LOCATION-AWARE NETWORK OPERATION FOR CLOUD RADIO ACCESS NETWORK

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ABSTRACT

One of the major challenges in effectively operating a cloud radio access network (C-RAN) is the excessive overhead signaling and computation load that scale rapidly with the size of the network. In this paper, the exploitation of location information of the mobile devices is proposed to address this challenge. We consider an approach in which location-assisted channel state information (CSI) acquisition methods are introduced to complement conventional pilot-based CSI acquisition methods and avoid excessive overhead signaling. A low-complexity algorithm is designed to maximize the sum rate. An adaptive algorithm is also proposed to address the uncertainty issue in CSI acquisition. Both theoretical and numerical analyses show that location information provides a new dimension to improve throughput for next-generation massive cooperative networks.

1. INTRODUCTION

Massive mobile terminals demand ubiquitous service. Ultradense cell deployment with cooperative operations will become an enabling technology for this vision [1]. For instance, the cloud radio access network (C-RAN) is an emerging network architecture which enables large-scale cooperation among base stations, and is capable of dealing with intensive inter-cell interference in ultra-dense networks [2].

To effectively manage inter-cell interference, the C-RAN needs to collect a large amount of channel state information (CSI) and then jointly determine network operations. However, the overhead signaling to acquire CSI and the computation load to determine network operations scale rapidly with the size of the infrastructure which makes the implementation of C-RAN challenging. On the other hand, recent works have shown a strong correlation between location of the mobile stations (MSs) and the CSI, as well as the temporal stability of CSI [3–6] in various scenarios. These facts illustrate the feasibility of using location information to reduce the overhead signaling to acquire CSI. Hence, we envision that the location information of the MSs can be exploited to address the challenge in effectively implementing C-RAN, as location information has the following properties: 1) *Scalability*: The dimension of the location information of an MS does not scale with the size of the network infrastructure, as opposed to the channels between the MS and the infrastructure. 2) *Availability*: Recent developments in localization techniques have paved the way for ubiquitous and highly accurate localization [7–11]. The high accuracy of location ensures its effectiveness in guiding network operations.

Location-aware communication has recently attracted much attention. In this paper, we design and optimize cooperative network operations for location-aware C-RAN. Specifically, we consider an approach in which a locationassisted CSI acquisition method is introduced to complement conventional pilot-based CSI acquisition methods. This approach enables the C-RAN to acquire reasonably accurate CSI without causing excessive overhead signaling. In [12], joint beamforming and clustering design subject to backhaul constraints was studied. In these schemes, the cloud sends the data of each MS individually to base stations (BSs) and then the BSs decode and locally precode the data. An alternative strategy was studied in [13], in which the cloud jointly precodes and compresses the MSs' messages before sending them to BSs. Then, the BSs can simply amplify and forward the received compressed signals. This paper adopts the latter strategy as it reduces the computational load at the BSs and the capacity requirements of the backhaul links. Network operations are designed to maximize the sum rate subject to the limits of backhaul capacity and BS transmit power. The main contributions of this paper include: 1) designing a low-complexity iterative scheme that converges to a local maximum of the sum rate, and 2) designing an adaptive algorithm to address the CSI uncertainty issue. The proposed CSI acquisition approach enables the C-RAN to trade off between CSI quality and signaling overhead cost.

2. PROBLEM DESCRIPTION

Consider a downlink C-RAN where a central processor (named cloud in this paper) delivers information to K MSs

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through N BSs. We focus on the downlink transmission in which the cloud delivers data to different MSs.

The cloud precodes source signals for all MSs, i.e.,

$$\tilde{\boldsymbol{x}} = \boldsymbol{G}\boldsymbol{s} \tag{1}$$

where $s = [s_1, s_2, \ldots, s_K]^T$; s_k is the desired signal of the kth MS and it is an encoded signal from a Gaussian codebook which satisfies $s_k \sim C\mathcal{N}(0, 1), k \in \mathcal{I}_K$; G is the precoder in the cloud which is to be determined; $\tilde{x} = [\tilde{x}_1, \tilde{x}_2, \ldots, \tilde{x}_N]^T$ is the precoded continuous signal. Let $\mathcal{I}_N = [1, 2, \ldots, N]$. Since the backhaul network has limited capacity, the original signal \tilde{x}_n for the *n*th BS is compressed as

$$x_n = \tilde{x}_n + q_n, \qquad n \in \mathcal{I}_N \tag{2}$$

where x_n is the compressed signal; the compression noise q_n is modeled as a circularly symmetric complex Gaussian (CSCG) random variable which follows $q_n \sim C\mathcal{N}(0, \mu_n^2)$. The compressed signals can be collectively represented by

$$\boldsymbol{x} = \tilde{\boldsymbol{x}} + \boldsymbol{q} = \boldsymbol{G}\boldsymbol{s} + \boldsymbol{q} \tag{3}$$

where $\boldsymbol{q} = [q_1, q_2, \dots, q_N]^{\mathrm{T}}$ is the quantized noise vector; $\boldsymbol{x} = [x_1, x_2, \dots, x_N]^{\mathrm{T}}$ is the aggregate transmit signal vector. The compressed signal is scaled by each BS before transmission, and the overall transmission can be written as

$$y_k = \boldsymbol{h}_k^{\dagger} \boldsymbol{A} \boldsymbol{g}_k s_k + \boldsymbol{h}_k^{\dagger} \boldsymbol{A} \sum_{j \neq k} \boldsymbol{g}_j s_j + \boldsymbol{h}_k^{\dagger} \boldsymbol{A} \boldsymbol{q} + v_k \qquad (4)$$

where s_k and y_k are the signal of interest and the received signal of the *k*th MS respectively; $h_k^* \in \mathbb{C}^N$ is the channel fading from all BSs to the *k*th MS; $A = \text{diag}\{a_1, a_2, \ldots, a_N\}$ and $a_n \in \mathbb{C}$ is the power amplifier of the *n*th BS; and v_k is a CSCG noise distributed as $v_k \sim C\mathcal{N}(0, \sigma^2)$. The transmitted power of each BS is bounded by $\mathbb{E}[|a_n x_n|^2] \leq P_0, n \in \mathcal{I}_N$.

