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2-layer Joint Interference Coordination for A Cellular System with Cluster-wise Distributed MU-MIMO

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Abstract In a cellular system with distributed MU-MIMO, virtual small cells (called the user-clusters) are formed to reduce the huge computational complexity. This system is referred to as the cellular system with cluster-wise distributed MU-MIMO. However, in this system, both the intercell interference and the intracell interference coexist, which significantly reduced the system capacity. In this study, we proposed a 2-layer joint interference coordination (IC) which relies on the combination of graph coloring algorithm (GCA) and the deep reinforcement learning (DRL). The simulation results reveals that our proposed 2-layer joint IC could achieve a significant increase in capacity.

Keywords Interference Coordination, Deep Reinforcement Learning, Graph Coloring, Distributed MU-MIMO

1. Introduction

In the context of 5G and beyond, massive Multi-User Multiple Input Multiple Output (MU-MIMO) has emerged as a highly promising technique [1]. Distributed MU-MIMO [2], harnessing the potential of distributed antennas (DAs) across the base station's coverage area (hereafter referred to as the cell), addresses radio link blockage issues arising from the use of mm-wave bands. However, implementing large-scale MU-MIMO entails an exceedingly high computational complexity. Hence, in our previous study, we proposed a cluster-wise distributed MU-MIMO [3], where users are adaptively divided into non-overlapping virtual small cells called user-clusters (hereafter, simply called clusters) based on the user location information to greatly reduce the computational complexity. However, in return, the problem of inter-cluster interference is produced.

In a cellular system implementing cluster-wise distributed MU-MIMO, the inter-cluster interference can be classified into two types: intracell interference and intercell interference. To ensure system scalability, we aim to jointly mitigate both types of interference in a decentralized manner, where each cell operates independently without exchanging information with other cells. In this decentralized framework, intracell interference coordination (IC), which focuses on reducing interference caused by clusters within the same cell, is relatively straightforward because each base station (BS) possesses all the information about its own clusters.

In recent years, the successful application of graph coloring algorithm (GCA)-based IC has showed promising potentials for intracell IC. In a small-cell network, L. Chen, et al. [4] applied GCA to mitigate the co-tier interference. Additionally, J. Mu, et al. [5] applied GCA to solve for IC in fast-changing wireless body area networks (WBANs) of the topology to enhance frequency resource utilization and system stability. In [6], B. Wang, et al. applied GCA to realize co-channel interference management in unmanned aerial vehicle (UAV)-assisted disaster relief networks.

On the other hand, the intercell IC, which aims to mitigate interference from clusters in surrounding cells that face each other along a cell boundary, presents a more challenging task. In recent years, the rise of artificial intelligence (AI) technology, especially the deep reinforcement learning (DRL) provides a promising way for intercell IC. In 2020, in order to solve the intercell IC problem in an ultra-dense small-cell network deployed in a residential area, Y. Wang, et al. [7] applied the actor-critic (AC) algorithm to minimize each BS’s transmit power so as to reduce the intercell interference to the user equipments (UEs) of the surrounding BSs. Similarly, in 2021, in order to solve the intercell IC problem in HetNets,

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M. Yan, et al. [8] applied the Double deep Q network (DQN) to schedule sub-channels to individual users.

In this paper, we propose a 2-layer joint IC, in which both the DRL and the GCA will be applied to jointly mitigate the intracell and intercell interference in a distributed manner under the O-RAN architecture [9].

The remainder of this paper is organized as follows. Section 2 provides the system model and the problem formulation. In section 3, the proposed 2-layer joint IC is described. The performance evaluation is conducted by computer simulation in Section 4, and Section 5 concludes this paper.

2. System model and the problem formulation

The proposed cellular system with cluster-wise distributed MU-MIMO is designed to be applied based on O-RAN architecture as shown in Fig.1. The key functional components introduced by O-RAN architecture is the near-real-time (near-RT) radio access network intelligent controllers (RICs), and the non-RT RIC. The near-RT RICs, with the control loop of 10ms ~ 1s, are designed to be the specific executor to control one or several cells, while the non-RT RIC, with the control loop of longer than 1s, is to provide guidance for the near-RT RICs with its global optimization and monitoring capability. The proposed 2-layer joint IC is designed to utilize the advantages of these two RICs.

