DESIGN OF INTELLIGENT CRUISE CONTROLLER OF MOTOR VEHICLES

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Abstract - Nowadays, due to traffic jam and many cars on traffic, it is very necessary to control the distance between cars and obstacle. Many car producers have been designed and manufacture Cruise Control Systems for cars. Reinforcement learning, one of the popular artificial intelligence techniques, is a method used to train autonomous systems in many different fields. In this simulation study, the adaptive cruise control (ACC) of a ring bus serving in the campus area is controlled with Deep Deterministic Policy Gradient, which is one of the reinforcement learning methods. This simulation study is carried out considering the speed limit in the campus area and the acceleration values required for a comfortable journey of the passengers. Acceleration, velocity and distance values are given with graphs. Consequently; the proposal neural predictor has superior performance to adapt and predict the distance, velocity and acceleration of ego vehicle (bus).

Keywords: Reinforcement Learning, DDPG, Adaptive Cruise Control.

1. Introduction

The necessity of intelligent transportation systems has been reinforced by the steadily rising number of vehicles on the road. So, driver assistance systems have grown rapidly over the last decade [1]. Thanks to these developed systems, it is aimed to make a safer journey by reducing driver fault. In addition to increasing safety, these systems also increase fuel economy by preventing unnecessary acceleration and deceleration [2].

Nowadays, artificial intelligence techniques are the basis of most of the driver assistance systems [3-5]. Driver assistance systems include purposes such as detecting vehicles [6,7], lane keeping [8], and collision avoidance [9]. One of the driver support systems is adaptive cruise control (ACC).

By altering the automobile's speed, the adaptive cruise control technology keeps a safe distance between the leading vehicle and the ego car. Rear collision risk is significantly reduced by the adaptive cruise control technology. The initial phase of a collision avoidance system is particularly helpful in reducing the number or severity of collisions and in saving fuel [10].

Kabasakal and Ucuncu designed ACC using PID and MPC in their study [11]. In addition to its accessibility, simpler design, and economic advantages, they came to the conclusion that the PID controller offers greater responses when compared to the MPC controller. Rout et al. employ a genetic algorithm technique for the optimization of PID controller parameters of an ACC [12].

In addition to these, the DDPG algorithm is also used in studies on energy consumption and efficient use [13]. Battery electric vehicles with four wheels and several motors on various axles are becoming more and more common because they provide excellent dynamic and safety performance without sacrificing construction complexity. But it's important and challenging to divide the power flow between the power sources effectively. Gui er al., are proposed an intelligent energy management strategy (EMS) for a specific dual-motor four-wheel-drive (DM-4WD) battery electric vehicle to reduce energy consumption in unknown traffic conditions [14]. The simulation results show that the proposed DDPG-EMS outperforms the abandoned action-based double deep Q-learning technique in unknown driving cycles, achieving 95.7%, 94.8%, and 95.5% of the benchmark dynamic programming-EMS energy performance. The simulation findings indicate that the suggested approach is productive and useful for multi-power battery electric vehicles EMS design.

Olivenza et al., designed the DDPG algorithm is employed with the aim of autonomous vehicle navigation, resulting in an agent capable of producing trajectories [15]. The Lyapunov function can be utilized as an evaluation tool for agents created by the DDPG algorithm, as shown by the two agents that are obtained and their stability comparison.

Wang et al., designed a reinforcement learning-based autonomous vehicle for underwater vehicles [16]. A path-following control approach based on the Simplified Deep Deterministic Policy Gradient (S-DDPG) algorithm is suggested to address the issue that the optimization time is too long in one control step for complex nonlinear situations. S-DDPG just takes into account the reward in the current state; the payout in the future does not need to be predicted. This reduces the amount of useless unsuccessful samples produced and streamlines the neural network training process (NNs). The simulation findings demonstrate that the S-DDPG has clear advantages over alternative approaches and can enable the AUV to execute path-following tasks.

In this study, it is aimed to design an ACC using Deep Deterministic Policy Gradient (DDPG) method, one of the reinforcement learning algorithms, for a ring bus moving in a university campus where the speed limit is 40 m/s.

2. Material and Method

Active safety systems in vehicles have developed over the years and have taken their place in the literature as accident prevention and driver support systems. These systems try to minimize the errors caused by the driver by supporting the driver in order to prevent the accident. One of these systems is ACC. ACC provides comfort in addition to the safety system. While this system drives the vehicle at the speed determined by the driver, it also provides automatic driving by adjusting the distance with the vehicle in front at the rate determined by the driver [17-19]. There are many different algorithms for ACC in the literature. The DDPG algorithm is a new algorithm for ACC.

Reinforcement learning works when an agent interacts with the environment based on the principle of trial and error. There is a reward value for each action taken. The goal of reinforcement learning is to maximize this reward value. Because of its ability to learn strategies through autonomous interaction between system and environment in an unknown environment, reinforcement learning has been widely studied by scholars both at home and abroad as an artificial intelligence technology, and it has become a major research area in the field of robotics and control [20].

