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Optimal Safety Planning and Driving Decision-Making for Multiple Autonomous Vehicles: A Learning Based Approach

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***Abstract*—In the early diffusion stage of autonomous vehicle systems, the controlling of vehicles through exacting decision-making to reduce the number of collisions is a major problem. This paper offers a DRL-based safety planning decision-making scheme in an emergency that leads to both the first and multiple collisions. Firstly, the lane-changing process and braking method are thoroughly analyzed, taking into account the critical aspects of developing an autonomous driving safety scheme. Secondly, we propose a DRL strategy that specifies the optimum driving techniques. We use a multiple-goal reward system to balance the accomplishment rewards from cooperative and competitive approaches, accident severity, and passenger comfort. Thirdly, the deep deterministic policy gradient (DDPG), a basic actor-critic (AC) technique, is used to mitigate the numerous collision problems. This approach can improve the efficacy of the optimal strategy while remaining stable for ongoing control mechanisms. In an emergency, the agent car can adapt optimum driving behaviors to enhance driving safety when adequately trained strategies. Extensive simulations show our concept's effectiveness and worth in learning efficiency, decision accuracy, and safety.**

***Keywords*—** Autonomous driving, Multiple vehicle collision, Robotics, Reinforcement Learning.

I. Introduction

The vast AI technology has enhanced traffic efficiency and safety while also opening the road for autonomous vehicles. Algorithms capable of handling complicated scenarios are required to build the next generation of driver assistance systems or autonomous driving systems. Many researchers have offered ways on perception, threat assessment [1], decision making, and vehicle control. However, one of the key impediments in autonomous driving is the decision-making process in critical situations. The decision-making process in critical scenarios is, nevertheless, one of the significant hurdles to autonomous driving. The issue to evaluate driving behavior is that most solutions are restricted to avoiding a single-vehicle collision without reliable trajectory forecasts of other participants. This research will focus on developing a safety planning decision-making scheme for autonomous automobiles in multi-vehicle crash scenarios to solve this difficulty. Numerous groups have looked into the problems of making solid strategic decisions on autonomous vehicles in a congested and dynamic urban setting. In *Figure: 1* is the evaluations of multiple vehicle collision and the avoidance time interventions of safety planing. It creates an optimal safety strategy based on reinforcement learning to protect the impending first and chain collisions and reduce the severity of multiple crashes [2]. The problem of multi-vehicle collision resolution during unexpected deceleration and lane change is described as a multi-objective optimization problem (MOP) [3], with acceleration as the single decision variable. Our research intends to design a cooperation planning scheme for collision prevention to produce sequences of maneuvered decisions in real-time [4]. Reinforcement learning is the strategy used for assessing actions made in any given state by learning an approximation value function and is employed to form an overall decision-making process in our system. Combinations between the position and the orientation of both vehicles are considered system conditions, whereas combinations between the movements of both vehicles are characterized as actions. Because the pair of state-action are multidimensional

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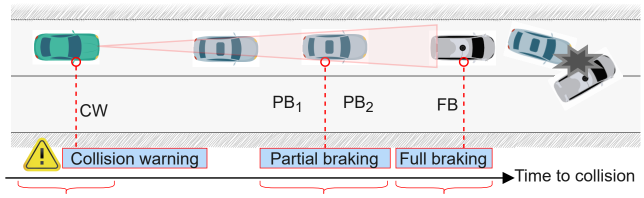

Figure 1: Evaluation of Multiple Collision Caused By Sudden Lane Change Where The Ego Vehicle Receive *CW* (Collision Warning) From The Leading Vehicle and Immediately Determine The PB_1 (Partial Break Time-1) and PB_2 (Partial Break Time-2) Then Finally The *FB* (Full Break Time).

