Fronthaul Compression and Passive Beamforming Design for Intelligent Reflecting Surface-aided Cloud Radio Access Networks

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Abstract—This letter studies a cloud radio access network (C-RAN) with multiple intelligent reflecting surfaces (IRS) deployed between users and remote radio heads (RRH). Specifically, we consider the uplink transmission where each RRH quantizes the received signals from the users by either point-to-point compression or Wyner-Ziv compression and then transmits the quantization bits to the BBU pool through capacity limited fronthaul links. To maximize the uplink sum rate, we jointly optimize the passive beamformers of IRSs and the quantization noise covariance matrices of fronthaul compression. An joint fronthaul compression and passive beamforming design is proposed by exploiting the Arimoto-Blahut algorithm and semidefinite relaxation (SDR). Numerical results show the performance gain achieved by the proposed algorithm.

Index Terms—C-RAN, IRS, fronthaul compression, Arimoto-Blahut algorithm.

I. INTRODUCTION

Cloud radio access network (C-RAN) is a prospective mobile network architecture, which provides an efficient way for multi-cell interference management [1]. In a C-RAN, the baseband processing function of conventional base stations is backward migrated into a baseband unit (BBU) pool and radio remote heads (RRH) are deployed close to users. Nevertheless, high-speed fronthaul links are required to connect the RRHs and BBU pool [2], which leads to high implementation cost and complexity for dense deployment of RRHs.

To tackle this issue, in this letter we propose the use of the recently-emerging intelligent reflecting surface (IRS) to enhance the access link between users and RRHs in the C-RAN. IRS consists of a large number of reflecting elements with which controllable phase shifts can impose on the impinging waves [3]. Benefited from this, IRS can generate desired reflection beams and create favorable propagation conditions [4]. Since IRS is basically a passive device and solely requires a low-rate control link, it provides an energy-efficient and cost-effective way to enhance the C-RAN. Most recently, a plethora of works have studied the design of IRS-assisted wireless communication systems [5]-[7]. In particular, IRS was considered in multi-cell systems to assist coordinated multiple point transmission (CoMP) [8] and enhance the cell edge performance [9]. The IRS-aided cell-free systems were investigated in [10] and [11], where the weighted system sum rate and network energy efficiency were optimized, respectively. Moreover, the authors in [12] exploited the advantage of deploying IRS to improve the accuracy of the over-the-air computation in the C-RAN.

In this letter, we focus on the uplink transmission design for a multi-IRS-assisted C-RAN. Due to the limited fronthaul capacity, the received signals at each RRH are compressed first before being conveyed to the BBU pool. There are mainly two approaches, i.e. point-to-point compression and Wyner-Ziv compression, wherein the latter has better performance but higher signal processing complexity [2]. Therefore, to fully exploit the advantage of IRS, the passive beamforming of each IRS should be jointly designed together with fronthaul compression, which has not been considered in the aforementioned works for multi-cell systems and cell-free networks. Specifically, with the goal of maximizing the uplink sum rate, we jointly optimize the IRS beamformers and the quantization noise covariance matrices under Wyner-Ziv-based fronthaul compression, which leads to a non-convex problem. By exploiting the Arimoto-Blahut scheme and semi-definite relaxation (SDR), we proposed a joint fronthaul compression and passive beamforming design algorithm. Note that the proposed algorithm can be simply extended to the case of point-to-point compression. Finally, numerical results are provided to show the performance gain from deploying IRS in the C-RAN under both point-to-point and Wyner-Ziv-based fronthaul compression.