The DDPG algorithm, which is based on the actor-critic system, is another type of reinforcement learning algorithm in which the agent learns the mapping function between environment and action without having to discretize the control action, so it has a wide range of applications in solving complex problems [21].

Deepmind proposed the DDPG method in September 2015 and uses deep neural networks to generate actor and critical values on the basis of the DPG algorithm. Deepmind also used the deep learning normalization mechanism as a reference. The actor critical technique is the basis of the DDPG algorithm. Establishing actor and critical networks is the goal of the actor-critical approach. The current approach is created using the actor network, and its benefits and drawbacks were assessed using the critical network. The target actor network and target critical network have been introduced in order to increase training stability [22-24]. The DDPG algorithm is given in Figure 1.

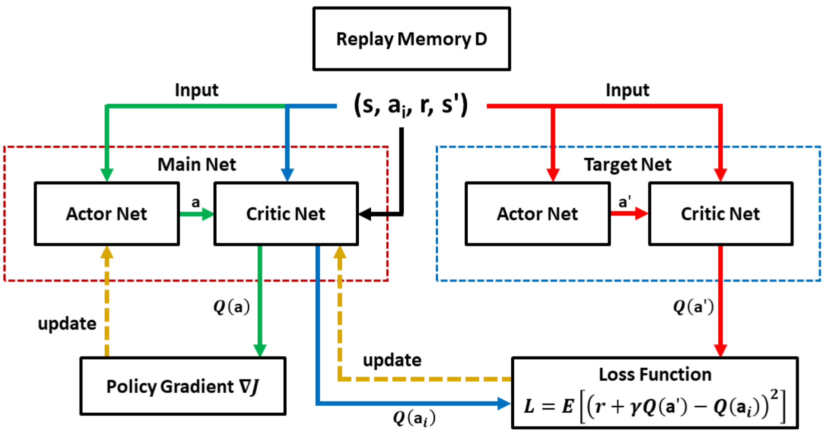

Figure 1: The DDPG algorithm [20]

3. Simulation Results

DDPG, one of the reinforcement learning methods, is used for ACC. Simulation studies were carried out using the MATLAB Adaptive Cruise Control System simulink model [25]. Simulation studies were carried out in MATLAB. During the simulation studies, some criteria were taken into consideration.

For a comfortable journey, the acceleration value is set to a maximum of +2.5 m/s2 and -2.5 m/s2 for acceleration and deceleration, respectively. It is accepted that the on-campus speed limit is 40 m/s and the speed of the bus is not requested to exceed this value.

In Figure 2, the safe and relative distance are illustrated.

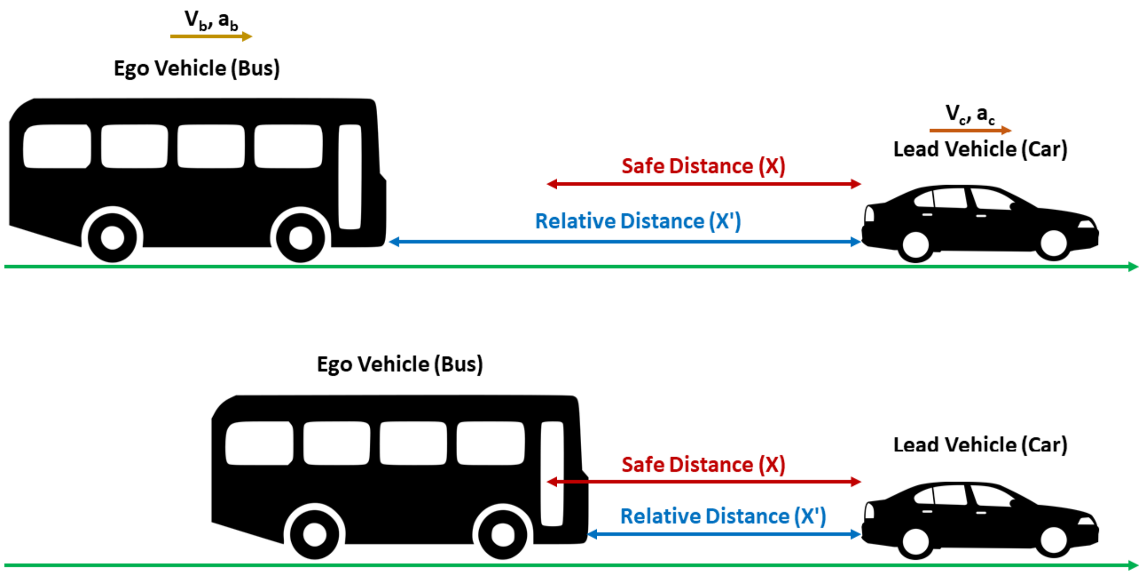

Figure 2: Safe and relative distance between bus and lead car

In the DDPG algorithm, the reward function is defined as $r_t = -(0.1e_t^2 + u_{t-1}^2) + M_t$. u_{t-1} is the control input from the previous time step. The logical value $M_t = 1$ if velocity error $e_t^2 <= 0.25$; otherwise, $M_t = 0$.

