Adversarial Deep Reinforcement Learning for Trustworthy Autonomous Driving Policies

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Abstract—Deep reinforcement learning is widely used to train autonomous cars in a simulated environment. Still, autonomous cars are well known for being vulnerable when exposed to adversarial attacks. This raises the question of whether we can train the adversary as a driving agent for finding failure scenarios in autonomous cars, and then retrain autonomous cars with new adversarial inputs to improve their robustness. In this work, we first train and compare adversarial car policy on two custom reward functions to test the driving control decision of autonomous cars in a multi-agent setting. Second, we verify that adversarial examples can be used not only for finding unwanted autonomous driving behavior, but also for helping autonomous driving cars in improving their deep reinforcement learning policies. By using a high fidelity urban driving simulation environment and vision-based driving agents, we demonstrate that the autonomous cars retrained using the adversary player noticeably increase the performance of their driving policies in terms of reducing collision and offroad steering errors.

Index Terms—deep reinforcement learning, multi-agent systems, autonomous cars, autonomous driving testing, adversarial learning

I. INTRODUCTION

Autonomous cars (ACs, also known as self-driving cars) are one of the revolutionary areas in the autonomous ecosystem. While the autonomous industry is advancing autonomous driving technology, there is a need of testing and validating such autonomous cyber-physical systems [1].

In the past few years, there has been a wide interest in testing ACs. The primary reason is that despite the claims companies make for their products, we still have seen failure scenarios where ACs ended up in bad accidents [2]. Unlike testing of traditional software, testing of AI-based software is a less mature area in the research community [3]. There has been a lot of progress made by researchers on testing AI-based models [4] [5], but the testing of ACs is another complex area to tackle. The autonomous software stack needs to be validated on various levels including the input state, model learning parameters, and output layer. There is no doubt that the highest level of ACs will help human drivers in solving a wide range of traffic problems in the future, but we need to make sure they are safe in order to build more trust for public use [6] [7].

Testing of ACs has been usually considered as a single-agent problem, where only one car is taken as a system under test (SUT). While a single-agent self-driving environment still has open challenges, there is a need to advance a multi-agent self-driving, as it represents a more realistic environment. In the near future, multiple ACs will co-exist on the road, and the more such cars start interacting with each other, as well as with human drivers, the more complex their testing becomes [8]. Multi-agent systems have been studied extensively in the field of reinforcement learning (RL) by various research groups [9] [10] [11], but they are still behind to be deployed in AC domain on a larger scale, partly due to the lack of proper testing.

Furthermore, adversarial machine learning has advanced recently for improving the testing of single-agent ACs, by finding failure test cases [12] [13]. There have been attempts to generate adversarial test cases mainly either by using Generative Adversarial Networks (GANs) [14] or optimization based methods [15] [16] targeting the input state of deep neural networks. Furthermore, RL has been used in different styles to test autonomous driving within simulations [17] [18]. However, while RL has shown great results as an adversarial agent, RL is still mainly used for testing ACs in a single-agent environment. Recent work [19] made progress towards testing connected and automated vehicles by injecting adversarial noise in a mixed-traffic-based network environment. However, this work is of limited practical use as it does not consider multiple non-communicating AC agents. Therefore, we propose a novel approach for testing non-communicating multi-agent ACs using an adversarial agent in an urban driving scenario. In our experiments, we demonstrate that a trained adversary player can assist in improving more than one vision-based autonomous driving policy for fewer collisions and offroad steering accidents.

In this paper we propose a framework ‘Multi-Agent Driving with Adversarial Reinforcement Learning MAD-ARL’ for testing a multi-agent AC setup. Specifically, we use deep RL for training an adversarial agent against two pre-trained ACs. Next, we test the pre-trained cars against the adversary, with the goal of exposing faults in the cars’ driving policies. Then we retrain these ACs with the adversarial policies to defend against adversarial attacks. The results are compared with the baseline autonomous models (adversary-free trained policies) to evaluate the effectiveness of the retraining strategy as a defense against adversarial attacks. The main idea is to use adversarial examples beyond testing purposes to improve the
robustness of ACs, since adversarial attacks are usually not considered when autonomous driving models are being trained in urban driving scenarios.