Notation: For a matrix $A$, $|A|$, Tr$(A)$, $A^T$ and $A^H$ denote the determinant, trace, transpose and conjugate transpose of $A$. diag$(A)$ denotes a column vector formed with the diagonals of $A$. For an index set $S$, unless otherwise specified, $A_S$ denotes the matrix with elements $A_i$ whose indices $i \in S$ and diag$(\{A_i\}_{i \in S})$ denotes the block diagonal matrix formed with $A_i$ on the diagonal where $i \in S$. $A \odot B$ denotes the Hadamard product of $A$ and $B$. $I$ denotes the identity matrix. $E[\cdot]$ stands for the expectation. Let $K = \{1, \ldots, K\}$, $L = \{1, \ldots, L\}$ and $M = \{1, \ldots, M\}$.
II. PRELIMINARY

A. System Model

As depicted in Fig. 1, we consider the uplink transmission of a C-RAN, where $K$ single-antenna users communicate with the BBU pool through $L$ RRHs, each equipped with $N_R$ antennas. $M$ IRSs are deployed to aid the communication between users and RRHs, each of which has $N_I$ reflecting elements. For simplicity, we assume global channel state information (CSI) at the BBU pool. Note that the CSI acquisition for the IRS link has been discussed in [13].

On the access link, user $k$ in $K$ transmits the signal $x_k$ to RRHs. Let $\mathbf{x} = [x_1, ..., x_K]^T$ with $\mathbf{x} \sim CN(0, P I)$, where $P$ denotes user transmit power. Then the signals received by RRH $l \in \mathcal{L}$ can be expressed as

$$y_l = \mathbf{H}_l \mathbf{x} + \sum_{m=1}^{M} \mathbf{G}_{l,m} \Theta_m \mathbf{H}_{R,m} \mathbf{x} + \mathbf{n}_l,$$

where $\mathbf{H}_l \in \mathbb{C}^{N_R \times K}$, $\mathbf{G}_{l,m} \in \mathbb{C}^{N_R \times N_I}$ and $\mathbf{H}_{R,m} \in \mathbb{C}^{N_I \times K}$ represent the channel matrix between users and RRH $l$, between IRS $m$ and RRH $l$, and between users and IRS $m$, respectively, $\mathbf{G}_{l,M} = [\mathbf{G}_{l,1}, ..., \mathbf{G}_{l,M}]$, $\mathbf{H}_{R,M} = [\mathbf{H}_{R,1}, ..., \mathbf{H}_{R,M}]^T$, $\Theta_m = \text{diag}(\{\theta_{m,n}\}_{n=1}^{N_I})$ represents the passive beamformer of IRS $m$ (we assume that the IRS can only adjust the phase shift, i.e., $|\theta_{m,n}| = 1$), $\mathbf{\Theta} = \text{diag}(\{\Theta_m\}_{m \in M})$, and $\mathbf{n}_l \sim CN(0, \sigma^2 \mathbf{I})$ is the additive white Gaussian noise.

RRH $l$ compresses its received signals and then transmits the quantization bits to the BBU pool through a wired fronthaul link with limited capacity. By adopting the Gaussian test channel model, the compressed signal recovered by the BBU pool can be expressed as [2]

$$\hat{y}_l = y_l + \mathbf{q}_l,$$

where $\mathbf{q}_l \sim CN(0, \mathbf{\Omega}_l)$ represents the quantization noise for RRH $l$ and $\mathbf{\Omega}_l$ denotes its covariance matrix which is determined by the corresponding quantization codebook.

B. Uplink Sum Rate and Fronthaul Constraints

From (1) and (2), the achievable uplink sum rate of the considered C-RAN is given by

$$R_{\text{sum}} = I(\mathbf{x}; \hat{\mathbf{y}}_l) = \log |\mathbf{I} + \mathbf{P} \mathbf{V}_l \mathbf{V}_l^H| - \log |\mathbf{\Omega}_l|,$$

where $\mathbf{\hat{y}}_l = [\hat{y}_1, ..., \hat{y}_L]^T$, $\mathbf{V}_l = \mathbf{H}_l + \mathbf{G}_{l,M} \mathbf{\Theta} \mathbf{H}_{R,M}$, $\mathbf{H}_l = [\mathbf{h}_{l,1}^T, ..., \mathbf{h}_{l,L}^T]^T$, $\mathbf{G}_{l,M} = [\mathbf{g}_{l,1}^T, ..., \mathbf{g}_{l,M}^T]^T$ and $\mathbf{\Omega}_l = \text{diag}(\{\Omega_{l,i}\}_{i \in \mathcal{L}})$.