The following definition applies to the bus's reference velocity, Vref. When the relative distance is closer than the safe distance, the bus follows the lead car's minimum speed and the driver-set speed. The bus keeps some distance from the lead car in this way. The bus tracks the driver-set velocity if the relative distance exceeds the safe distance. The bus's reference tracking velocity is based on the safe distance. The initial values for the bus and lead car are given in Table 1. The simulation time is set to 40 seconds. The velocity value of the lead car is changed according to an acceleration value with amplitude of 0.7 and frequency of 0.2 rad/sec.

Table 1. Initial values for the bus and lead car

Initial	Value
Position for bus (m)	15
Position for lead car (m)	30
Velocity for bus (V_b) (m/s)	40
Velocity for lead car (V_c) (m/s)	37

While creating the DDPG structure, 48 neurons, 5 fully connected layers and 3 relu layers were used. The maximum episode value is set to 5000 and the episode reward value is set to 750. Episode reward or maximum episode is used as a stopping criterion. The simulation stopped by reaching the maximum episode value. The simulation results are given in Table 302. The graph of the DDPG algorithm training process is given in Figure 2.

Table 2. Simulation results

Episode number (epochs)	5000
Average reward	254.7553
Total agent steps	1986473

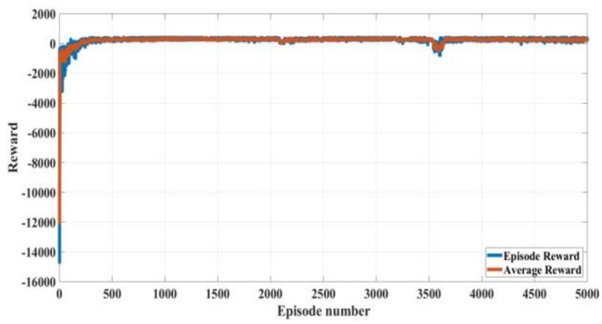

Figure 3: The graph of the DDPG algorithm training process

The distance, velocity and acceleration graphs obtained from the simulation results are given in Figure 4, Figure 5 and Figure 6, respectively.

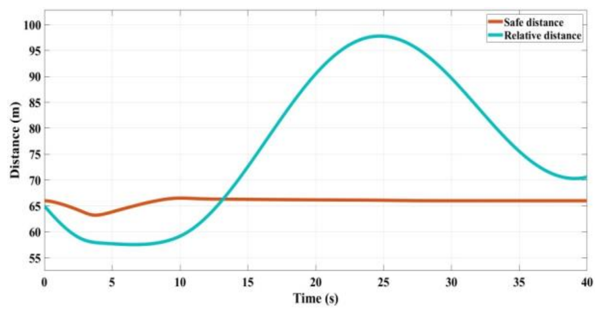

Figure 4: Results of distance between bus and lead car

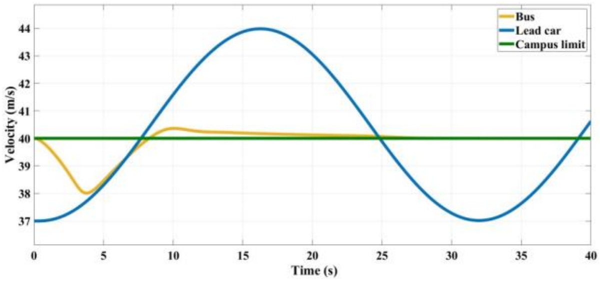

Figure 5: Results of velocity for bus and lead car

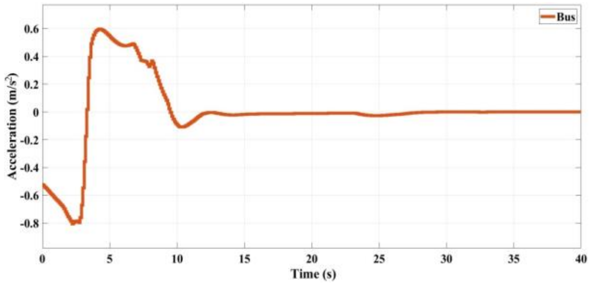

Figure 6: Results of acceleration for bus

As seen in Figure 4, since the relative distance is smaller than the safe distance between 0 and 13.17 seconds, the bus tried to equate its speed with the speed of the ego car. After 13.17 seconds, the relative distance has become greater than the safe distance. However, due to the determined speed limit, the ring bus did not exceed 40 m/s. As can be seen in Figure 6, the acceleration values did not rise to very high values (0.6 and 0.8 m/s2), providing a comfortable ride.

4. Discussion and Conclusion

In this study, the ACC design of a ring bus moving through the university campus was carried out. The DDPG algorithm was used for controller design. In the resulting graphs, we see that when the relative distance falls below the safe distance value, the reinforcement learning algorithm is successful to make the bus equate its speed to the lead car's speed. In the other case, where the relative distance value is greater than the safe distance value, it is aimed to equate the speed of the bus with the speed of the car in front. However, it was observed that the speed limit for the bus did not exceed the predetermined speed limit while ensuring the equality of speeds. In addition, when the acceleration graph is examined, it can be said that a comfortable journey was made. In this sense, the simulation study was carried out successfully.

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