3D Placement Optimization of MEC enabled UAV for Data Transmission with Lower Latency and Energy Consumption

Rabeya Sadia, Seokhoon Yoon*
Department of Electrical, Electronic and Computer Engineering, University of Ulsan
rabeyasadia8@gmail.com, * seokhoonyoon@ulsan.ac.kr

Abstract

An energy-efficient UAV-assisted mobile edge computing (MEC) system is considered to provide MEC service to mobile devices (MDs) having delay-sensitive applications. However, optimal deployment of UAV is required to improve the connectivity of mobile devices to offload computation-intensive tasks. Therefore, we formulate an optimization problem aiming at minimizing the transmission latency and energy consumption to offload the task of mobile devices by optimizing UAV position. The proposed approach is resolved by formulating a Markov decision process and applying deep reinforcement learning (DRL).

Ⅰ. Introduction

IoT devices' constrained computing power and battery life make it challenging to accomplish delay-sensitive applications locally. Fortunately, the UAV-aided MEC system can offer convenient services by bringing computing resources closer to mobile devices to perform computation-intensive tasks effectively [2]. However, deploying the UAV at the best possible position will improve the system's performance through secure communication. In this framework, we propose a UAV-assisted MEC system in which mobile devices offload their computing task to the UAV-MEC server for computation. We attempt to optimize the 3D position of the UAV to enhance the data transmission process while offloading delay-sensitive tasks. To address the 3D deployment problem of the UAV-MEC server, we apply the deep reinforcement learning (DRL).

Ⅱ. Problem definition

We consider a UAV-aided MEC system in which a set of mobile devices are randomly distributed and have a wireless connection with the UAV that offers MEC service. Each MD has computation-intensive tasks of different sizes that cannot be handled locally and must be offloaded to the UAV-MEC server. From the optimal location, a UAV can serve mobile devices more efficiently, and the mathematical equation to optimize the UAV's position is considered as follows:

$$\Phi = \alpha T_{avg} + (1-\alpha) E_{avg} \qquad \alpha \in [0,1]$$

The objective of the work is to deploy the UAV in its optimal position with the goal of minimizing the weighted sum of average transmission latency and average transmission energy consumption of mobile devices for task offloading. A nonlinear optimization problem is formulated to optimize the UAV's 3D position.

Ⅲ. Algorithm

In our proposed DRL based algorithm, the agent UAV-aided MEC server continuously learns in accordance with the rewards or punishments acquired in interactions with the environment so that agent's state is closer to the target state.

The state space, action space, and rewards of the UAV agent are defined as follows:

The state space: S = 3D positions of UAV are defined as states.

The action space: A = There are a total of seven distinct actions: moving up, moving down, moving in the positive direction of the x axis, moving in the negative direction of the x axis, moving in the positive direction of the y axis, moving in the negative direction of the y axis, and holding the current position.

The reward: The reward is constituted as the minimization of the sum of weighted scaled transmission latency and weighted scaled transmission energy consumption.

The algorithm's aim is to relocate the UAV-MEC server to an area with the lowest possible transmission latency and mobile device transmission energy consumption to offload tasks.

Ⅳ. Simulation results

In our simulation, we consider a 100m x 100m area with 10 mobile devices in a random position and one UAV-MEC server. The task offload request rate for each MD is between [1, 10] tasks/sec using a Poisson distribution, and the size of each task is created uniformly within [2, 10] MB. The UAV's 3D starting position is chosen randomly. As the learning process advances, the UAV progressively moves to the optimum position and stays substantially stationary. In Fig. 1, the black dot represents the position of the mobile devices, red the UAV's moving process.

Fig.2 depicts the reward during the iterative process of the algorithm. It illustrates how the system gradually develops as the reward gets better with each iteration and how the system eventually stabilizes as the reward remains flat.

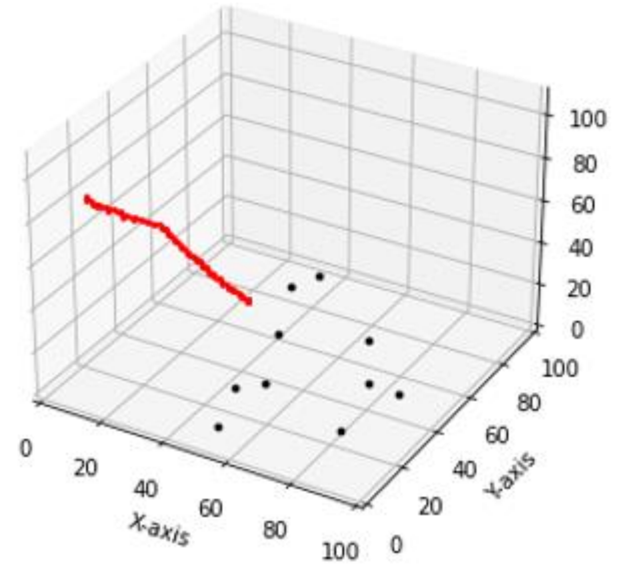

Fig.1 MEC-enabled UAV location moving process using DQN algorithm

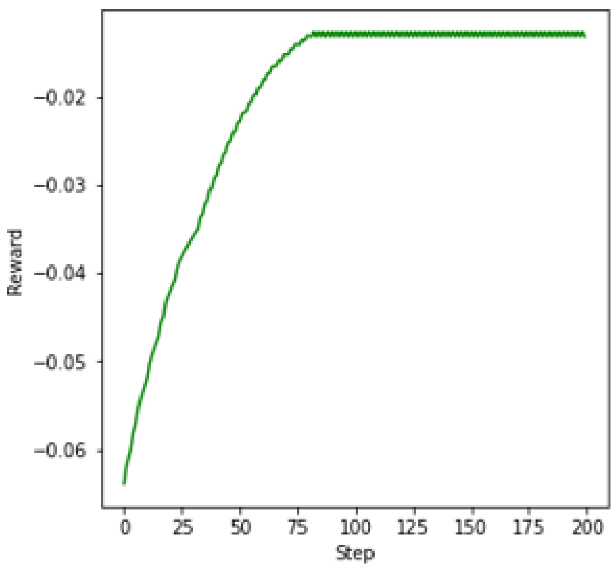

Fig.2 Reward during the iterative process of the algorithm

V. Conclusion

The DRL algorithm is used to determine the optimal deployment location of the UAV-MEC server. The simulation result shows that our agent swiftly determines the ideal deployment location by learning environment characteristics appropriately.

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