IEEE INFOCOM 2024 - IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS) | 979-8-3503-8447-5/24/$31.00 ©2024 IEEE | DOI: 10.1109/INFOCOMWKSHPS61880.2024.10620848

Link Topology-Adaptive Offloading Method On Vehicular Edge Computing

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***Abstract*—Offloading methods play a key role in optimizing computation, minimizing latency, and enhancing the overall performance of the Vehicular Edge Computing (VEC) system by transfer of tasks between vehicles and edge servers or other computational resources. However, many works neglect topological links generated by the request for privacy, the different preferences for communications and the qualities of transmission, where the topological links greatly influence on the search space of the optimal offloading decisions. In this work, we propose a Graph reinforcement learning (GRL) method to adaptively optimize the sum of the delay of tasks in joint vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I), which is called link topology-adaptive Offloading (LTAO) method. The LTAO method is composed of two modules in series: the Graph Convolutional Network (GCN) module and the Deep Reinforcement Learning (DRL) module, where the former module extracts features from the current state and the latter module outputs offload decisions for the state. Extensive experimental results demonstrate the effectiveness and superiority of the proposed LTAO method.**

***Index Terms*—Vehicle-to-vehicle, Graph reinforcement learning, Task Offloading, Vehicular edge computing**

I. Introduction

In the realm of the Internet of Vehicles (IoV), the amalgamation of Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) offloading stands out as a promising strategy, aiming to harness excess computing capabilities from proximate devices. This innovative approach unfolds as a means to augment the scope of computing resource provisioning within the IoV framework.

The high dynamism of the Internet of Vehicles leads to unstable connections and a reduction in channel quality [1]. Nevertheless, numerous works tend to neglect the information on topological links that caused by the request for privacy, the differences in link preference and other factors such as the quality of transmission. The motivations are as follows:

- The optimal offloading decisions differ across different link topologies due to the variations in the search space. How to make the best offloading decisions when links are topologically communicated?
- The potential forms of topological links experience an exponential increase with the growth of vehicles as Fig .1. How to cope with different topological forms of links adaptively?

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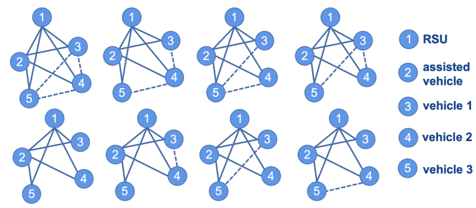


Fig. 1: Examples of potential topological link forms when the number of vehicles is 4. The number of potential topological forms of graphs with N different nodes is 2^N.

To cope with the offloading decision-making problem under topological links, we propose a new offloading method, called Link Topology-Adaptive Offloading (LTAO), to adaptively offload tasks in joint V2V and V2I systems. We summarize the contributions of this work as follows:

- To the best of our knowledge, this is the first work about adaptively offloading for topological links of the V2V and V2I systems.
- We propose a novel offloading framework called LTAO to effectively find the optimal offloading decisions by a GRL method composed of the GCN and DRL modules, where the GCN module extracts features from the IoV and the DRL module achieves adaptively offloading by the features.
- Experiments have been conducted to evaluate the performance of LTAO and the results demonstrate its effectiveness and superiority.

The rest of the paper is organized as follows. First, the problem definitions are provided in Sec. II. Then, we elaborate on the proposed method in Sec. III. We present the experiments in Sec. IV. Finally, We conclude the paper and provide future work in Sec. V.

II. Problem Definition

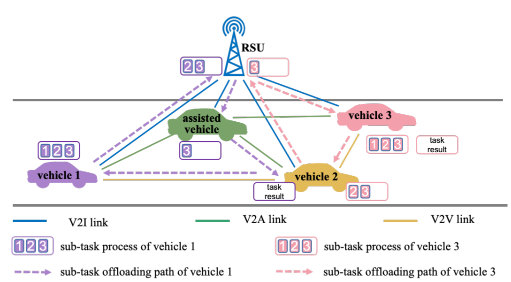


Fig. 2: An example of the proposed system model, where vehicle 1 lacks a connection to vehicle 3 due to factors such as privacy, distance, or communication quality

We consider a joint V2V and V2I model, which is composed of a roadside unit (RSU), an assisted vehicle and M ordinary vehicles. Vehicles generate tasks at random times and each task can be divided into less than L sequential subtasks. Sequential subtasks can be executed on multiple devices. As shown in Fig. 2, the task of vehicle 1 can be divided into three sequential subtasks, the first of which is offloaded to RSU. The second subtask is generated on RSU and offloaded to the assisted vehicle. The third subtask is generated on the assisted vehicle and offloaded to vehicle 2. Finally, the result of the task is generated on Vehicle 2 and transmitted back to Vehicle 1. So we regard the best offloading decisions as the best paths of subtasks for minimizing the sum of delay of the vehicles.

III. Proposed Method

In this section, we proposed the LTAO method to adaptively offload tasks in a joint V2V and V2I system as shown in Fig. 3.