The key research contributions in this paper are:

1) Introducing a deep RL framework for testing driving policies of independent non-communicating agents in a multi-agent AC environment.
2) Training an adversary that can effectively drive an AC into error states by creating natural (i.e. realistic) observations for the AC's driving policies, without whitebox access to its input state.
3) Experimentally demonstrating that retraining deep RL-based driving policies of ACs using adversary driving models can be an effective defence against adversarial attacks.

II. RELATED WORK

While there exist different approaches for testing ACs in simulation, in this review we focus on those that use some kind of adversarial examples to test ACs. Adversarial examples aim to perturbate the input space for an AC in order to find rare scenarios leading the driving model into accident states. Adversarial attacks can be performed manually [12][20] by using hardcoded out-of-distribution images added to autonomous driving environments. Attacks can also be added intelligently using adversarial machine learning [19], where noise perturbations are mixed within the input images of the driving models in order to predict and analyze steering angles. Among the latter category, there are several types of approaches proposed.

RL Approaches. Recent work [19] proposes to use RL-based driving agents to test connected cars by perturbing both the inputs and outputs of an AC during training. However, this approach targets a mixed-traffic driving with a single AC and multiple human-driven cars, thus it does not consider complex scenario having more than one non-communicating AC agents. Another work [17] performs adversarial RL for testing a multi-agent driving environment by training more than one rule-based driving model. While the results look promising, the approach only covers the cases where the trained adversarial cars are exposed to a single AC. As another limitation, the approach has not been evaluated on more complex adversarial driving scenarios, such as T-intersection, which we target in our work. Another work [18] uses RL to stress-test ACs in a simulated environment. The extension of this work [21] proposes the idea of reward augmentation for increasing the search space for finding failure cases in driving policies. Compared to our work, they lack multi-agent test cases even on a small scale. Besides, the work is tested neither in a vision-based simulator nor in real-world driving conditions. Furthermore, they add adversarial perturbations as noise in the simulation model itself, unlike our approach, where we add perturbations by the adversary car’s policy, thus adding adversarial actions as example trajectories for improving AC’s driving policies.

Optimization-based Approaches. Authors in [22] propose a Bayesian optimization-based method for testing ACs. Their method involves creating adversarial scenarios in a Carla-based urban driving simulation to expose the weaknesses of autonomous driving policy. Another work [15][16] also uses an optimization technique for producing physical attacks on driving lanes, in order to attack vision-based driving models. Compared to our work, these works are lacking multi-agent AC scenarios.

Authors in [23] also worked in the direction of testing ACs by triggering as many neurons in the driving model as possible for finding failure scenarios. They approach this work as an optimization problem where the authors apply gradient ascent over the results of test inputs in order to maximize the chances of finding corner cases. As a limitation, their method is based on whitebox testing of the model, and also the driving scenarios are only tested in a single-agent environment. Our work on the other hand is focused on blackbox adversarial testing of ACs in a multi-agent driving environment.

GAN-based Approaches aim at validating the performance of an AC’s input state when receiving adversarial inputs from LiDAR, GPS, or camera feeds. For example, the work [13] uses a GAN model to generate adversarial objects able to attack LiDAR-based driving systems. Another work [24] uses GAN to apply metamorphic testing to CNN-based driving models. However, neither of these approaches has been tested in an RL-based multi-agent AC environment.

III. BACKGROUND

A. Reinforcement Learning

Reinforcement Learning is primarily modeled as a Markov decision process (MDP), where the main goal of an RL-based agent is to learn the optimal policy in order to maximize cumulative reward by interacting in an environment. The MDP model can be defined as $M(S, A, P, R, \gamma)$, where $S$ is a set of states, $A$ is a set of actions, $P : S \times A \rightarrow S$ is the transition probability describing the stochastic probability distribution of a next state $s' \in S$ given actions, $R : S \times A \rightarrow \mathbb{R}$ is the reward function provided as the result of each action, and $\gamma$ is the discount rate in the range $[0,1]$. Such a system obeys Markov property since the agent is dependent on the previous state only to make future decisions.