and continuous, reinforcement learning aids the difficult task of determining the value function of this multidimensional problem. Our scheme is innovative in that the collision-avoidance safety planning challenge is articulated as a sequential decision method in a continuous multidimensional structure [5] and addressed via reinforcement learning in the interior a continuous action space. The presenting of two solutions to collision avoidance multi-objective optimization problems is the work's key contribution. First, the deep deterministic policy gradient (DDPG) algorithm of reinforcement learning with continuous actions is applied in the cooperative [6] and competitive aspects to maximize the overall driving benefits. Because of the predicted gradient of its action-value function, DDPG can be estimated significantly more reliably than a typical stochastic policy gradient. The suggested decision-making approach and calculation algorithms were evaluated in numerous typical scenarios using a simulation and verification platform based on Unity3D Game Engine with ML agents and Python API. The following are the key concerns of this paper:

1) In order to avoid multi-vehicle crashes in emergency and severe conditions, a general decision-support safety scheme for multiple autonomous vehicle driving is presented, which combines two alternative driving techniques and retains the efficiency of the driving strategy.
2) To keep the steering and acceleration of the ego vehicle bound, a novel driving strategy is developed.
3) Using Unity3D Game Engine, the new strategy will be created and tested. The associated performance outcomes are assessed.

The following is how the rest of the paper is organised: The prior work in this domain is represented in Section II. The approach employed in this study is discussed in Section III, which includes an overview of the deep deterministic policy gradient algorithm for reinforcement learning and the simulation setup and model training details. In Section IV the introduces the simulation verification platform for evaluating the proposed method's efficacy and reliability. Finally the future works and Conclusions are provided in Section V.

II. Related Works

Collision avoidance for multiple vehicles is a hotly debated topic in academia [7]. The majority of the early research focused on two-dimensional safety path planning in the context of a group of autonomous vehicles attempting to avoid stationary objects. Researchers have recently focused on the necessity of automobile collision avoidance. Some ways [8] consider other vehicles to be movable impediments for each vehicle. By projecting their measured velocities, one can estimate where other vehicles will be in the future and prevent collisions accordingly [8] has presented a collide-free approach to navigate a collection of independent unmanned vehicles. The individual positioning and orientation information is translated into a navigation variable to provide the navigational function. But the vehicle's continuous speed or turning radius cannot be restricted by that lone way. Since the safe operation of the current time stage may lead to future collisions, vehicles could have to alter direction immediately, which in many realistic circumstances is not possible due to these vehicles' movie limits. Other investigations [9] use parametric curves to shape the way in which every movable object of the environment may take smooth distances and ultimately reach its target. For vehicles to trace these routes, however, their speed and direction must constantly vary, and the size of the change is huge and not practical. We, therefore, believe that cars are traveling at a constant speed and gradually shifting their orientation by means of circular bows in order to make it easy to execute the proposed algorithm in real-time with massive scenarios for safe path planning.

In previous related research, each vehicle calculates its near-optimal path and plans its motion solitary by following a collection of local rules [10]. In an earlier related study, every vehicle determines its almost optimum trajectory and plans its movement by obeying an assortment of local regulations alone [11]. In [12], a localized soccer robots route planning technique is provided; the turning radius limits and the robot's speed constraints are explored. In many circumstances, however, a localized track planning scheme [13] cannot manage arbitrary traffic because of the cinematic unpredictability of the individuals concerned. Heuristic techniques like the genetic algorithm are utilized in a certain study in order to reach resolutions to this challenge by including all vehicles in the scheme [14]. For instance, research conducted in [15] proposes an optimal crash avoidance strategy between multiple robots, enabling them to avoid prospective collisions without any new collision. But it is difficult for a vehicle to alter its route if it has several potential crashes since the system needs tremendous computational work [16], [17].