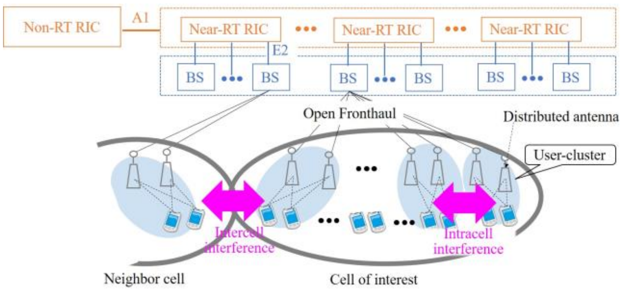

Fig. 1. Cellular system with cluster-wise distributed MU-MIMO under O-RAN architecture.

In our proposed joint IC, the entire bandwidth is segmented into M sub-bands, where M is called the bandwidth segmentation factor, and one of the sub-bands is allocated to each cluster. The set of clusters in the entire communication service area and the set of clusters which are allocated the m^{th} sub-band in the entire communication service area are denoted by κ and κ_m, $m \in \{1, \dots, M\}$, respectively. In this paper, the numbers of users, DAs, and clusters in κ are denoted by N_U, N_A, and N_C, respectively. While those in κ_m are denoted by N_U^m, N_A^m, and N_C^m, respectively. The i^{th} user in the k^{th} cluster in κ_m is denoted by $u_{i,k}^m$. Below, the matrices are represented as bold upper-case letters and the superscripts $(i,:)$ and $(:,i)$ represent the i^{th} row and column vectors of the matrix, respectively. Assuming the zero-forcing (ZF) based cluster-wise MU-MIMO to eliminate the multi-user interference within each cluster and by approximating the sum of inter-cluster interference and noise as a complex Gaussian process, the received signal-to-interference plus noise ratio (SINR) of user $u_{i,k}^m$ is given as

$$SINR_{u_{i,k}^m} = \frac{P_k \left\| \mathbf{H}_k^{(i,:)} \mathbf{W}_k^{(:,i)} \right\|^2}{\sum_{l=1, l\neq k}^{N_C^m} P_l \sum_{j=1}^{N_{U,l}^m} \left\| \mathbf{H}_{k,l}^{(j,:)} \mathbf{W}_l^{(:,j)} \right\|^2 + 1}, \tag{1}$$

where $\mathbf{W}_k$ and $\mathbf{W}_l$ are the ZF precoder matrices, $\mathbf{H}_k$ and $\mathbf{H}_{k,l}$ are respectively the channel matrix of the k^{th} cluster and the interference channel matrix between users in the k^{th} cluster and DAs in the l^{th} cluster in κ_m. $N_{U,k\ or\ l}^m$ denotes the number of users in the k^{th} or l^{th} cluster in κ_m. P_k and P_l are the transmit powers allocated to the k^{th} and l^{th} clusters, respectively and can be expressed as

$$P_{k\ \mathrm{or}\ l} = \frac{N_{U,k\ \mathrm{or}\ l}^m P}{\left\| \mathbf{W}_{k\ or\ l} \right\|_F^2}, \tag{2}$$

where P is the transmit power-to-noise ratio equal to all N_U users. Using the SINR expression in Eq. (1), the user capacity of user $u_{i,k}^m$ can be expressed as

$$C_{u_{i,k}^m} = \frac{1}{M} \log_2 (1 + SINR_{u_{i,k}^m}). \tag{3}$$

Assigning different sub-bands to different clusters is equivalent to dividing the clusters into different cluster subsets $\{\kappa_m; m \in \{1, \dots, M\}\}$. Therefore, our goal is to select optimal cluster subset $\kappa_m \subseteq \kappa$ which maximizes the sum capacity. We set our optimization objective as follows:

$$\begin{aligned} &\max_{\kappa_m \subseteq \kappa} \sum_{m=1}^{M} C_m \\ &s.t.\quad \forall m \in M, \\ &\quad \bigcup_{m \in M} \kappa_m = \kappa, \text{ and } \kappa_n \cap \kappa_m = \varnothing, \ \forall n \neq m, \end{aligned} \tag{4}$$

where

$$C_m = \sum_{k=1}^{N_C^m} \sum_{i=1}^{N_{U,k}^m} C_{u_{i,k}^m}. \tag{5}$$

3. 2-layer joint IC based on GCA and DRL

The framework of our proposed 2-layer joint IC is illustrated in Fig.2. The clustering, along with the specific

IC, is applied on each near-RT RICs in the 2nd layer. While the non-RT RIC from the 1st layer is responsible for the cellular reconstruction and provides support for the application in the 2nd layer of each near-RT RICs.