B. Multi-agent Reinforcement Learning

In the domain of robotics and autonomous systems, the agents are only limited to partial observability and therefore they do not have access to the entire state space. This can be termed as Partially Observable Markov decision process (POMDP) [25]. In POMDP, a single RL-based agent takes actions at each time step $t$ against partial observations of a state space and receives a cumulative reward, as well as the probability of the next state $s'$.

In order to incorporate a multi-agent environment in POMDP, we can use Markov Games [26] which helps us reformulate MDP in a game-theoretic stochastic approach. POMDP can be extended as Partially Observable Stochastic
Games (POSG) [27], where we re-define Markov games using reinforcement learning as a tuple \((I, S, A, O, P, R)\). \(I\) is a finite set of agents or actors in an environment and \(O\) is a set of observations for each actor in \(I\).

During each time step \(t\), an actor \(i\) from \(I\) receives its observation from a joint observation state \(o_i \in O\) and performs actions \(a_i \in A\) by using a learned policy \(\pi_i : O_i \rightarrow A_i\). At the return of each agent’s action is a reward value \(r_i \in R\).

C. Deep Reinforcement Learning

Deep reinforcement learning (DRL) is an advanced and alternative method to the traditional RL methods, where we approach MDP by using deep neural networks. The policy \(\pi\) and value function \(Q = value(s)\) of a DRL is learned using neural network parameters \(\theta\), which defines the model weights learned during the exploration of the agent. In our approach, we focus on model-free based DRL, where the policy is learned directly by the agent without using the transition probability function.

D. Policy Gradient Algorithms

Policy gradient methods are one of the famous RL algorithms which rely on Monte Carlo estimations as a model-free based approach. Policy gradient algorithm performs in two main steps: i) a collection of transitions using old policy and ii) improving the existing policy by replacing it with the newly learned one.

For the first step, policy gradient methods collect transitions of tuple \((S, R, A)\) using an existing policy. These transitions are ultimately used to update the current policy in the next step, which is why they are known as on-policy methods. Hyperparameters associated with epochs, batches, and episode rollouts contribute to the collection of trajectories.

In the next major step, we update the old policy with the new one based on experiences learned in the form of batches and episodes. This problem is approached using hyperparameters such as surrogate loss function and KL penalty to smoothly update the existing policy.

E. Adversarial Reinforcement Learning

Adversarial Reinforcement Learning (ARL) is a sub-branch of machine learning where RL-based methods are used to create disturbances such that the model under test produces failure outputs when exposed to the adversarial examples. Our adversarial agent resides in the same environment as the self-driving agents and has no white box access to the SUTs. This allows us to find adversarial trajectories in an intelligent way, instead of hardcoded techniques. Moreover, our approach uses the same adversarial results to retrain the autonomous driving models in order to evaluate their performance in comparison with the baseline models. Following a zero-sum game approach, the main goal of the adversarial agent is to learn a policy where the reward is incentivized by taking actions against self-driving models under test.

IV. MAD-ARL Formulation

Our work addresses the problem of adversarial testing of two autonomous cars in a multi-agent driving environment. We model our problem as a 2-player Markov game, where one type of a player is the autonomous driving agent under test, which we call a victim, and the other player is the adversarial driving agent, which we call an adversary, and who is trying to exploit the weakness of the victim. We denote our victims and adversary agent as \(T_1\), \(T_2\) and \(\alpha\), respectively (we consider two ACs under test). The Markov game \(M = (S, O, \{A_{T_1}, A_{T_2}, A_{\alpha}\}, P, \{R_{T_1}, R_{T_2}, R_{\alpha}\})\) in a multi-agent environment consists of \(O\) set of state observations and \(A_T, A_{\alpha}\) represents action set. \(P\) is a joint state transition probability function \(P : S \times A_T \times A_{\alpha} \rightarrow \Delta(S)\), where \(\Delta(S)\) defines the probability distribution of the next state. Reward function \(R\) is based on maximizing the cumulative sum of rewards as \(R : S \times A_T \times A_{\alpha} \rightarrow \mathbb{R}\). Each player in the set \(\{T_1, T_2, \alpha\}\) depends on the current state observation to perform actions and reach the next state while receiving the desired rewards.