The compression rates at each RRH should not exceed the fronthaul link capacity. With point-to-point compression, the corresponding fronthaul constraints are given by [2]

$$I(\mathbf{y}_l; \hat{\mathbf{y}}_l) \leq C_l, \ \forall l \in \mathcal{L},$$

where $C_l$ represents the fronthaul capacity from RRH $l$ to the BBU pool. The mutual information term can be evaluated according to (1) and (2). Let $\mathbf{V}_l = \mathbf{H}_l + \mathbf{G}_{l,M} \mathbf{\Theta} \mathbf{H}_{R,M}$. Constraints (4) can be written as

$$\log |\mathbf{P} \mathbf{V}_l \mathbf{V}_l^H + \sigma^2 \mathbf{I} + \mathbf{\Omega}_l| - \log |\mathbf{\Omega}_l| \leq C_l.$$ 

For the case where Wyner-Ziv compression is applied, we consider sequential decompression at the BBU pool, which is easy for practical implementation [2]. Explicitly, the BBU pool sequentially recovers the compressed signal from each RRH and the recovered signals are utilized as side information for the decomposition of the signals from the remaining RRHs. Denoting the decomposition order as $\pi(\cdot)$, then the corresponding fronthaul constraints are given by [2]

$$I(\mathbf{y}_{\pi(l)}; \hat{\mathbf{y}}_{\pi(l)}(\hat{\mathbf{y}}_{\pi(l-1)})) \leq C_{\pi(l)}, \ \forall l \in \mathcal{L},$$

where $\hat{\mathbf{L}}(l) = \{\pi(1), ..., \pi(l)\}$. By evaluating the mutual information term on the left, the above constraints can be rewritten as

$$\log |\mathbf{P} \mathbf{V}_{\hat{\mathbf{L}}(l)} \mathbf{V}_{\hat{\mathbf{L}}(l)}^H + \sigma^2 \mathbf{I} + \mathbf{\Omega}_{\hat{\mathbf{L}}(l)}| - \log |\mathbf{\Omega}_{\hat{\mathbf{L}}(l)}| - \log |\mathbf{P} \mathbf{V}_{\hat{\mathbf{L}}(l-1)} \mathbf{V}_{\hat{\mathbf{L}}(l-1)}^H + \sigma^2 \mathbf{I} + \mathbf{\Omega}_{\hat{\mathbf{L}}(l-1)}| \leq C_{\pi(l)},$$

where $\mathbf{V}_{\hat{\mathbf{L}}(l)} = \mathbf{H}_{\hat{\mathbf{L}}(l)} + \mathbf{G}_{\hat{\mathbf{L}}(l)} \mathbf{\Theta} \mathbf{H}_{R,M}$ and $\mathbf{\Omega}_{\hat{\mathbf{L}}(l)} = \text{diag}(\{\Omega_{\hat{\mathbf{L}}(l),i}\}_{i \in \mathcal{L}}(\hat{\mathbf{L}}(l))).$

III. Joint Design of IRS Beamforming and Fronthaul Compression

Due to the fact that the received signals are correlated across different RRHs, Wyner-Ziv compression, with which joint decompression is performed at the BBU pool, is expected to be superior to point-to-point compression [2]. In this section, we first consider the joint optimization of IRS beamforming and fronthaul compression under Wyner-Ziv compression. The optimization for the case of point-to-point compression will be discussed later.