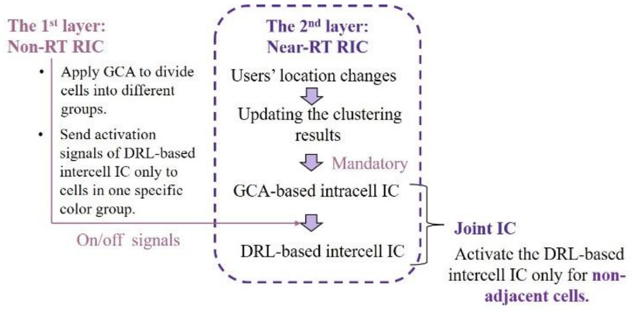

Fig.2. The framework of 2-layer joint IC.

In the 1st layer, the non-RT RIC is designed to apply GCA to divide all the cells into different color groups. According to GCA, the cells in each color groups are not neighboring to each other.

In the 2nd layer, each near-RT RIC conducts a GCA-based intracell IC and a DRL-based intercell IC. During the communication, each near-RT RIC independently updates the clustering results based on the users' movement and associates the DAs to each cluster according to the principle of proximity. The updating of the clustering results will trigger the GCA-based intracell IC (described in Sect. 3 (1)) to allocate the different sub-bands to the neighboring clusters to mitigate the intracell interference. After that, the non-RT RIC in the 1st layer with its broader system-level view will send commanding signals to the near-RT RICs to turn on the DRL-based intercell IC (described in Sect.4(C)) in one color group's cells, and the activated cells will then work independently to mitigate the intercell interference with only the locally observed information. Because the cells belong to one color group will not adjacent to each other, therefore as a result, only the non-adjacent cells will turn on the DRL-based intercell IC.

3.1. GCA-based intracell IC

In our previous study [10], we already proposed a GCA that is able to solve the intracell interference in each cell. In this paper, the GCA proposed in [10] will be used as the GCA-based intracell IC.

3.2. DRL-based intercell IC

In our previous study [11], we already tried to apply the DRL to slightly changed the existing GCA results so as to eliminate the color collision near cell-edge to further mitigate the intercell interference. In this paper, we adopt the method proposed in [11] as the DRL-based intercell IC.

4. Simulation results

We consider a normalized area of 5×5 over which 25 cells are constructed. In our simulation, the user locations are generated randomly 100 times, and for each generation of user locations, the quasi-static channel is realized as follows. The distance dependent pathlosses are computed based on the generated user locations. The log-normally distributed shadowing losses are generated 10 times for each generation of user locations. The Rayleigh fading gains are generated 10 times for each generation of shadowing losses. In this paper, the cell which is located in the center area and receives the intercell interference from every direction is selected as the cell of interest to evaluate the performance of our proposed joint IC. Other detailed parameters are shown in Table I.

PARAMETER SETTING

Total number of DAs, N_A	3200
Total number of users, N_U	2400
Total number of clusters, N_C	200
The number of sub-bands, M	4
Pathloss exponent	3.5
Shadowing loss standard deviation in dB	8
P in Eqs. (2)	0dB

In Fig.3, we plot the cumulative distribution function (CDF) of the sum capacity to evaluate our proposed 2-layer joint IC when 8 clusters are formed in each cell. As for the cell of interest when the DRL-based intercell IC is deactivated (indicated as the blue dashed line). Because the GCA-based intracell IC can successfully mitigate the severe intracell interference, the proposed 2-layer joint IC increased the capacity at CDF=50% by 35.2% compared to the no IC case (indicated as the black line). While when the DRL-based intercell IC is activated in the cell of interest (indicated as the blue solid line), not only the intracell interference, but also the intercell interference can be considered, thus can further increase the sum capacity by 10.7% (by a total of 45.9% compared to the no IC case).

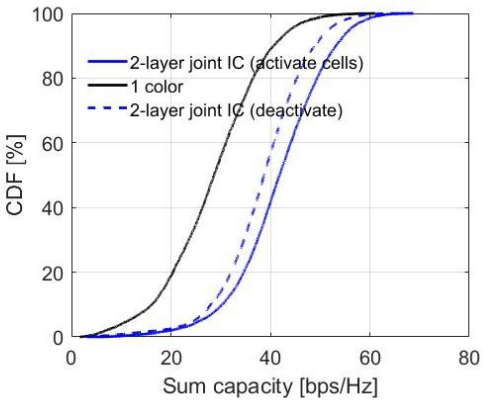

Fig. 3. The CDF of sum capacity.

5. Conclusion

In this paper, we proposed a 2-layer joint IC combining the advantage of graph coloring algorithm and deep reinforcement learning under the O-RAN architecture to mitigate both the intercell interference and intracell interference in cellular system with cluster-wise distributed MU-MIMO. The simulation results have revealed that the proposed 2-layer joint IC achieves a significant capacity increase compared to the no IC case.

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