In any dynamic and continuous autonomous driving situation, when confronted with the challenge of safety planning, artificial potential field(APF) techniques [18] are equated with continuous, static likely pitch equivalent equations. In real-time, APF systems for control and navigation can be quickly deployed and executed. These algorithms attempt to achieve an objective by employing virtual forces to avoid impediments on the trajectory, which attract or pull it away. One advantage of this approach is that it may take account of various limits solely by adding particular forces. In order to utilize APFs in distinct autonomous driving scenarios, the different new potential was proposed depending on road structure or vehicle physics [19], and intersection. Various enhancements have been suggested to address additional constraints of the classic autonomous driving APF algorithm. In order to prevent local minimum challenge, the modified APF model can also have a virtual obstacle or a location addressed of target point. The close obstacle problem can be addressed by changing the computation of APF utilizing fuzzy logic. A further artificial friction force to reduce oscillations was introduced in [20], [21]. While APF algorithms may be sufficient for the outcome, the vehicle's final design is unpredictable, resulting in hazardous scenarios.

Another essential drawback with this approach is that it is difficult to consider the vehicle's kinematic restrictions [22]. This approach cannot be ensured the mechanical feasibility of paths. The methods of elastic bands (EB) are likewise derived from physical similarities. The anticipated path of the goal is represented by a succession of springs, which can be distorted in response to environmental changes. The EB's intrinsic forces restrict neighbouring path nodes, although the approach struggles with exact kinematic constraints. Choosing the final point for the trajectory is likewise a challenging emergency question. In the autonomous driving manner, vehicle control [23] is responsible for following the theoretic trajectory predicted using the prospective algorithm [24], [25]. Vehicle kinematics models, such as the bicycle model, have been employed in a series, mostly steering angle and accelerated, of commandments for translating this trajectory (x(t), y(t)). Several control methods were utilised for comparatively low-speed driving environment, including: PID controls, pure persecution controllers, and Stanley controllers. At high speeds or with a significant curvature change rate, the dynamic model-based control approaches function better. The nonlinear control and adoption of the Model Predictive Control, as well as the feedback feedforward controlling, can boost vehicle stability at high speeds. These methods, however, presuppose that the traffic environment is fully known, including the intentions of other road users. In view of the environmental unpredictability, the safety decision-making job is typically modelled on the Markov Decision Process that sometimes was partially observable and applied to numerous driving scenarios. The primary theme of the safety planning method is the planning of driving manoeuvres, i.e. the development of optimum driving behaviours for a particular scenario, based on the tracks of participant vehicles. The rapid growth of machine learning allowed a mix of classical methods and ways of improved learning to make autonomous decisions in very interactive environments such as the learning process or, more recently, Reinforcement Learning.

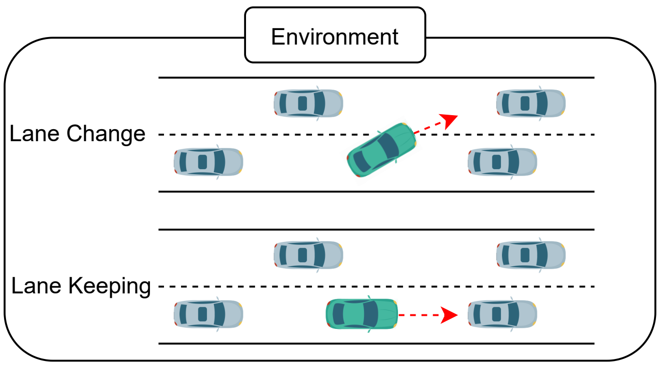

Figure 2: Design of Training Environment for SPS (Safety Planing Scheme) Mechanism of Avoid Multiple Vehicle Collision.

III. Methodology

This study is based on the concept of a cooperative and competitive strategy in multiple autonomous agent vehicles. In order to build a conceptual framework involving perception, communication and co-operation, threat assessment, decision making, and finally, the vehicle control modules, certain components are required as part of our core project. A multi-constrained issue was resolved by an optimal safety planning application to mitigate multiple vehicle collisions, including risk prediction. As far as general architecture is concerned, we are developing an environment scenario in which the ego vehicle takes safety decisions based on upcoming obstacles, lane maintenance and lane-change decisions, and the overall demonstration in *Figure: 2*.