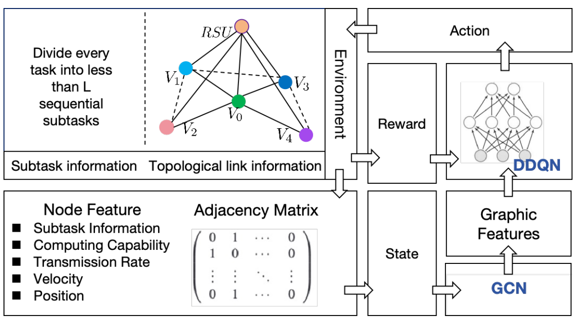


Fig. 3: The framework of LTAO-DDQN method

GCN is the classical method for processing graph data, which through convolutional operations makes nodes obtain information about neighboring nodes, and the final node representations can effectively capture the implicit information in the graph [2]. Therefore, we utilize GCN to capture the implicit information from node features and adjacency matrix as representations of the network constituted by the proposed V2V and V2I systems. Then, we further utilize DRL methods such as Double Deep Q-Network (DDQN) to make the optimal action for the current representation generated by the GCN module, which composed of MainNet and TargetNet [3]. We define the state as $S_p = [NF_p, A_p]$, where NF_p represents the node features of the corresponding subtask and its vehicle, including subtask information, computing capability, transmission rate, velocity and the current position at the time step t_p, and A_p represents the current adjacency matrix of topological links. Input the S_p to a two-layer GCN:

$$h_p = GCN(NF_p, A_p) = \tilde{A}_p ReLU(\tilde{A}_p NF_p W_0) W_1, \quad (1)$$

where h_p is the representation at t_p, W_0 and W_1 are the weight matrices, and $\tilde{A}_p = D^{-\frac{1}{2}} A_p D^{-\frac{1}{2}}$ is the symmetrically normalized adjacency matrix. Then input h_p to a two-layer Multilayer Perceptron (MLP):

$$Q_p = MLP(h_p) = W_3 ReLU(W_2 h_p), \quad (2)$$

where Q_p is the Q-value and W_2 and W_3 are the weight matrices of two-layers MLP. The Q-function of MainNet in DDQN is updated as [3]:

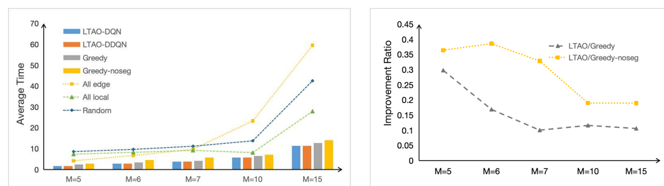
$$\hat{Q}_{M_p} = r_p + \gamma Q_T\big(h_{p+1}, \arg\max_{a_{p+1}}, Q_M(t_{p+1})\big), \quad (3)$$

where r_p is the reward measured by time delay in t_p and Q_T is the output of the TargetNet of DDQN.

IV. Experiments

In this section, we conducted experiments on the LTAO methods (LTAO-DQN and LTAO-DDQN) and five baselines refer to [3]. LTAO methods achieve state-of-the-art effects. We set two layers GCN whose input dimension of each node is $(2 \times L + 6)$ and the dimensions of the hidden layers are both set to 128 refer to [2]. The DQN and DDQN settings are the same as [3].

As shown in Fig. 4(a), LTAO methods achieve significantly better results than other approaches. For instance, when M is 5, LTAO-DDQN achieves 3.71%, 16.90%, 38.63%, 58.49%, 66.26% and 71.76% improvements when compared with LTAO-DQN, Greedy, Greedy-noseg, All edge, All local and Random, respectively.



(a) Average time (b) Performance improvement ratio

Fig. 4: Experiment results

Fig. 4(b) shows the performance improvement ratio when LTAO-DDQN compared with Greedy and Greedy-noseg. When $M = [5, 6, 7, 10, 15]$, LTAO-DDQN achieves 29.81%, 16.90%, 10.05%, 11.62% and 10.60% improvements when compared with Greegy method and achieves 36.47%, 38.63%, 32.90%, 18.99% and 18.96% improvements when compared with Greedy-noseg method. The performance improvement of the LTAO decreases with the increase of M due to the computing capability of the V2V and V2I becomes insufficient as M increases attributed to the constant computing capability of the RSU, which implies the diminution of the optimizable space.

V. Conclusion

In this paper, aiming to adaptively offload under different topological link forms, we propose a GRL-based algorithm named LTAO to offload sequential subtasks along topological links. Experimental results demonstrate that the proposed LTAO algorithm is far superior to greedy-based offloading algorithms. For the future work, we intend to consider the V2V system with multiple RSUs and dynamic assisted vehicles.

References

[1] P. Dai, M. Wu, K. Li, X. Wu, and Y. Ding, "Joint optimization for quality selection and resource allocation of live video streaming in internet of vehicles," *IEEE Transactions on Services Computing*, pp. 1–14, 2023.

[2] T. N. Kipf and M. Welling, "Semi-supervised classification with graph convolutional networks," in *International Conference on Learning Representations*, 2017.

[3] H. Tang, H. Wu, G. Qu, and R. Li, "Double deep q-network based dynamic framing offloading in vehicular edge computing," *IEEE Transactions on Network Science and Engineering*, vol. 10, no. 3, pp. 1297–1310, 2023.