epsilon$ and a significance level $\eta$ according to the following lemma.

Lemma 1 (see [23]): If (3) is feasible and has a unique optimal solution $\lambda^*$, and

$$\epsilon \geq \frac{2}{K} \left(\ln \frac{1}{\eta} + 1\right),$$  \hspace{1cm} (4)

where $\epsilon$ and $\eta$ are the pre-defined error rate and the significance level, respectively, then with confidence at least $1 - \eta$, the optimal $\lambda^*$ satisfies all the constraints in $\Theta$ but only at most a fraction of probability measure $\epsilon$, i.e., $\mathbb{P}(\|f(\theta) - \rho(\theta)\| > \lambda^*) \leq \epsilon$.

a) Neural network verification: After we have the absolute distance evaluation $\lambda^*$, one can use existing neural network verification tools like DeepPoly [24] and MILP [25] to determine whether

$$f(\theta) - \lambda^* \geq \tau, \forall \theta \in \Theta$$  \hspace{1cm} (5)

where $f(\theta) - \lambda^*$ serves as a probabilistic lower bound of the original model’s fitness function $\rho$, and we remind that $\tau$ is the threshold for safety requirements. Finally, when Equation (5) holds, the verification returns SAFE, and we can conclude that the autonomous driving system satisfies the safety property with error rate $\epsilon$ and significance level $\eta$:

$$\mathbb{P}(\rho(\theta) \geq \tau) \geq \mathbb{P}(\rho(\theta) \geq f(\theta) - \lambda^*)$$

$$\geq \mathbb{P}(\|f(\theta) - \rho(\theta)\| \leq \lambda^*) \geq 1 - \epsilon.$$  \hspace{1cm} (6)

In summary, by given enough samples $\Theta_{\text{sample}}$, the verification results on a learned surrogate model $f$ can be transferred to the original fitness function $\rho$ with guarantee.

b) Surrogate model learning: As mentioned above, we adopt model learning to approximate, with the guarantee in Lemma 1 the original fitness function. Here, we present our learning procedure depicted in Algorithm 1. The major part of the algorithm is a while loop, in which the surrogate model is trained iteratively with the parameter set $\Theta$ (and the corresponding simulation outcome). After each iteration of training, the absolute distance evaluation $\lambda^*$ is calculated (in Line 5), and the learning procedure terminates when $\lambda^*$ is small enough. Otherwise, the model is not sufficiently trained, and new parameters will be added into the parameter set (see Line 9–11) for the next training step. In addition to
Algorithm 1: Surrogate Model Learning

**INPUT:** A driving scenario, error rate $\epsilon$, significance level $\eta$

**OUTPUT:** Surrogate model $f$, Absolute distance $\lambda^*$

1: initialise a surrogate model $f$
2: sample a parameter set $\Theta \subset \Theta$
3: while the time threshold is not met do
4: \hspace{1em} train $f$ with all $\theta \in \Theta$ and $\rho(\theta)$.
5: \hspace{1em} $\lambda^*$ ← the solution of the optimization problem (3)
6: \hspace{1em} if $\lambda^*$ is small enough then
7: \hspace{2em} break
8: \hspace{1em} else
9: \hspace{2em} incrementally sample the parameters $\Theta_{inc} \subset \Theta$
10: \hspace{2em} generate the extreme parameters $\Theta_{ex} \subset \Theta$
11: \hspace{2em} $\Theta \leftarrow \Theta \cup \Theta_{inc} \cup \Theta_{ex}$
12: \hspace{1em} end if
13: end while
14: return $f$, $\lambda^*$

The incrementally sampled parameters $\Theta_{inc}$, we further derive the extreme parameters (denoted by $\Theta_{ex}$) that potentially deviate far from the fitness function at current step, where the surrogate model has minimum and maximum outputs. These parameter samples can be generated by using the attack algorithms (such as PGD [26]) with maximization and minimization directions. Finally, the surrogate model is obtained, as well as the distance $\lambda^*$ from the fitness function guaranteed with the error rate $\epsilon$ and the significance level $\eta$.

C. Parameter space exploration

However, since autonomous driving systems are complex combinations of many components and algorithms, it is hard for them to stay safe in the whole parameter space. When the verification does not return SAFE, it is meaningful to further analyse the relationship between the unsafe behaviour and the parameters, which will provide an important reference for improving the system. Thus, based on the parameters we care about, which we called associated parameters, we divide the parameter space into cells, and in a quantitative way, an indicator $\varrho \in [0, +\infty]$ can be computed to express how unsafe the model is within each cell.