The adversary and victim agents work as independent non-communicating competitive players. This means that they have no white box access to each other’s input state, as well as no shared information to weights parameters. The victim agents are first given the shared environment to train their policies \(\pi_{T_1}\) and \(\pi_{T_2}\) with the absence of an adversarial player. The adversary, however, is provided access to the action state sampled from \(\pi_T\). Since the adversary’s policy \(\pi_{\alpha}\) is trained using pre-trained AC policies, we assume that the victim players have fixed weights during adversarial policy training. This represents a scenario where RL-trained policies for ACs are deployed to the real world and their weights are fixed in order to train any adversarial agent for testing. At this point, the Markov game consisting of two players can be treated as one player MDP problem, since the victim policy \(\pi_{T}\) is held fixed.

The goal of the adversarial player is to learn a policy \(\pi_{\alpha}\) maximizing the sum of discounted rewards:

\[
\pi_{\alpha} = \sum_{t=0}^{\infty} \gamma^t R_{\alpha}(s(t), a_{\alpha}(t), s(t+1))
\]

where \(a_{\alpha} \sim \pi_{\alpha}(.)|s(t))\) are actions sampled from the adversary policy and \(s(t+1) \sim P_{\alpha}(s(t), a_{\alpha}(t))\) is the next state given the transition probability. Since the current problem is scoped as a model-free approach, the MDP dynamic model \(P_{\alpha}\) is unknown.

When the adversarial policy is trained, we use it to find uncommon behavior patterns for the victim’s players by adding natural observations (see Section V) for the victim deep RL policies \(\pi_{T}\). Once we observe the effectiveness of the adversary in finding failure test cases for the ACs, we retrain the victim models by unfreezing their weight parameters, while keeping the trained adversarial player as part of the training environment. Thus, the goal of the autonomous
agents \( \{\pi_{T1}, \pi_{T2}\} \) is to maximize the sum of the discounted reward independently, that is:

\[
\pi_{T1} = \sum_{t=0}^{\infty} \gamma^t R_{T1}(s^{(t)}, a_{T1}^{(t)}, s^{(t+1)})
\]

\[
\pi_{T2} = \sum_{t=0}^{\infty} \gamma^t R_{T2}(s^{(t)}, a_{T2}^{(t)}, s^{(t+1)})
\]

V. MAD-ARL Framework

In this section, we present the proposed framework for testing driving policies in a multi-agent AC environment. An overview of the framework architecture is illustrated in Figure 1.

In MAD-ARL Framework, we consider two victim driving agents and one adversary driving agent. An agent is an entity that is able to observe the environment and perform actions in order to make an intelligent decision in the given environment. The observations of our multi-agent driving environment for the victim agents are manipulated by adding an adversarial agent in the environment. The adversarial agent is trained to take actions such to create observations that appear natural to the victim agents, while being adversarial in nature. As an example, the adversary is learning to steer offroad most of the time while crossing the intersection. Such unusual behavior will act as an adversarial noise to the visual observations of victim ACs.

A. Proximal Policy Optimization

Our AC agents use Proximal Policy Optimization (PPO) [28] as a policy gradient method to learn a driving policy by encountering simulated environment in each training episode. The PPO helps perform on-policy learning within simulation instead of a dataset (replay buffer) type learning. It also helps focus on policy update with stability while learning over change in data distributions, as well as to address a large hyperparameter initializing space.

The details of the hyperparameters selected for the training of the victim and adversary driving agents are given in Table I.