Recalling (6), the decomposition order affects the fronthaul constraints as well as the overall system performance. However, it is prohibitive to find the optimal decomposition order $\pi(\cdot)$, since there are $L!$ possible order in total. Therefore, we adopt an efficient heuristic order selection scheme proposed...
in [2] and [14]. Specifically, the BBU decompresses firstly for the RRH with a larger value of:

$$C_l - \log \det (P V_l V_l^H + \sigma^2 I),$$  \hspace{1cm} (8)$$

where $\Theta = I$ in $V_l$. The rationale is to decompress first the signals from the RRH with either larger fronthual capacity or lower received signal power, which will suffer lower quantization noise.

By fixing $\pi(l)$, with the goal of maximizing the uplink sum rate (3) under the fronthual constraints (6), the problem for joint optimizing IRS beamforming and fronthual compression signals from the RRH with either larger fronthual capacity or the RRH with a larger value of:

$$\text{maximize} \ \max_{\Theta, \Omega_l} \log \left( P V_l^H V_l + \sigma^2 I + \Omega_l \right) - \log \left( \sigma^2 I + \Omega_l \right)$$  \hspace{1cm} (9)$$

subject to:

$$\log \left( P V_l^H V_l + \sigma^2 I + \Omega_l \right) - \log \left( \sigma^2 I + \Omega_l \right) \leq C(\pi), \forall l,$$

$$|\theta_{m,n}| = 1, \forall m, n,$$

$$\Omega_l \geq 0, \forall l.$$  \hspace{1cm} (10)$$

The equality is achieved by:

where $C_l = \sum_{l \in L} C_l + lN_R$. With (10) and (16), we reformulate the original problem (9) as follows:

$$\text{maximize} \ \max_{\Omega_l} \mathbb{E} \left[ \log \left( \frac{CN(W \hat{y}, \Sigma)}{CN(0, P_I)} \right) \right]$$  \hspace{1cm} (11)$$

subject to:

$$\log \left( \frac{CN(W \hat{y}, \Sigma)}{CN(0, P_I)} \right) \leq C_l, \forall l,$$

$$|\theta_{m,n}| = 1, \forall m, n,$$

$$\Omega_l \geq 0, \forall l.$$  \hspace{1cm} (12)$$

Remark 1: According to (14), any feasible solution to problem (17) is also feasible to original problem (9), which indicates that we can solve problem (17) to obtain a suboptimal solution to the original problem.

Then we tackle problem (17) using an efficient alternating optimization approach. In each iteration, we first update the auxiliary variables $W$, $\Sigma$ and $E_l$, while fixing all the other variables. Obviously, the optimal $\Omega_l$ and $\Sigma$ is given by (11) and (12), respectively. $E_l$ is updated with (15), which follows the successive convex optimization approach [18].

By fixing the auxiliary variables, we optimize $\Theta$ and $\Omega_l$. Firstly, we evaluate the expectation term in the objective as follows:

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$$\text{maximize} \ \max_{\Theta, \Omega_l} \mathbb{E} \left[ \log \left( \frac{CN(W \hat{y}, \Sigma)}{CN(0, P_I)} \right) \right]$$  \hspace{1cm} (13)$$

subject to:

$$\log \left( \frac{CN(W \hat{y}, \Sigma)}{CN(0, P_I)} \right) \leq C_l, \forall l,$$

$$|\theta_{m,n}| = 1, \forall m, n,$$

$$\Omega_l \geq 0, \forall l.$$  \hspace{1cm} (14)$$

where $\tilde{C}_l = \sum_{l \in \tilde{L}(l)} C_l + lN_R$. With (10) and (16), we reformulate the original problem (9) as follows:

$$\text{maximize} \ \max_{\Omega_l} \mathbb{E} \left[ \log \left( \frac{CN(W \hat{y}, \Sigma)}{CN(0, P_I)} \right) \right]$$  \hspace{1cm} (15)$$

subject to:

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where in (a), we have the following notations: $\hat{\theta} = \text{diag}(\Theta)$,

$$A = G_L^H W \Sigma^{-1} W G_L, B = PH_{R,M} H_{R,M}^T,$$

$z_1 = \text{diag}(PG_L^H W \Sigma^{-1} W G_L H_L^H - \sqrt{P} G_L^H W \Sigma^{-1} H_L^H),$