Based on two associated parameters, saying $\theta_1$ and $\theta_2$, we can split the two-dimensional parameter space into a $l$-by-$l$ grid where each square has the same length $\delta = 1/l$. Namely, the whole parameter space is divided into $l^2$ cells as $\Theta = \bigcup_{i,j=0,\ldots,l-1} \Theta_{i,j}$ where

$$\Theta_{i,j} = [i\delta, (i+1)\delta] \times [j\delta, (j+1)\delta] \times [0, 1]^{m-2}.$$  

Then, for the cell $\Theta_{i,j}$, we can define the quantitative unsafe indicator $\varrho_{i,j}$ as its minimal value satisfying

$$\forall \theta \in \Theta_{i,j} \quad f(\theta) \geq \tau - \varrho_{i,j}.$$  

Note that the quantified formula can be encoded by linear constraints, so we can compute $\varrho_{i,j}$ by MILP. Intuitively, each $\tau - \varrho_{i,j}$ indicates the maximal threshold such that the surrogate model is safe with all $\theta \in \Theta_{i,j}$. So, the region

$$\Theta_{safe} = \bigcup_{\varrho_{i,j} = 0} \Theta_{i,j}$$

is exactly an under-approximation of the parameter region that the surrogate is safe, and a larger $\varrho_{i,j}$ implies that the ADS is more prone to unsafe behaviour in such scenario within the corresponding parameter region. In this work, we focus on the analysis for two associated parameters since the results can be easily visualised by heat map, but it is straightforward to generalise this analysis to more associated parameters.

IV. EXPERIMENTS

In this section, we apply the proposed verification in Section III together with the state-of-the-art autonomous driving system LA V [22] The safety requirement is to assure a safe road distance between the ego agent and the NPCs in various scenarios.

**Setup:** Five traffic scenarios in Figure 2 and Figure 4 are considered. There are two variants for each scenario at different locations, labelled with “Case #1” and “Case #2”. Besides similar parameters as detailed in Figure 2, there are also 8 weather parameters in each scenario, including cloudiness, fog density, precipitation, precipitation deposits, sun altitude angle, sun azimuth angle, wetness and wind intensity. Furthermore, an additional parameter is introduced to control the initial distance between the ego vehicle and the NPC vehicle. The minimal safe distance between agents is $\tau = 0.1$ for all the scenarios.

The surrogate model is a 3-layer FNN with 100 neurons in each hidden layer. The error rate $\epsilon$ and the significance level $\eta$ of the surrogate model are 0.01 and 0.001 respectively. The number of the initial learning samples is 900, and we train the surrogate model in 10 iterations of refinement by

1 LA V is ranked the 3rd place in the CARLA Leaderboard but the first two systems are not publicly available before submission.
increasing 40 random samples and 10 extreme samples after each iteration. All the experiments are conducted on a server with AMD EYP 7543 CPU, 128G RAM and 4 Nvidia RTX 3090.

### A. Discovery of ADS glitch

Before the verification, our framework can help discover functional glitches for the LAV autonomous driving system. We find that sometimes the absolute distance evaluation $\lambda^*$ between the surrogate model $f$ and the fitness function $\rho$ is very large, for instance in the Follow Pedestrian scenario and Through Redlight scenario. Such unusual $\lambda^*$ is an indication of an abnormal ADS behaviour. By outlier detection and checking the corresponding simulation records, we identify 1 and 26 abnormal cases in 3000 runs for the two scenarios, respectively. These cases expose a functional glitch of the LAV system: the ego car can randomly halt in the middle of the road for no reason, resulting in an extremely large distance.

To eliminate the influence of the glitch, we have to discard the abnormal cases. After the surrogate models are retrained, the absolute distance $\lambda^*$ is reduced sharply from 13.4346 to 0.7087 in the Follow Pedestrian scenario, and from 12.0283 to 2.6678 in the Through Redlight scenario.

### B. Safety verification

We first verify whether the ADS can always keep a safe distance in the studied scenarios. The results are reported in Table II. The safe distance threshold $\tau$ is set to 0.1 for all scenarios. The verification concludes that one emergency braking scenario and two Follow Pedestrian scenarios (out of ten) are safe.

While the results in Table II indicate that certain scenarios (e.g., when NPCs are in front of the ego vehicle) are more safe than the others (e.g., when NPCs intrude from the sides), it is not surprising that there exist road hazards that result in safety violation in the verification, given the rich parameter conditions. This fact confirms the importance of the parameter space exploration phase.

