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A Dynamic Queue Adjustment Algorithm for Task Offoading in Vehicular Edge Computing based on MADDPG

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Introduction

As wireless communication and related technologies advance rapidly, Internet of Vehicles plays a very important role in intelligent transportation systems. In-vehicle applications are increasingly enhancing people's daily lives, including autonomous driving and augmented reality.

We study a unidirectional road with a number of task vehicles and service vehicles randomly distributed on the road. The task vehicles generate tasks at different time slots with a certain probability, and the tasks generated by the task vehicles can be computed locally in the task vehicles or offloaded to the service vehicles within their communication range.

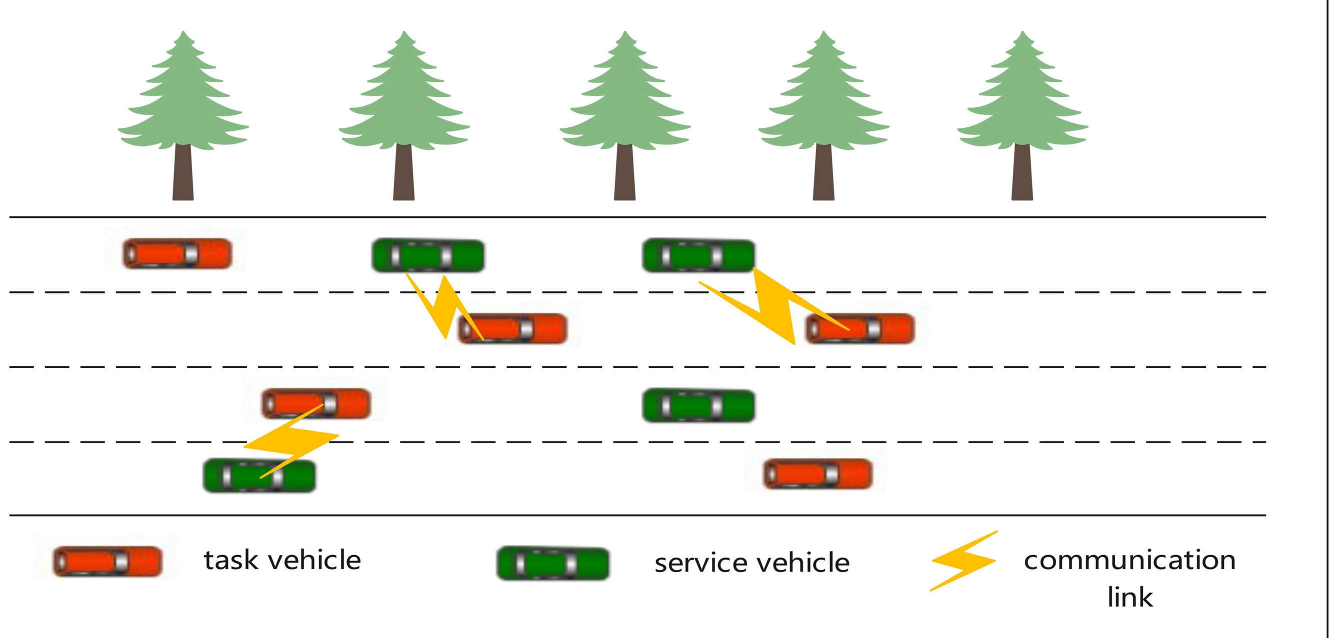

Figure 1. System Model

Research objectives

- To maximize the utility of all tasks over a period of time.
- To maximize the success rate of all tasks over a period of time.

Methods

A dynamic queue adjustment algorithm based on MADDPG is used to solve the optimization problem.
The algorithm we designed can be divided into two sub-algorithms, sub-algorithm one is the task scheduling decision-making algorithm based on MADDPG. With sub-algorithm one, task vehicles can decide whether their tasks are to be executed locally or offloaded to a nearby service vehicle for execution. Sub-algorithm two is a task waiting queue dynamic adjustment algorithm, unlike the FIFO algorithm commonly used in previous research, sub-algorithm two can dynamically adjust the position of the task in the queue according to the urgency of the task, specifically, whenever the task queue receives a task request, the task is first inserted into the tail of the waiting queue, and then the current computation time and the waiting time will be calculated, which can be used to get the urgency of the task, and try to swap the task with a lower urgency, but the exchange needs to ensure that the task is completed within the deadline, otherwise the exchange stops.