A. Deep Deterministic Policy Gradient

The learning method is like human learning, depicted as a Markov decision-making process (S, A, P, R). DeepMind proposed the DQN algorithm in 2013, which opened a new era in deep reinforcement learning. The key enhancement of the algorithm is the utilization of expert replay and the construction of a second target network to erase the link among the training samples and increase the training stability [26]. Certain DQN developed algorithms have significantly advanced in the discrete action space problem. However, the issue of continuous strategic control is quite challenging to understand. DeepMind proposed the DDPG method based on the DPG and DQN algorithms in 2015, and the standardization process was imported into the deep learning environment. Experiments have shown that the approach provided works effectively on numerous types of continuous control issues. A new actor-critics technique is the DDPG algorithm.

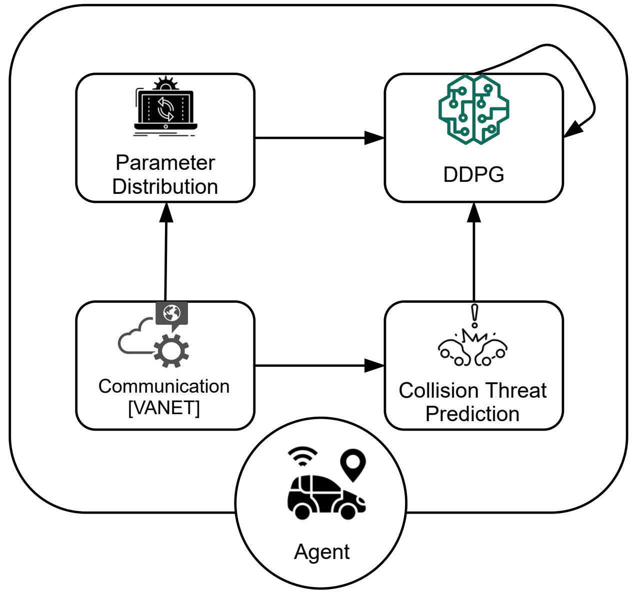

Figure 3: Demonstration of SPS (Safety Planing Scheme) Agent.

The actor function $\pi(s|\mu)$ creates an action given current status in an actor-critical algorithm. The critic criticizes an action-value $Q(s, a|A)$ function on the basis of the output of the actor and the current state. The TD errors created by the critic drive learning in the critical network, and then the actor's network is upgraded on the basis of the policy gradient. The DDPG algorithm merges the benefits of the actor-critical and DQN algorithms to facilitate convergence. DDPG introduces certain DQN ideas, which use the target network [27]. According to this cognitive manner we build a training agent and the we illustrate it in *Figure: 2*.

B. Experimental Setup

Extensive experiments are conducted to quantify the two main autonomous driving metrics, namely the total rewards, which show the overall success of our scheme and the number of collisions across both cooperative and competitive approaches to the system. We use the Unity3d game engine to create the environment depicted in *Figure: 2* to explain the entire driving system. Since the road is approximately 886 m and 15 m as width and length is intended. We progressively introduced vehicles to the path and observed the performance in relation to their learning behavior. For example, two conventional vehicles (CVs) operate on the highway in these simulations. We then change the number of DDPG-equipped autonomous driving vehicles (AVs) for testing the proposed driving scheme. Defining reward function, we follow the *Figure: 4* and the equation deployed by *N.Sugiyama et al.* [28] i no of vehicles motion and velocity model:

$$\frac{\mathrm{d}^2 z_i}{\mathrm{d}t^2} = a\{V(\Delta zi) - \frac{dz_i}{\mathrm{d}t}\}$$