$J_1 = \text{Tr}(PH^H \Sigma^{-1} WH_L H_L^H) - 2\text{Re}(\text{Tr}(\sqrt{P} \Sigma^{-1} WH_L H_L^H))$

$$+ \text{Tr}(\sigma^2 W^H \Sigma^{-1} W) + \text{Tr}(\Sigma^{-1} + \log |\Sigma| - K),$$

and in (b), we have $\bar{\theta} = [\hat{\theta}^T, 1]^T$, $\bar{\Theta} = \hat{\theta} \bar{\theta}^H$ and

$\Psi = \left( \begin{array}{cc} A \odot B^T & z_1 \\ z_1^T & 0 \end{array} \right).$
Now the optimization problem (17) can be rewritten as follows:
\[
\begin{align*}
\min_{\Theta, \Omega_l} & \quad \text{Tr}(\Psi) + \text{Tr}(W^H \Sigma^{-1} W \Omega_L) \\
\text{s.t.} & \quad \text{Tr}(Y_l \Theta) + \text{Tr}(E_l^{-1} \Omega_L(l)) - \log \left| \Omega_L(l) \right| \\
& \quad \leq C_l - J_{2,l}, \quad \forall l \\
& \quad \text{rank}(\Theta) = 1, \quad \Theta \succeq 0, \quad |\Theta_{i,i}| = 1, \quad \forall i, \\
& \quad \Omega_l \geq 0, \quad \forall l.
\end{align*}
\]

(20)

We apply SDR by relaxing the rank-one constraint and the resulted problem becomes convex. Thus it can be effectively solved by standard convex optimization tools like CVX [19].

Remark 2: Note that in Step 4, since SDR is applied, we solely obtain a suboptimal solution to problem (20). Therefore, we check whether the obtained \( \Theta \) and \( \Omega_l \) decrease the objective value compared with that achieved by the solution in the last iteration. With this, the convergence of the proposed algorithm can be guaranteed since the objective function in problem (17) is monotonically increasing for both Step 3 and Step 4. The computational complexity of Algorithm 1 is dominated by Step 3 which involves solving problem (20). Since problem (20) is convex after SDR, it can be efficiently solved by the interior-point method with computational complexity in the problem size given by \((MN_j)^2 + LN_R^2 \) [14]. The overall complexity of Algorithm 1 is given as the product of the number of iterations and the above complexity.

Remark 3: The extension to the case of point-to-point compression is straightforward, by replacing constraints (7) in problem (9) with fronthaul constraints (5) for point-to-point compression. We can similarly tackle the non-convex objective and fronthaul constraints as (10) and (14). Then the joint optimization algorithm can be obtained by simply removing Step 1 and modifying Steps 3 and 4 in Algorithm 1. Due to the limited space, the detailed algorithm is not given here.

IV. NUMERICAL RESULTS

In this section we present numerical results to validate the effectiveness of the proposed algorithm. In the simulation, four users are uniformly distributed within a circle centered at the origin with radius of 20m, two RRHs each equipped with four antennas are located at (-20m,80m) and (20m,80m), respectively. Two IRSs are deployed at (-25m,80m) and (25m,80m).

The path loss is modeled as \( k = \xi d^{-\alpha} \), where \( d \) is the link distance, \( \alpha \) is the path loss exponent, and \( \xi \) is set to -30dB. We model both the user-IRS link and IRS-RRH link as LoS channel. The path loss exponent \( \alpha \) for user-RRH link, user-IRS link, IRS-RRH link is set to 3.6, 2.2 and 2.2, respectively. As for small-scale fading, we assume that the user-RRH link follows Rayleigh fading, and the user-IRS link and the IRS-RRH link follow Rician fading with a Rician factor of 10dB. The relative reflection gain of the IRS element over the user-RRH link is set to 5dB [21]. The Gaussian noise variance is set to -80dBm.