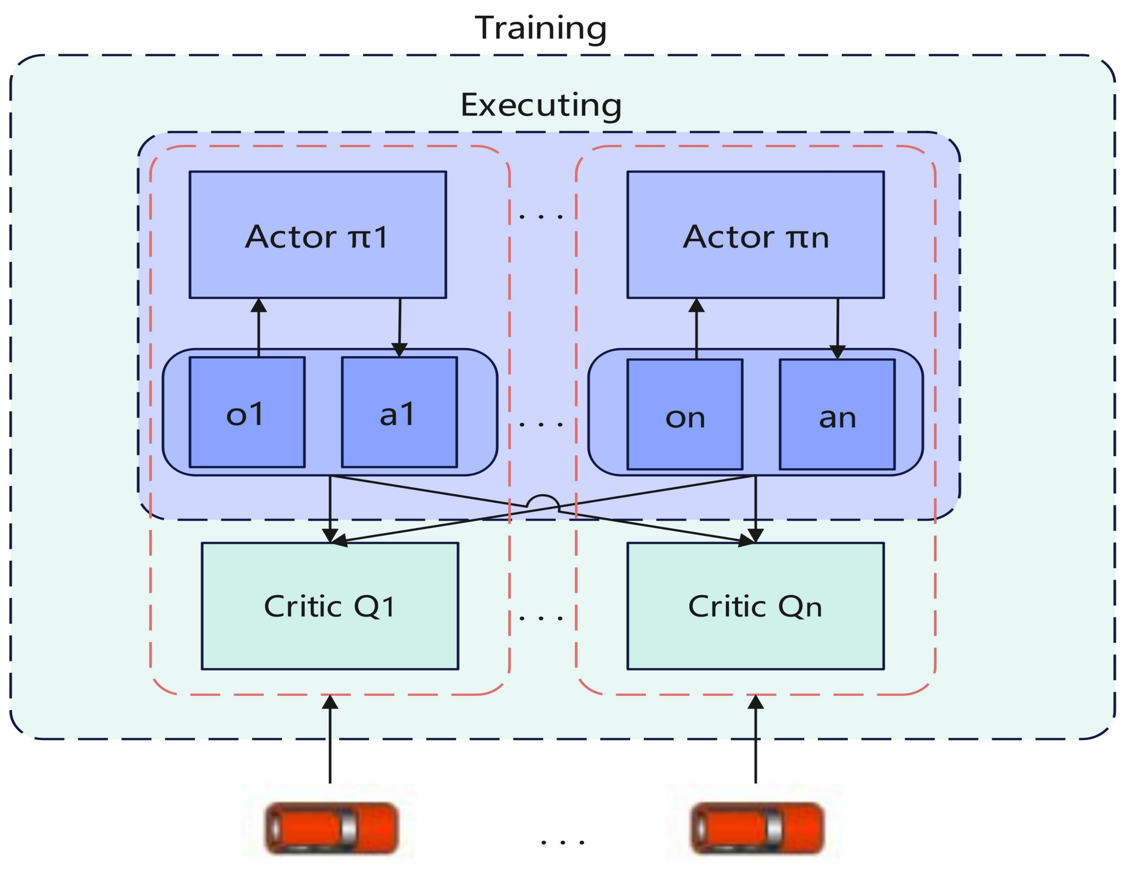

Figure 2. MADDPG-based Dynamic Queue Adjustment Algorithm

Results

In order to evaluate the performance of the proposed solutions in this paper, several comparison algorithms are designed for reference, which are MADDPG-based first-come-first-served algorithm, the random-based algorithm and the greedy-based Algorithm. The overall utility and the task success rate are compared under different conditions.

It can be seen that the algorithm we proposed achieves the best performance.

