Optimization of IRSs-assisted Cell-free Massive MIMO Systems

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Abstract

We propose a multiple intelligent reflecting surfaces (IRSs)-assisted cell-free massive multiple-input multiple-output (MIMO) system (IRSs-CFMM). The objective is to maximize the minimum downlink rate per user by jointly optimizing the phase shift of all IRSs and power allocation of all access points. To address this problem, we propose an optimization algorithm based on deep deterministic policy gradient. Numerical results show that the proposed algorithm tackles the complex optimization problem given that traditional methods such as convex optimization are unable to deal with it.

Ⅰ. Introduction

Massive multiple-input multiple-output (MIMO) is still a key component of future wireless networks to meet extremely high throughput, massive connectivity, and reliability demands [1]. We focus on cell-free massive MIMO (CFMM), an advanced and scalable variant of co-located massive MIMO distinguished by a significant number of service antennas known as access points (APs) [2]. Each AP in CFMM has a few antennas, as opposed to the co-located counterpart where the base station (BS) is outfitted with relatively large antennas (a few hundred or thousands). As a result, APs are preferred in practice since they can be built from straightforward, inexpensive, low-power components. Recently, intelligent reflecting surfaces (IRSs) have been recognized as a new technology to improve the performance of wireless networks [3]. Recently, the concept of deploying IRSs in existing communication systems has emerged as a cost-effective solution. IRSs are metasurfaces that reflect received signals from the source to destination by adjusting the phase shifts of the signals [4]. These metasurfaces can be employed in different systems, such as microwave millimeter wave CFMM system, non-orthogonal multiple access, and simultaneous wireless information and power transfer systems.

In this paper, we consider a max-min downlink rate optimization problem in an IRSs-assisted CFMM system. We provide an optimization method based on deep reinforcement learning to identify at least a locally optimal solution. The rest of this paper is organized as follows. In Section II, IRSs-CFMM is presented. Section III describes the optimization problem of power allocation and phase shift in IRSs-CFMM with the proposed optimization algorithm. In Section IV, we present simulation results. Finally, Section V concludes the paper and suggests future research directions.

Ⅱ. System Model

Fig. 1 illustrates a CFMM system consisting of M single-antenna APs serving K single-antenna users ($M \gg K$). The CFMM system is assisted by multiple (S) IRSs, each composed of N passive reflecting elements installed in the line-of-sight of the APs. We assume

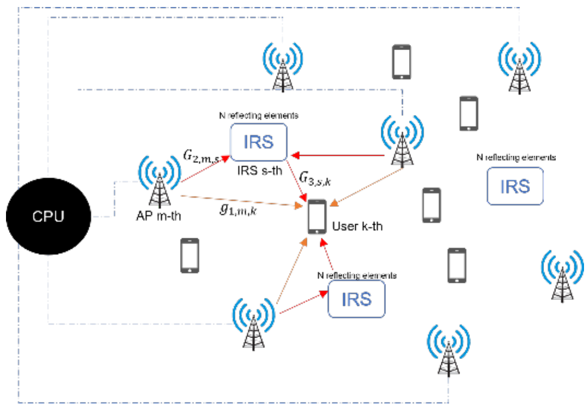

Fig. 1. IRSs-CFMM system model.

that APs, users and IRSs are uniformly distributed in $D_m \times D_m$ area. APs utilize uplink training phase to obtain the local channel, and conjugate beamforming is used for data transmission in the downlink transmission phase. In the uplink training phase, the number of users is assumed to be less than that of the orthogonal pilot sequences. This implies that there is no pilot contamination among users. Thus, we assume that each AP knows perfect channel state information between itself and users thanks to the channel estimation via pilot sequences. We consider a time division duplex (TDD) protocol. In massive MIMO systems employing TDD, the channels between APs and users are reciprocal. The signal transmitted at AP_m in the downlink can be expressed as $x_m = \sqrt{p_d}\sum_{k=1}^{K}\sqrt{\eta_{m,k}}w_k s_k$. Accordingly, the received signal at UE_k is expressed as $y_k = \sum_{m=1}^{M}\left(\sum_{s=1}^{S} G_{2,m,s}\Phi_s G_{3,s,k} + g_{1,m,k}\right)x_m + n_k$, where $\Phi_s = \mathrm{diag}\left(e^{j\phi_{s,1}}, e^{j\phi_{s,2}}, \ldots, e^{j\phi_{s,N}}\right)$ denotes diagonal phase shift matrix of the s-th IRS (IRS_s), $\phi_{s,n} \in [0,2\pi]$. Besides, $g_{1.m,k}, G_{2,m,s}, G_{3,s,k}$ denote the channels between AP_m and UE_k, AP_m and IRS_s, and IRS_s and UE_k, respectively. The channel is influenced by small-scale fading and large-scale fading. We assume that each AP knows the large-scale fading and the small-scale fading coefficient follows complex Gaussian distribution with zero mean and unit variance. We define the composite downlink channel at the user end, i.e., the channel between AP_m and UE_k via all IRSs, as $H_{m,k} = \sum_{s=1}^{S} G_{2,m,s}\Phi_s G_{3,s,k} + g_{1,m,k}$. In the downlink transmission phase, each AP employs conjugate beamforming to transmit signals to users using channel estimates, which are assumed to be perfect in this paper. Therefore, the transmit signal at AP_m can be re-expressed as $x_m = \sqrt{p_d}\sum_{k=1}^{K}\sqrt{\eta_{m,k}}H_{m,k}^{*}s_k$, and it has to satisfy the following power constraints:

$$\|x_m\|^2 \le p_d \quad (1)$$
$$\rightarrow \left\|\sum_{k=1}^{K}\sqrt{\eta_{m,k}}\left(\sum_{s=1}^{S} G_{2,m,s}\Phi_s G_{3,s,k} + g_{1,m,k}\right)^{*}\right\|^2 \le 1.$$