### C. ADS behaviour analysis

In our approach, parameter space exploration is conducted (see Sect. III-C) to analyse the behaviour of LAV, following driving hazards identified via the verification. For two associated parameters, we divide the range $[0, 1]$ evenly into 20 intervals, and the quantitative indicator $\rho_{i,j}$ for all parameter cells can be calculated. Here, we analyse a) the cut-in scenario #1 with three different parameters and b) the Pedestrian Crossing scenario in two different cases with the same parameters.

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**TABLE II**

| Scenario               | Case | $\lambda^*$ | Counter-example |
|------------------------|------|-------------|----------------|
| Emergency Braking      | #1   | 6.8699      |                 |
|                        | #2   | 5.4194      | ✓              |
| Follow Pedestrain      | #1   | 0.7087      | ✓              |
|                        | #2   | 4.2193      | ✓              |
| Through Redlight       | #1   | 4.6885      | -5.8308        |
|                        | #2   | 2.9944      | -5.0789        |
| Pedestrian Crossing    | #1   | 2.6678      | -0.5953        |
|                        | #2   | 2.8866      | -1.7328        |
| Cut-in with Obstacle   | #1   | 0.4004      | -0.5991        |
|                        | #2   | 0.8790      | 0.0772         |

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**Fig. 5.** By heatmap, the results of parameter space exploration is illustrated for the cut-in scenario #1. The grid marked with darker color implies the ADS is more likely to violate the safety property with the parameters in it.
Fig. 6. Parameter space exploration is applied on the pedestrian crossing scenarios. The heatmaps show obviously different characteristics for Case #1 (with a cyclist) and Case #2 (with a walking pedestrian).

a) For the cut-in scenario #1, we focus on three associated parameters—initial distance, trigger distance, and NPC velocity. The analysis result is illustrated in Figure 5. From the left most figure and the middle figure, it is clear that the ADS is more likely to keep the safe distance of the ego vehicle when the NPC velocity is high and the initial distance and trigger distance are large enough. This is reasonable as a faster NPC car and a longer distance leave more room for the ADS to overtake and make a braking response to avoid collision.

Interestingly, the unsafe indicator values are much larger in the right most figure, and it means that by the two distance parameters alone, the initial distance and the trigger distance, it is unable to reach a safe condition. In other words, the proper NPC velocity parameter value is required for any safe traffic scenario.

b) Here, we report the quantitative unsafe indicator for two Pedestrian Crossing cases regards the NPC velocity and trigger distance in Figure 6. In the Pedestrian Crossing scenario #1, we spawn a cyclist instead of a walking pedestrian, and the trigger distance is larger. It needs to be mentioned that the cyclist is faster (2-3 m/s) than the walking pedestrian (1-2 m/s).

From Figure 6, we can conclude that larger NPC velocity and larger trigger distance make both scenarios safer for the ADS. Besides, the smaller unsafe indicator values also imply that the scenario #1 are even safer than the scenario #2. These meet the intuition that larger velocity and longer trigger distance make both scenarios safer for the cyclist are faster (2-3 m/s) than the walking pedestrian (1-2 m/s).

V. CONCLUSION AND FUTURE WORK

In this paper, we propose a novel approach to verify the safety property of a given ADS with a probabilistic guarantee. The safety property is quantified by a fitness function with scenario parameters. A surrogate model is learned for approximating this fitness function under the traffic scenario, and the safety property verified in the surrogate model can be transferred to the original ADS with specified confidence and error rate. When the verification fails, the parameter space is partitioned into safe and unsafe regions with quantitative indicators. This parameter space exploration further helps the testing and improvement of autonomous driving under different scenarios. The experiments validate the utility of our approach with promising results and vivid examples.

As for future work, we believe that the verification driven surrogate model learning will be an important direction for AI safety and security in general. We are also interested in applying the parameter analysis in this work to the “design space exploration” of autonomous driving systems.