### TABLE I: Hyperparameters for the PPO Deep RL model.

| Stage                  | Hyperparameter          | Value  |
|------------------------|-------------------------|--------|
| Gathering Experience   | Minibatch Range         | 64     |
|                        | Epochs per Minibatch    | 8      |
|                        | Batch Mode              | Complete Episodes |
| Updating Policy        | Discount factor (\(\gamma\)) | 0.99   |
|                        | Clipping (\(\alpha\))   | 0.3    |
|                        | KL Target               | 0.03   |
|                        | KL Initialization       | 0.3    |
| Other Hyperparameters  | Value Loss Coefficient  | 1.0    |
|                        | Entropy Regularizer     | 0.01   |

B. Deep Neural Network Model

The summary of the deep RL architecture, including the input, hidden, and output layer is displayed in Figure 1. The input state \( S \in \mathbb{R} \) of our deep RL algorithm receives a partial observation of \( 84 \times 84 \times 3 \) dimension images from the camera sensors. Cameras are mounted in front of each driving model which provides feeds as an input state observation to the autonomous and adversary cars model at each step of the simulation. The 3-dimensional input images are passed through convolutions and hidden layers to reach the output layer for control commands.

At the output layer, we have nine discrete values as the action space which are used by each driving agent to make control decisions. All of the discrete actions can be summed into three main actions: Steer, Throttle, and Brake.

C. Reward Functions

Each agent is following MDP described in the MAD-ARL formulation, and therefore, at each time step, the driving models collect trajectories of \((S, R, A)\). \(R\) is the reward gained in return for the actions chosen by the driving car’s policy function, given the input observations. We are defining two different types of reward functions for the adversarial player to see which one performs better in testing and retraining the policies of the victim ACs. The two adversarial reward functions associated with the policies \(\pi_{a1}\) and \(\pi_{a2}\) are named \(R_{collision}\) and \(R_{offroad}\). \(R_{collision}\) aims to maximize the rate of collision and \(R_{offroad}\) steering during the adversarial training. \(R_{collision}\) is formulated as:

\[
R_{collision} = (D_{t-1} - D_t) + (F_t)/10 + 5.0(CV_t + CO_t) + 0.05(IO_t + IOL_t) + \beta
\]

where \(D\) is the distance covered, \(F\) is the forward speed of the agent, \(CV\) and \(CO\) are the boolean values telling whether there is any collision with other vehicles and environment objects, and \(IO\) along with \(IOL\) refers to driving offroad at the intersections and outside the desired lane represented as boolean. At the end of the equation is a constant \(\beta\) used to encourage driving in a desired ground truth lane. \(R_{offroad}\) aims to maximize the rate of \(\text{offroad}\) steering. \(R_{offroad}\) is formulated as:

\[
R_{offroad} = (D_{t-1} - D_t) + (F_t)/10 + 0.05(IO_t + IOL_t) + \beta
\]

On the other hand, the victim policies are trained as driving ACs with the goal to safely reach as close to the desired destination as possible. The victim agents reward can be described as:

\[
R_{Victim} = (D_{t-1} - D_t) + (F_t)/10 - 100.0(CV_t + CO_t) - 0.5(IO_t + IOL_t) + \beta
\]

From the above equation, it is clear that the victim driving policies are sensitive towards any \(\text{offroad}\) steering errors and collisions.
Fig. 1: End-to-end architecture with deep reinforcement learning model for autonomous and adversary agents. Each agent receives an input image of 84x84x3 which is passed to PPO based deep RL model. The actions are selected at the output layer of every agent and are performed in the next time step of the simulation in order to obtain reward and new observation state.

D. Hyperparameters

The hyperparameters used in different phases of training of all ACs are shown in Table II. During the testing phase, explained in Section VII, we run five total episodes, each having 2000 simulation steps per driving agent.

TABLE II: Hyperparameters for the training of the baseline victim AC models, the adversarial model, and retrained victim AC models

| Hyperparameter            | Baseline | Adversarial | Retrained Victim |
|---------------------------|----------|-------------|------------------|
| Total Training Steps      | 300672   | 57728       | 133888           |
| Total Training Episodes   | 610      | 101         | 306              |
| Learning Rate             | 0.0006   | 0.0006      | 0.0006           |
| Batch Size                | 128      | 128         | 128              |
| Optimizer                 | Adam [29]| Adam        | Adam             |

VI. EXPERIMENTS

The experiments aim to demonstrate the effectiveness of the proposed framework for testing and improving driving policies in a multi-agent car environment. To this end, first, we train a single adversary AC against two victim AC agents to test their driving policies. The purpose of the adversary is to expose errors in the driving policies of the AC agents, such as the inability to avoid collisions and off-road steering accidents. Later we retrain the AC agents using the adversarial inputs and evaluate how much their driving policies improved compared to their baseline performance.

