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Multi-Agent Traffic Signal Control System Using Deep Q-Network

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In urban areas, temporal and economic losses due to traffic congestion are getting worse. It has a great influence on our lives. As a cause of traffic congestion, on ordinary road, inappropriate signal switching may be cited. Parameter manipulation in the general signal control is set based on experiences by human hands, and it is never optimal. Therefore, controlling traffic lights to improve traffic behavior is possible way to solve traffic congestion. In this study, we combine multi agent system with Deep Q-Network method. We used an intersection as an agent and conducted experiment in road environment with multiple intersections. As a result, it was shown that agents can perform appropriate parameter manipulation by mutual exchange of information among agents.

1. Introduction

In recent years, temporal and economic losses due to traffic jams in urban areas are getting worse and exert a great influence on our lives. Parameter manipulation in the general signal control is set based on experiences by human hands and it is never optimal. Therefore, controlling traffic lights and improving traffic behavior is one way to solve traffic congestion. In this study, we combine a multi-agent system with a method using Deep Q-Network (DQN) [Mnih et al.2013]. This is a combination of deep learning with high feature extraction capability and Q learning which is one of reinforcement learning methods to learn optimal behavior based on rewards. In consequence, we propose a signal control system aiming at appropriate parameter manipulation in road environment with multiple intersections.

2. Traffic Signal Control with Deep Q-Network

Previous study[Sato et al.2017] uses DQN to control traffic signal. However, it is necessary to cover the operation pattern of traffic lights as many as the number of intersections. If the number of traffic lights increases, the amount of calculation becomes enormous and it becomes difficult to perform appropriate parameter control. Therefore, we propose a multi-agent signal control system using DQN aiming at reducing the computational complexity compared with method of Sato et al. by preparing agents as many as the number of intersections where signal operations are performed and coordinating agents together.

3. Proposed Method

In this study, we use the traffic flow simulator image as input value by using DQN. Design of DQN in a single agent, we follow Sato et al. In order to cooperate among agents, we have the agent exchange information on other agent's behavior. In order to be able to share behaviors among agents, we use 513 values by adding the value of action of other agent to 512 input values in fully connected layer. As

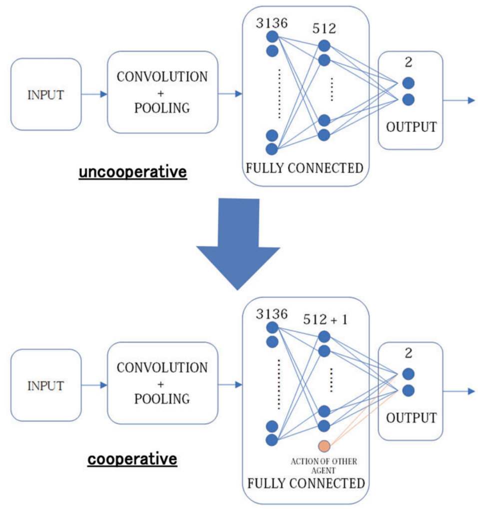

Figure 1: CNN in uncooperative / collaborative learning

a result, the values of the actions is updated considering the behavior of other agents. (See Figure 1).

4. Experiment and Evaluation

We used the number of waiting cars as evaluation criteria and compared them with several methods and examined the effect of the proposed method and its usefulness. In this study, we performed experiments using the micro traffic flow simulator SUMO. This is an open source simulator developed around the German Aerospace Center. It is possible to set various parameter freely, such as the speed of the car, the acceleration, the traveling route and the installation of traffic lights and roads. We prepared the following three comparative methods.

4.1 Comparative method 1: static signal control

First, we prepared a static situation in which traffic lights are switched at regular intervals according to the traffic

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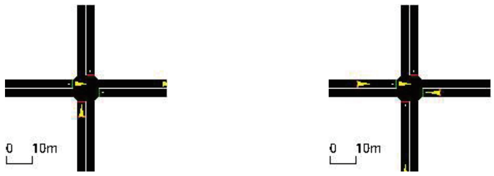

Figure 2: Input image of SUMO for multi-agent

Figure 3: Input image of SUMO for single-agent

flow. We set the offset [*1] to 15 seconds.

4.2 Comparative method 2: Signal control by non-cooperative multi-agent using Deep Q-Network

Second method is an situation with multiple agents with DQN as agent and agents do not share information(Figure 2).

4.3 Comparative method 3: Signal control by single-agent using Deep Q-Network

Third method is a single agent situation using method of Sato et al. DQN is used as an agent which learns while reading the entire road situationnt image(Figure 3).

5. Experimental Result

For both the proposed method and the comparative methods, we performed 500,000 step experiments and showed the result of simulation by taking the average of the number of waiting cars every 6,000 steps(Figure 4). The horizontal axis is every 6,000 steps and the vertical axis is the number of waiting cars as negative reward. For each line, the proposed method, comparative method 1, method 2 and method 3 are corresponding to “Cooperation_multi”, “static ”, “multi”, “single” respectively. As the number of episodes increases, Comparative Method 3 was better than any other methods and it is understood that it was the ideal method to solve the most congestion, but it took about 1.8 times as long as the proposed method. In addition, the proposed method surpassed Method 1 and Method 2, and was approaching Method 3. Therefore, the proposed method can reduce the computational complexity while obtain the similar result as Sato et al ’s method.

6. Conclusion

In this study, we proposed the method of traffic signal control with multi-agent Deep Q-Network. Experimental result showed it was able to control traffic signals appropriately with reducing the computational complexity than the comparative method. Cooperation among agents in signal control using DQN worked effectively in our experiment. However, it is impractical to use images taken from the sky at each intersection. Therefore, we replace the information obtained from the radar with a simulator(Figure 5). By using radio wave radar we get information on the speed, length, position etc. of the car. Information obtained from the simulator is entered into the agent as a matrix. In this way, we are beginning to examine even the reality-appropriate method.

*1 Number of seconds to shift the timing at which traffic lights switch to green light for each intersection.

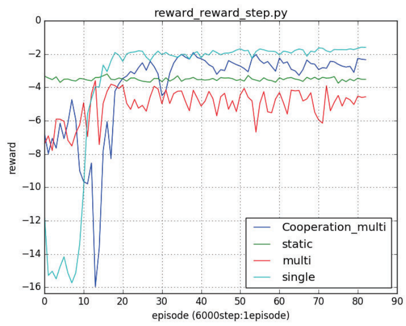

Figure 4: Experimental Results of Proposed Method and Comparative Method

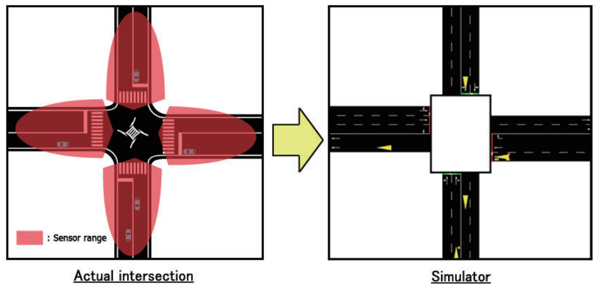

Figure 5: Convert real road to simulator

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