REFERENCES

[1] A. Dosovitskiy, G. Ros, F. Codevilla, A. Lopez, and V. Koltun, ”CARLA: An open urban driving simulator,” in CoRL, 2017.
[2] BeamNG GmbH. (2022) BeamNG.tech. [Online]. Available: [https://www.beamng.tech/]
[3] D. J. Fremont, T. Dreossi, S. Ghosh, X. Yue, A. L. Sangiovanni-Vincentelli, and S. A. Seshia, “Scenic: a language for scenario specification and scene generation,” in PLDI, 2019, pp. 63–78.
[4] R. B. Abdessalem, S. Nejati, L. C. Briand, and T. Stijler, “Testing vision-based control systems using learnable evolutionary algorithms,” in ICSE, ACM, 2018, pp. 1016–1026.
[5] P. Arcaini, X. Zhang, and F. Ishikawa, “Targeting patterns of driving characteristics in testing autonomous driving systems,” in ICST. IEEE, 2021, pp. 295–305.
[6] A. Cabò, P. Arcaini, S. Ali, F. Hauer, and F. Ishikawa, “Generating avoidable collision scenarios for testing autonomous driving systems,” in ICST. IEEE, 2020, pp. 375–386.
[7] M. Borg, R. B. Abdessalem, S. Nejati, F.-X. Jegeden, and D. Shin, “Digital twins are not monoyzogetic-cross-replicating adas testing in two industry-grade automotive simulators,” in ICST. IEEE, 2021.
[8] A. Gambi, M. Mueller, and G. Fraser, “Automatically testing self-driving cars with search-based procedural content generation,” in ISSTA, 2019.
[9] A. Gambi, M. Müller, and G. Fraser, “Asfault: Testing self-driving car software using search-based procedural content generation,” in ICSE-Companion. IEEE, 2019, pp. 27–30.
[10] H. Tian, Y. Jiang, G. Wu, J. Yan, J. Wei, W. Chen, S. Li, and D. Ye, “Mosat: finding safety violations of autonomous driving systems using multi-objective genetic algorithm,” in ESEC/FSE, 2022, pp. 94–106.
[11] F. U. Haq, D. Shin, and L. Briand, “Efficient online testing for dnn-enabled systems using surrogate-assisted and many-objective optimization,” in ICSE, 2022, pp. 811–822.
[12] M. M. Minderhoud and P. H. Bovy, “Extended time-to-collision measures for road traffic safety assessment,” Accident Analysis & Prevention, vol. 33, no. 1, pp. 89–97, 2001.
[13] R. Li, P. Yang, C. Huang, Y. Sun, B. Xue, and L. Zhang, “Towards practical robustness analysis for dnn based on pac-model learning,” in ICSE. ACM, 2022, pp. 2189–2201.
[14] R. Ivanov, J. Weimer, R. Alur, G. J. Pappas, and I. Lee, “Verisig: verifying safety properties of hybrid systems with neural network controllers,” in HSCC, 2019, pp. 169–178.
[15] H.-D. Tran, X. Yang, D. Manzanas Lopez, P. Musau, L. V. Nguyen, W. Xiang, S. Bak, and T. T. Johnson, “Nnv: the neural network verification tool for deep neural networks and learning-enabled cyber-physical systems,” in CAV. Springer, 2020, pp. 3–17.
[16] R. Ivanov, T. J. Carpenter, J. Weimer, R. Alur, G. J. Pappas, and I. Lee, “Verising 2.0: Verification of neural network controllers using taylor model preconditioning,” in TEC. ACM, vol. 20, no. 1, pp. 1–26, 2020.
[17] R. Ivanov, T. Carpenter, J. Weimer, R. Alur, G. Pappas, and I. Lee, “Verising 2.0: Verification of neural network controllers using taylor model preconditioining,” in CAV. Springer, 2021, pp. 249–262.
[18] C. Huang, J. Fan, W. Li, X. Chen, and Q. Zhu, “Reachnn: Reachability analysis of neural-network controlled systems,” TECS, 2019.
[19] J. Fan, C. Huang, X. Chen, W. Li, and Q. Zhu, “Reachnn*: A tool for reachability analysis of neural-network controlled systems,” in ATVA. Springer, 2020, pp. 537–542.
[20] C. Huang, J. Fan, X. Chen, W. Li, and Q. Zhu, “Polar: A polynomial arithmetic framework for verifying neural-network controlled systems,” in ATVA. Springer, 2022, pp. 414–430.
[21] K. Chutta, A. Prakash, B. Jaeger, Z. Yu, K. Renz, and A. Geiger, “Transfuser: Imitation with transformer-based sensor fusion for autonomous driving,” PAMI, 2022.
[22] D. Chen and P. Krähenbühl, “Learning from all vehicles,” in CVPR, 2022, pp. 17222–17231.
[23] M. C. Campi, S. Garatti, and M. Prandini, “The scenario approach for systems and control design,” Annu. Rev. Control., 2009.
[24] G. Singh, T. Gehr, M. Püschel, and M. T. Vechev, “An abstract domain for certifying neural networks,” Proc. ACM Program. Lang., vol. 3, no. POPL, pp. 41:1–41:30, 2019.
[25] S. Dutta, X. Chen, S. Jha, S. Sankaranarayanan, and A. Tiwari, “Sherlock-a tool for verification of neural network feedback systems: demo abstract,” in HSCC, 2019, pp. 262–263.
[26] I. J. Goodfellow, J. Shlens, and C. Szegedy, “Explaining and harnessing adversarial examples,” in ICLR, Y. Bengio and Y. LeCun, Eds., 2015.