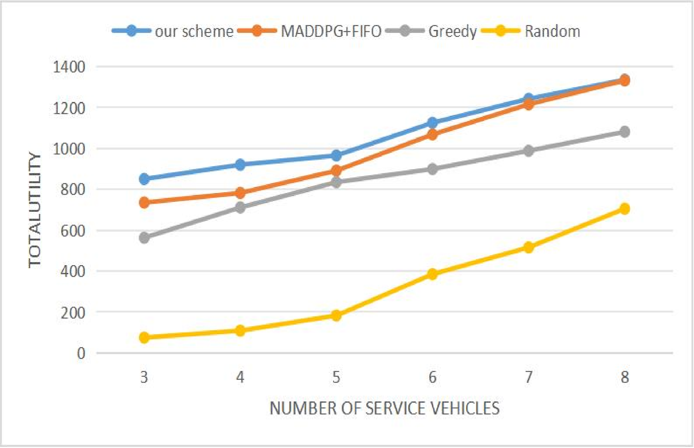

Figure 3. Number of service vehicles(Utility)

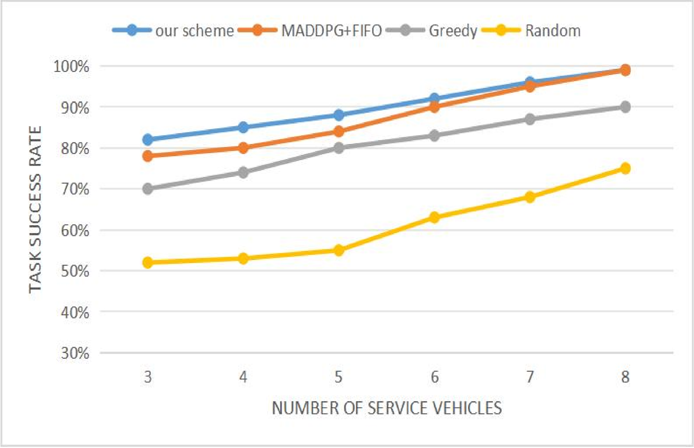

Figure 4. Number of service vehicles(success rate)

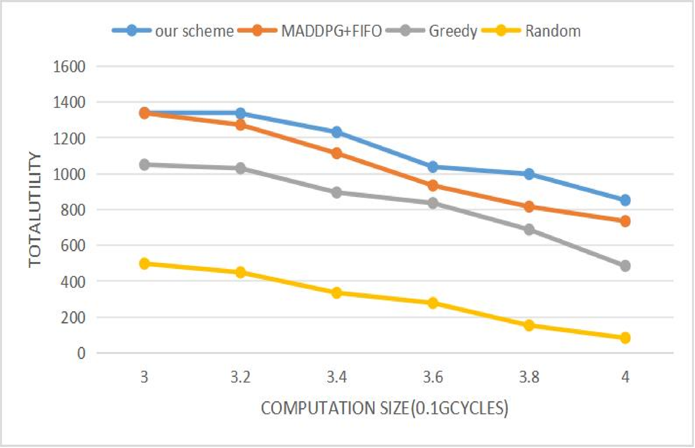

Figure 5. Computation Size(Utility)

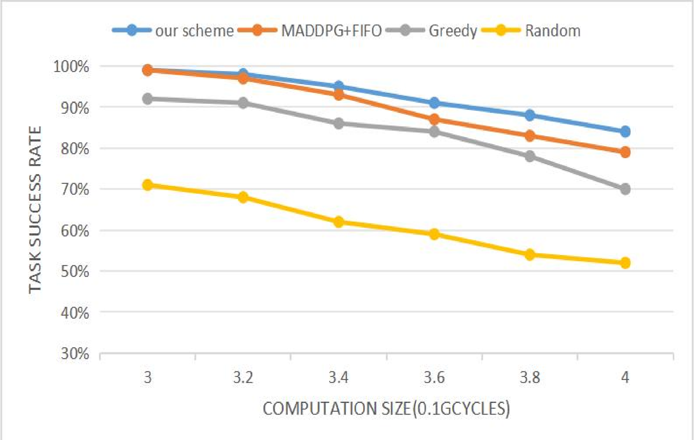

Figure 6. Computation Size(success rate)

Conclusions

- A utility evaluation function for evaluating the tasks from the perspective of the task vehicles is designed and the optimization problem of this papaer is formulated
- In order to solve this optimization problem, based on MADDPG and different from the usual first-come-first-served approach , this paper adjusts task's position in the waiting queue dynamically according to the real urgency of the task. Combined with the multi-agent algorithm, the solution of this paper is designed.
- the effectiveness and the reliability of the proposed solution in this paper is verified through extensive simulation experiments.

Acknowledgement

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