here the optimal-velocity function presented by $V(\Delta zi), z_i(t)$ indicates the position of ith vehicle at time t, and a is the sensitivity (the inverse of the suspension of vehicle i at time t, $z_i(t)(= z_{i+1}(t) - z_i(t))$ is the headway of time). This is achieved by comparing different simulations performances. In order to achieve cooperative and competitive approaches, the reward values alter, and each vehicle's R communication range is 80 [0; 80] meters. The vehicles have a speed range of 80 km=h and 120 km=h, respectively. The values of the other parameters are defined as steering [-45,45], acceleration [0,1], brake [0,1], angle [-90,90]. In TensorFlow, we have built the driving arrangement by using two hidden-layer networks with neurons as a non-linear function in order to get the optimum policy. In each layer, there are about 300 and 400 neurons. The learning rate is $1e{-}6$, and the batch size is 32. In order to compare the performance of our proposed approach, we apply the decentralized collision avoidance policy for multi-robot systems called POMDP suggested by *Pinxin et al.* [29]. POMDP employs a multi-agent deep reinforcement learning architecture to enable several robots to develop an ideal collision avoidance technique. An experimental episode indicates a stage on the real-world circuit and hence a whole race from the beginning to the end. However, the race finishes abruptly in other cases, like when one agent turns back or leaves the track edge owing to the accident. As a leading agent, a vehicle sends its learned model parameters to its following agents within one local network while the following agents sit inactively and are awaiting the learned by their leading agent. As we developed an autonomous non-deterministic driving environment, we performed 10 experiments and calculated the average results for all runs.

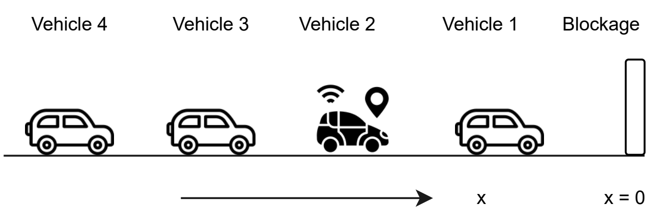

Figure 4: Presentation of Rewards Function Regarding The Conditions of Multiple Vehicle Collision by Sudden Slow-down.

IV. Result & Discussion

The agents learn the optimal driving comportment during simulations for mastering the avoidance of collision by using the proposed driving scheme in Unity3D. The objective of the agent is to improve its conduct dynamically by learning to prevent collision with other agents and things near them. In the meantime, their time of arrival is also minimised. An autonomous vehicles system must scale efficiently as there are fluctuations in the number of participants. We thus test the system's scalability in the different densities of participating AVs. To assess driving performance, we employed two Conventional Vehicle (CVs), and one Autonomous Vehicles (AVs) installed with DDPG. The AVs agents performance is evaluated by considering mainly the number of collisions suffered by the agents and the rewards achieved during tests presented in *Figure: 5* and *Figure: 6*. The first cooperative and the second one are competitive in results, which indicate that the driving scheme includes two CVs with one and two AVs working with DDPG. In *Figure: 6*, the average number of collisions over a span of 500 episodes during the training process is presented. Average collisions during the training phase are given in *Figure: 6* for the episodes. In this figure, every point of collision is measured by adding up to every 50 episodes. From the data, we note that the average number of collisions in all scenes is decreased as the number of episodes rise. The average number of competitive collisions is approximately 211% higher compared to the cooperative strategy. The reason is that in the system, the distribution parameter approach of the DDPG is used to increase AVs performance. The DDPG rewards for nearby autonomous vehicles in a communication network compare us to each vehicle's optimal driving policy. The highest reward is the best conduct of autonomous vehicles. Furthermore, we see that DDPG's competitive technique requires more training time to reach zero collision in *Figure: 6*. The highest reward represents the best driving behaviours of autonomous vehicles. Additionally, we also notice that a longer training time is needed by the competitive approach of DDPG to achieve zero collision in *Figure: 6*. Compared to DDPG's cooperative approach, the zero collision objective in the training phases is 13%faster.