Before the performance comparison, we first numerically verify the convergence of Algorithm 1 (denoted as “Subopt \( \pi \), continuous”) and the joint optimization modified from Algorithm 1 for the case of point-to-point compression (denoted as “P2P, continuous”). Fig. 2 plots the average sum rate versus the iteration number under different number of reflecting elements of each IRS, where the user transmit power is set as \( P = 10 \)dBm and the fronthaul capacity for each RRH equals 5bps/Hz. It can be observed that both algorithms can converge in a few rounds of iterations, which validates the convergence analysis.

Besides the proposed algorithms, we also simulate the following cases for comparisons. For Wyner-Ziv compression, the benchmark schemes are: 1) Opt \( \pi \), continuous: Step 1 in Algorithm 1 is replaced by exhaustively searching the optimal decomposition order; 2) Subopt \( \pi \), b-bit: the IRS phase shift takes \( 2^b \) discrete value, i.e., \( \{e^{j2\pi k / 2^b} | k = 0,1,\ldots,2^b-1 \} \). In this case the optimized IRS phase shifts obtained by Algorithm 1 are projected to the nearest discrete values and \( \Omega_l \) is scaled to meet the fronthaul constraints. 3) Subopt \( \pi \), random: IRS phase shifts are uniformly distributed within \([0, 2\pi]\) while only \( \Omega_l \) is optimized; 4) Subopt \( \pi \), no IRS: the IRS is removed while \( \Omega_l \) is optimized. For point-to-point compression, the following benchmark schemes are considered: 1) P2P, b-bit; 2) P2P, random; 3) P2P, no IRS, which are defined accordingly.

Fig. 3 plots the average achieved uplink sum rate by all the aforementioned schemes versus the fronthaul capacity. Firstly, it can be found that for both point-point compression and Wyner-Ziv compression, deploying IRSs can enhance the
the system rate with the proposed optimization algorithm. Finally, it is noted that this work can be extended to the uplink scenario with multi-antenna users. We leave it as the future work.

V. CONCLUSIONS

We have studied a joint design of passive beamforming and fronthaul compression for multi-IRS-aided C-RAN uplink. We proposed an alternating approach which efficiently optimizes the IRS beamformers and the quantization noise covariance matrices to maximize the uplink sum rate under point-to-point compression and Wyner-Ziv compression. Numerical results verified that deploying IRS can significantly improve system performance, especially with the proposed joint optimization algorithm. Furthermore, the restriction for discrete IRS phase shift solely brings limited rate loss. It can also be observed that Wyner-Ziv compression generally outperforms point-to-point compression, in accordance with the existing literature. Finally, it is shown in Fig. 3 that the heuristic decompression order selection is quite efficient, i.e., the rate loss is negligible. Fig. 4 plots the average achieved sum rate versus the number of reflecting elements for each IRS, which also validates the performance gain of the proposed algorithm. It can be observed that the uplink sum rate increases along with the increase of $N_I$. Nevertheless, under fixed fronthaul capacity, the growth of sum rate becomes slower when $N_I$ is large.

REFERENCES

[1] M. Peng, C. Wang, V. Lau, and H. V. Poor, “Fronthaul-constrained cloud radio access networks: Insights and challenges,” IEEE Wireless Commun., vol. 22, no. 2, pp. 152-160, Apr. 2015.

[2] S. H. Park, O. Simeone, O. Sahin, and S. S. Shitz, “Fronthaul compression for cloud radio access networks: Signal processing advances inspired by network information theory,” IEEE Signal Process. Mag., vol. 31, no. 6, pp. 69-79, 2014.

[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, January 2020.

[4] C. Yuen, V. Sciancalepore, G. C. Alexandropoulos, J. Hoydis, and H. Gacanin, “Smart radio environments empowered by AI reconfigurable meta-surfaces: An idea whose time has come,” arXiv preprint arXiv:1903.08925, 2019.