Specifically, the research questions aim to evaluate:

RQ1: How effective is the adversarial AC policy in finding failure driving scenarios in victim ACs?

RQ2: Does retraining the victim ACs using adversary inputs improve the agent’s performance in terms of reducing collisions and offroad steering errors?

A. Experimental Setup

We use Town 3 scenario as provided by the Python Carla API and Macad-gym [30] in our partially-observable urban-based driving environment. This environment has three independent non-communicating agents spawned close to the T-intersection throughout the training and testing steps, where two are the victim ACs $T_1$ and $T_2$, and one is the adversarial AC $\alpha$. The choice of T-intersection as a driving scenario is based on its higher complexity for an AC agent in real life as well as in the autonomous driving research.

The goal of $T_1$ and $T_2$ is to drive straight across the intersection without errors, while $\alpha$ aims to take a left turn in the same driving situation. The starting and ending state locations of each driving agents are:

- $T_1$ start: $[188, 59, 0.4]$, end: $[167, 75.7, 0.13]$
- $T_2$ start: $[147.6, 62.6, 0.4]$, end: $[191.2, 62.7, 0]$
- $\alpha$ start: $[170.5, 80, 0.4]$, end : $[144, 59, 0]$

where victim ACs strictly follow the mentioned coordinates as ground truth to improve their driving policies. On the contrary, the adversary player is less focused on reaching the desired
destination and aims to deviate towards collision and offroad steering behavior.

The sequence of the training and testing for victim and adversary agents are as follows.

1) Step1: Training Victim AC Agents for Baseline: We train both AC policies $\pi_{T1}, \pi_{T2}$ in a multi-agent environment with the absence of any adversarial policy as shown in Figure 2. After 610 episodes and 300672 steps mentioned in Section V-D, we move towards our first testing phase to record the baseline performance of both autonomous cars.

2) Step2: Training Adversarial AC Agent: Next, we introduce the adversarial AC agent. We train its policy $\pi_\alpha$ by providing the victim AC policies, keeping their weight parameters constant during the adversarial training phase. The number of episodes for training the adversary agent is kept lower than the number of episodes assigned for the victim’s baseline model training.

We train the adversarial policy using two different adversarial reward functions, $R_{\text{collision}}$ and $R_{\text{offroad}}$, separately, as shown in Figure 3. We use 101 episodes to train the adversarial policy using both reward functions. In the end, we test the behavior and control decisions of both victim AC agents when exposed to the trained adversarial driving agent and compare the results with our baseline victim policies.

3) Step3: Retraining Victim AC Agents for Improvement: Finally, we unfreeze the weights of the victim AC agents to retrain their end-to-end driving policies by keeping the adversarial agent in the same environment. Since there are two different adversarial reward-based policies involved, the retraining of the victim ACs is done twice separately, as depicted in Figure 3. After the retraining is done, we test the victim ACs to see how much they improved compared to their baseline performance (collected in steps VI-A1 and VI-A2).

B. Simulation Setup

We use the following frameworks in the experiments:

RLlib [31] is a submodule of the Ray framework which is an open source project that provides a very fine-tuned and scalable RL implementation interface. Using RLlib, we can integrate existing deep RL algorithms, along with their hyperparameters, in our environment setup, while creating a multi-agent scenario with non-shared policy graphs. We are currently using version 0.8.4.

Carla [32] is an urban driving simulation framework, widely used for training, testing, and validating various autonomous driving cars in large accessibility of scenarios and map conditions. For our problem, we are currently using version 0.9.4.