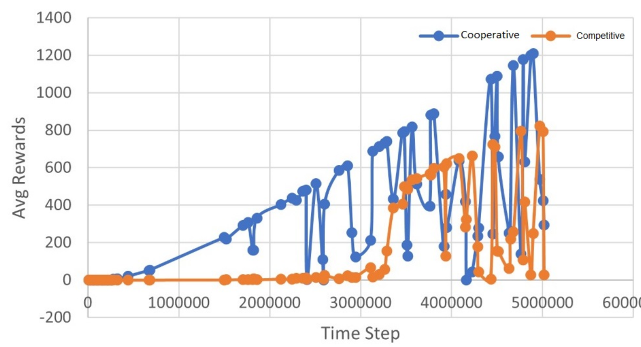

Figure 5: For Each Approach, The Average Episode Rewards Against Time Step.

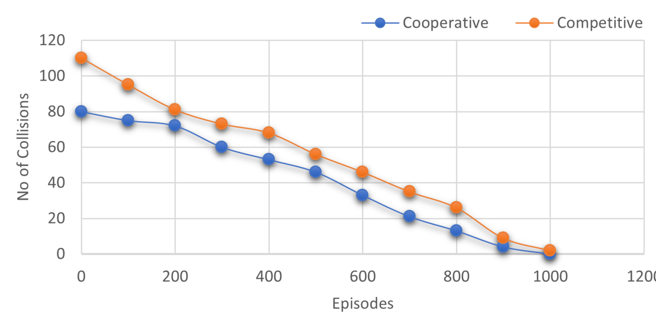

Figure 6: For Each Approach, The Number of Collisions Per Episode.

The cooperative rewards gain by autonomous driving vehicles are measured, and the results are shown in *Figure: 5*. The results show the sum of the reward recorded for the entire time steps of training. The average reward increases for the safety scheme as the number of episodes grows. At first, the reward is low in all situations; especially since the cooperative approach of each autonomous vehicles has been initiated with random learning parameters in the initial stage, the competitive approach has been very low in a few periods. The vehicles can therefore not choose the right action for their following move, leading to chain crashes. The cooperative strategy penalizes unsuccessful acts by reducing rewards, allowing DDPG to learn from its mistakes. Then, depending on its previous experiences, it may choose the correct action in the future episode. As the agent's learning experiences improve with each episode, the rewards begin to rise. The reason is because the cars learnt to take an appropriate action to prevent collisions. In this situation, rewards are given to encourage and limit the desired driving behaviour. We note that DDPG's competitive technique has the lowest reward compared to this cooperative strategy over a period of 500 episodes. Approximately 33% greater than the average competitive DDPG Driving Vehicle reward for cooperation is paid by autonomous driving vehicles. In addition, when a collision is possible, the DDPG algorithm additionally awards penalties when the agents move too close together. Interestingly enough, the agents are not colliding with other vehicles because they acquired better policies.

V. Conclusions

We analysed in depth the needs and the design objectives of multiple autonomous vehicles in this paper. In order to achieve such objectives, we have presented an effective and safety planning scheme. We have devised an efficient collision prevention technique using a multi-actor hierarchy. The DDPG's rewards are defined by taking into account collision avoidance in the field of cooperative and competitive approaches, minimising time of arrival, and road maintenance. Its worth indicates the superiority of driving action; for example, a superior reward indicates optimum safety driving behaviour. To boost up the speed of learning process, the parameter distribution approach is used. Using a privately-held communication technique with a follower-leader multi-agent manner. We have demonstrated that the safety scheme efficiently reduces the count of collisions and scales with an increasing number of autonomous vehicles through rigorous testing at Unity3d. We also exposed meticulous safety learning, in which vehicles learnt not to collide with other vehicles but to go off the lane and stop. This enhanced driving behaviour while lowering danger and liability.As part of our future work we intend to improve safety by the incorporation of camera-based images or videos of the environment into the learning process. In addition, to adapt it to the situations where roads have no necessity for speed range, we contemplate enhancing the safety scheme.

VI. Acknowledgment

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