The downlink data rate of UE_k is expressed as

$$R_k = \log_2\left(1 + \frac{\left|\sum_{m=1}^{M}\sqrt{\eta_{m,k}}H_{m,k}*H_{m,k}^{*}\right|^2}{\sum_{k'=1|k'\neq k}^{K}\left|\sum_{m=1}^{M}\sqrt{\eta_{m,k'}}H_{m,k}H_{m,k'}^{*}\right|^2 + \frac{|n_k|^2}{p^2}}\right). \quad (2)$$

Ⅲ. Problem Formulation and Proposed Algorithm

Optimization problem that maximizes the max-min downlink rate of all users in the IRSs-assisted CFMM system can be formulated as

$$\begin{aligned} \max_{\eta,\phi} \quad & \min_{k} R_k \qquad (3)\\ \text{s.t.} \quad & \|x_m\|^2 \le p_d \\ & \eta_{m,k} > 0 \ \ \forall m,k \\ & 0 \le \phi_{s,n} \le 2\pi \ \ \forall s,n. \end{aligned}$$

Deep Deterministic Policy Gradient (DDPG) is a reinforcement learning technique that combines the best of deep Q learning and actor-critic methods into an algorithm that can be used in environments with continuous action spaces. In this paper, we propose to use the DDPG-based algorithm to solve the problem (3). By utilizing deep function approximators, DDPG is a model free and off-policy actor-critic algorithm. It develops policies in a high-dimensional continuous action space. Relying on the DDPG technique, the proposed algorithm enables deterministic maps of a specific action. Then, the Q value is utilized to criticize the given action. As a result, the goal of DDPG is to maximize the output Q value. Furthermore, DDPG uses experience replay to solve the problem that the hypothesis of independent and identically distributed samples becomes invalid when the samples are generated sequentially.

IV. Simulation Results

Fig. 2 shows simulation results obtained by running the DDPG-based optimization algorithms. Main simulation parameters are tabulated in Table I. The results confirm that the DDPG-based algorithms operate properly and converge after 2500 episodes. Furthermore, it demonstrates that joint optimization of the phase shift and power allocation yields superior performance to a technique that considers only the phase shift with maximum transmit power. As a result, utilizing the proposed method to jointly optimize phase shift and power control results in not only good performance but also power efficiency in IRSs-assisted CFMM system.

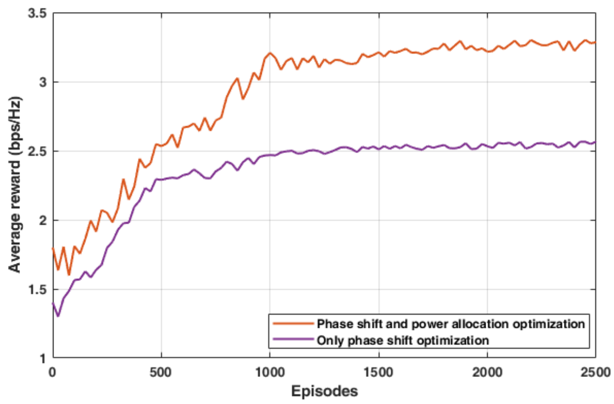

Fig. 2. Minimum downlink rate of different DDPG-based optimization strategies with K = 10 and M = 20.

TABLE I. SIMULATION PARAMETERS

Parameter	Value
Carrier Frequency	1.9 GHz
Bandwidth	20 MHz
Noise figure	9 dB
AP antenna height	15m
User antenna height	1.65m
σ_{sh}	8dB
d_1, d_0 Hatacost	50,10m
Number of IRSs (S)	5
Number of reflecting elements (N)	10

V. Conclusion

In this paper, the DDPG-based algorithm is proposed to deal with the problem of max-min downlink rate by jointly optimizing the phase shift and power allocation. In the future, we will extend the IRSs-CFMM system by taking the imperfect channel estimation into account. Besides, a novel IRSs-CFMM integrated with the NOMA technique will be considered.

Acknowledgment

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References

[1] M. Matthaiou, O. Yurduseven, H. Q. Ngo, D. Morales-Jimenez, S. L. Cotton, and V. F. Fusco, "The road to 6G: Ten physical layer challenges for communications engineers," *IEEE Commun. Mag.*, vol. 59, no. 1. pp. 64-69, Jan. 2021.

[2] H. Q. Ngo, A. Ashikhmin, H. Yang, E. G. Larsson, and T. L. Marzetta, "Cell-free massive MIMO versus small cells," *IEEE Trans. Wireless Commun.*, vol. 16, no. 3, pp. 1834–1850, Mar. 2017.

[3] Q. Wu and R. Zhang, "Towards smart and reconfigurable environment: Intelligent reflecting surface aided wireless network," *IEEE Commun. Mag.*, vol. 58, no. 1, pp. 106–112, Jan. 2019.

[4] E. Bjornson and L. Sanguinetti, "Power scaling laws and near-field behaviors of massive mimo and intelligent reflecting surfaces," *IEEE Open J. Commun. Society*, vol. 1, pp. 1306–1324, Feb. 2020.