Macad-gym [30] is an open source platform created by integrating Carla and Open AI’s Gym toolkit in order to enable research opportunities in multi-agent urban driving environments. By taking the basic functionalities of macad-gym, we have modified the framework for our scope of work, although Carla’s environment interface and parameters are kept as it is for the sake of reproducibility. The current stable version of macad-gym in use is 0.1.4.

Tensorflow [33] is one of the leading frameworks used to create machine learning based algorithms. We are using version 2.1.0 within the RLlib library.

VII. RESULTS & ANALYSIS

In this section, we present and discuss experimental results.
A. Effectiveness of adversarial AC policy in finding failure driving scenarios in victim ACs

We evaluate the performance of victim ACs by looking at three metrics: i) the amount of collision with other vehicles, ii) the amount of collision with any other road objects, and iii) the number of times an AC went off-road from its driving ground truth lane. To evaluate the effectiveness of the adversarial AC policy in finding failure driving scenarios in victim ACs, we compare the AC's baseline performance (no adversary in the environment) with its performance when trained with an adversary present in the environment. The evaluation results are shown in Table III.

For conveying the results more clearly, we take an average among 5 episodic test runs, where in each episode we take 2000 simulation steps to evaluate the performance of victim agents. At the end of testing episodes, we compute the average percentage of errors. Victim policies having values closer to 0 are performing error-free driving, whereas values closer to 1 indicate a higher failure state of the victim policy.

In the baseline scenario, both victims made no collision with each other during test episodes. Victim policies made uncertain decisions by creating collisions with footpaths and performing off-road steering errors. This is because we are testing the victim agents more than they have explored the environment in each episode. Victim 1, which is on the right side of the scenario, has a better driving policy in most cases than Victim 2. Consequently, in most cases, Victim 2 is more affected than Victim 1 once we add adversarial attacks in the environment.

After introducing the adversarial policies to the environment ($R_{\text{collision}}$ and $R_{\text{offroad}}$) we see that the overall decision making process of both victim ACs is disturbed and their driving performance is decreased. Specifically, the rate of collision with other cars increased for both victims, as they ended up colliding with each other, as well as with the adversarial agent. Consequently, the rate of collision with other road objects has been reduced in most cases, due to early stopping after collision with other vehicles. Furthermore, both victims encountered more off-road steering errors.

In summary, the results of the experiments demonstrate that introducing an adversarial AC policy to the environment is an effective strategy for finding failure driving scenarios in ACs.

B. Improving victim ACs performance by retraining

By retraining the victim ACs using inputs from $R_{\text{collision}}$- and $R_{\text{offroad}}$-based adversaries, we check whether the ACs’ driving performance improved in terms of reduced collisions and off-road steering errors, compared to the stage before retraining. The evaluation results are shown in Table III. Specifically, the rate of collision with cars and other objects decreased for the victims retrained using $R_{\text{offroad}}$-based adversary in most cases. The reason is that $R_{\text{offroad}}$-based adversary provides adversarial examples for victim ACs by maintaining collision-free distance, therefore helping victims to learn how to avoid collisions while crossing an intersection. Although the $R_{\text{collision}}$-based adversary helped reveal more faults in the victim agents, in most cases, compared to the $R_{\text{offroad}}$-based adversary, it did not help much during the retraining process of the victim agents. It is mainly due to its collision-focused driving nature and thus the victims were unable to learn to avoid collision with each other. Victim 2, being a weaker policy among the two ACs, also ended up colliding with road objects. On the contrary, the number of off-road steering errors is reduced for the victims retrained using $R_{\text{collision}}$-based adversarial policy since they slowed down after having collisions with other cars.

In summary, these results show that while both victim ACs retrained using $R_{\text{offroad}}$-based adversary learned to avoid collision in the majority of cases, the ACs still have to improve their driving policy for better lane decisions. The offroad steering still happens because the number of steps in the training phase is 500 per episode, which is less than the number of steps in the testing phase. This is one of the points of future work we aim to explore next. Specifically, we will run more experiments by varying training and testing episodic steps to evaluate the trade-off between exploration and exploitation in RL-based agents, and its effect on the driving performance of the agents. Overall, the results show that $R_{\text{offroad}}$-based adversary is more effective in making ACs more robust against collisions.