[5] X. Hu, C. Zhong, Y. Zhu, X. Chen, and Z. Zhang, “Programmable metasurface based multicast systems: Design and analysis,” IEEE J. Sel. Areas Commun., vol. 38, no. 8, pp. 1763-1776, Aug. 2020.

[6] Y. Zhang, C. Zhong, Z. Zhang, and W. Lu Sum rate optimization for two way communications with intelligent reflecting surface, IEEE Commun. Lett., vol. 24, no. 5, pp. 1090-1094, May 2020.

[7] X. Hu, J. Wang, and C. Zhong, “Statistical CSI based design for intelligent reflecting surface assisted MISO systems,” Science China: Information Science, vol. 63, no. 12, 222303, 2020.

[8] M. Hua, Q. Wu, D. W. K. Ng, J. Zhao, and L. Yang, “Intelligent reflecting surface-aided joint processing coordinated multipoint transmission,” IEEE Trans. Commun., Early Access, 2020.

[9] C. Pan, H. Ren, K. Wang, and W. Xu, “Multicell MIMO communications relying on intelligent reflecting surfaces,” IEEE Wireless Commun., vol. 19, no. 8, Aug. 2020.

[10] S. Huang, Y. Ye, M. Xiao, H. V. Poor, and M. Skoglund, “Decentralized beamforming design for intelligent reflecting surface-enhanced cell-free networks,” IEEE Wireless Commun. Lett., 2020.

[11] Y. Zhang, B. Di, H. Zhang, J. Lin, and Y. Li, “Beyond cell-free MIMO: energy efficient reconfigurable intelligent surface aided cell-free MIMO communications,” arXiv preprint arXiv:2011.08473, 2020.

[12] D. Yu, S. H. Park, O. Simeone, and S. S. Shitz, “Optimizing over-the-air computation in IRS-aided C-RAN systems,” in proc. Signal Process. Wireless Commun. (SPAWC), pp. 1-5, 2020.

[13] Z. Wang, L. Liu and S. Cui, “Channel Estimation for Intelligent Reflecting Surface Assisted Multiuser Communications: Framework, Algorithms, and Analysis,” IEEE Trans. Wireless Commun., vol. 19, no. 10, pp. 6607-6620, Oct. 2020.

[14] Y. Zhou and Wei. Yu, “Fronthaul compression and transmit beamforming optimization for multi-antenna uplink C-RAN,” IEEE Trans. Signal Process., vol. 64, no. 16, pp. 4138-4151, Aug. 2016.

[15] Y. Zhang, C. Zhong, Z. Zhang, and W. Lu “Sum rate optimization for two way communications with intelligent reflecting surface,” IEEE Commun. Lett., vol. 24, no. 5, pp. 1090-1094, May 2020.

[16] T. M. Cover and J. A. Thomas, Elements of information theory. New York: John Wiley & Sons, Inc., 1991.

[17] S. M. Kay, Fundamentals of statistical signal processing: Estimation theory. Upper Saddle River, NJ: Prentice Hall PTR, 1993.

[18] G. Scutari, F. Facchinei, L. Lampariello, and P. Song, “Distributed methods for constrained nonconvex multi-agent optimizationPart I: Theory,” IEEE Trans. Signal Process., vol. 65, no. 8, pp. 1945-1960, Apr. 2017.

[19] M. Grant and S. Boyd, “CVX: Matlab software for disciplined convex programming, version 2.1,” Jun. 2015. [Online] Available: http://cvxr.com/cvx/doc/CVX.pdf

[20] N. D. Sidiropoulos, T. N. Davidson, and Z. Q. Luo, “Transmit beamforming for physical-layer multicasting,” IEEE Trans. Signal Process., vol. 54, no. 6, pp. 2239-2251, Jun. 2006.

[21] Q. Wu, and R. Zhang, “Intelligent reflecting surface enhanced wireless network: Joint active and passive beamforming design,” in Proc. IEEE Globecom, Dec. 2018, pp. 1-6.