We visualize the driving performance of the victim AC agents in Figure 5. The figure shows a 2-dimensional aerial view of the victim ACs’ driving coordinates. Plots (a) and (b) represent the performance when the victim agents are exposed to the adversary for the first time, while plots (c) and (d) represent the improvement in their driving policies as the results of retraining. The plots do not take time factors into consideration, which is important to mention since any victim car overlapping with the adversary does not necessarily mean a collision state. Plot (a) depicts Victim 1 driving offroad without crossing the intersection, due to the adversarial agent. Plot (b) depicts a failure scenario where Victim 2 collides with the adversary as well as drives offroad. Error states in these two plots are marked with red stars. Plot (c) and (d) depict cases of improved (retrained) driving policies of the victim agents, who are now able to avoid collision with cars and other road objects, as well as to stay on the driving lane, while crossing the intersection.

VIII. CONCLUSION & FUTURE WORK

In this work, we propose a framework named MAD-ARL which is a multi-agent driving environment designed for training and testing autonomous cars using adversary driving models. Adversarial reinforcement learning is trained against victim players in order to find unwanted driving decisions of autonomous cars that are also trained on Deep RL-based policy. By exposing the same adversarial car against the victim agents for retraining, the agents show improvements in their end-to-end decision driving controls, mainly in terms of fewer collisions compared to their originally trained (adversary-free) policies.
TABLE III: Comparison of the behavior of victim ACs before and after adding adversarial car in the environment, and after retraining using adversarial policies. Victim ACs have more collisions and off-road steering errors under the presence of adversary agent, compared with baseline victim models. Retraining victim ACs with adversarial inputs improves their driving policies.

|                      | Baseline | After Adversarial Training | After AC Retraining |
|----------------------|----------|---------------------------|---------------------|
|                      |          | $R_{collision}$ | $R_{offroad}$ | $R_{collision}$ | $R_{offroad}$ | $R_{collision}$ | $R_{offroad}$ |
| Collision with cars  | 0.0      | 0.19468        | 0.0956       | 0.0         | 0.1902 | 0.2184        | 0.2563 | 0.3934 | 0.0831 | 0.0698 |
| Collision with other objects | 0.0184 | 0.0398 | 0.0 | 0.1533 | 0.0 | 0.0022 | 0.0 | 0.1912 | 0.0 | 0.0566 |
| Offroad steering error | 0.0929 | 0.2828 | 0.1645 | 0.3769 | 0.0951 | 0.3544 | 0.0425 | 0.2112 | 0.0358 | 0.3688 |

![Fig. 5: 2D visualization of the victim and adversary driving coordinates. (a) and (b) display two failure scenarios found while testing victim cars in the presence of an adversarial agent. (c) and (d) illustrates the same victim policies performing better once they are retrained with the adversarial policies.](image)

**Discussion:** Deep RL research for ACs is mainly focused on driving in a single-agent stationary MDP environment, whereas MAD-ARL framework is based on POMDP formulation where every agent is following MDP by receiving partial observations in a competitive environment. In multi-agent non-stationary environments, each agent’s transition probability and reward function depends on the actions of all the agents since they change every time with the actions performed by the agents. The driving behavior of AC agents is therefore affected a lot when tested in a multi-agent scenario due to the non-stationary driving environment [34].

**Future Work:** This work can be further extended to ACs operating in mass-traffic scenarios having more cars, pedestrians, and a traffic light network as part of the multi-agent environment. In such complex environments, mixed competitive ACs need to be tested in larger state space for finding edge cases using adversarial agents. Furthermore, we plan to investigate how retraining the adversarial agent affects both the performance of victim autonomous cars. We also plan to explore and compare the robustness of different Deep RL algorithms used for autonomous driving research, when they are exposed to different types of adversaries. Also, we will extend current driving scenario with different training and testing episodic steps for evaluating the driving performance of RL-based models.

**IX. ACKNOWLEDGMENT**

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