Next, we briefly review conventional CSI acquisition methods and then discuss the idea of obtaining CSI from location information in the downlink C-RAN. In [3–5], the authors indicated that CSI and location of the MSs are highly correlated, and CSI remains stationary over reasonably a large time scale (minutes or even hours). These facts illustrate the feasibility of using location information to complement conventional pilot-based CSI acquisition techniques and hence reduce the overhead in C-RAN.

We consider a system that adopts both types of CSI acquisition methods. First, we define \mathcal{T} as the set of MSs which estimate CSI by pilots, whereas other MSs use the locationassisted method to acquire CSI. We further define an indicator $\mathbb{1}_{\mathcal{T}}(k)$ which is 1 when $k \in \mathcal{T}$, and 0 otherwise. Then, the estimated CSI satisfies¹

$$\mathcal{H}\{\varepsilon_{kn}\}: |h_{kn} - \hat{h}_{kn}| \le \varepsilon_{kn}, \quad n \in \mathcal{I}_N, \quad k \in \mathcal{I}_K$$
 (5)

where h_{kn} is the true CSI; \hat{h}_{kn} is the estimated CSI from either pilots or location information which is represented by

$$\hat{h}_{kn} = f\left(\bar{p}_k, \tilde{p}_n; \mathbb{1}_{\mathcal{T}}(k)\right), \quad k \in \mathcal{I}_K, \ n \in \mathcal{I}_N$$
(6)

where \bar{p}_k and \tilde{p}_n are the locations of the *k*th MS and the *n*th BS, respectively; ε_{kn} is the channel uncertainty parameter which is given by

$$\varepsilon_{kn} = \epsilon_c \left(\bar{p}_k, \tilde{p}_n \right) \mathbb{1}_{\mathcal{T}}(k) + \epsilon_\ell \left(\bar{p}_k, \tilde{p}_n \right) \left(1 - \mathbb{1}_{\mathcal{T}}(k) \right) \tag{7}$$

where $\epsilon_c(\bar{p}_k, \tilde{p}_n)$ is the uncertainty function when estimating channel by pilots and $\epsilon_\ell(\bar{p}_k, \tilde{p}_n)$ is the uncertainty function due to location-assisted CSI acquisition. The former type of uncertainty exists due to pilots being contaminated by noise during channel estimation. The latter type of uncertainty exists due to dynamic nature of the waveform propagation environment. The proposed algorithm applies to general uncertainty functions and thus the specific forms of $\epsilon_c(\cdot, \cdot)$ and $\epsilon_\ell(\cdot, \cdot)$ are not discussed in this paper.

The system jointly optimizes the CSI acquisition method, transceiver design, backhaul compression rate, and transmission power to maximize the worst-case weighted sum rate with respect to (w.r.t.) an uncertain channel subject to the backhaul limit and BS power limit. In particular, the worst-case weighted sum rate is defined by minimizing the weighted sum rate under a channel uncertainty constraint. Let $\mathcal{V} \triangleq (G, A, U)$. Then, this problem is written as

$$\max_{\mathcal{T},\mathcal{V}} \min_{\boldsymbol{H}\in\mathcal{H}} \left(1 - \sum_{k\in\mathcal{I}_K} \tau_k\right) \sum_{k\in\mathcal{I}_K} \varpi_k R_k(\mathcal{V},\boldsymbol{H}) \quad (8a)$$

subject to
$$B_n(\boldsymbol{G}, \boldsymbol{U}) \le C_n, \ n \in \mathcal{I}_N$$
 (8b)

$$P_n(\boldsymbol{G}, \boldsymbol{A}, \boldsymbol{U}) \le P_0, \ n \in \mathcal{I}_N$$
 (8c)

$$\tau_k = \tau_c \mathbb{1}_{\mathcal{T}}(k) + \tau_\ell \left(1 - \mathbb{1}_{\mathcal{T}}(k) \right), \ k \in \mathcal{I}_K \quad (8d)$$

where τ_k is the overhead of the kth MS; τ_c and τ_ℓ are the overheads of pilot-based and location-assisted schemes, respectively; ϖ_k is the weight. Note that we use $u_n \triangleq \mu_n^2$, $n \in \mathcal{I}_N$, to denote the variable in the optimization, which is the *n*th diagonal element of the diagonal matrix variable $U = \text{diag}\{u_1, u_2, \ldots, u_N\}$. The constraints (8b) and (8c) are the backhaul limit and the BS power limit. The rate of the kth MS in (12a) can be calculated as

$$R_{k}(\boldsymbol{G}, \boldsymbol{A}, \boldsymbol{U}, \boldsymbol{H}) = \log\left(1 + \frac{\boldsymbol{h}_{k}^{\dagger}\boldsymbol{A}\boldsymbol{g}_{k}\boldsymbol{g}_{k}^{\dagger}\boldsymbol{A}^{\dagger}\boldsymbol{h}_{k}}{\sum_{\substack{j\neq k\\j\in\mathcal{I}_{K}}}\boldsymbol{h}_{k}^{\dagger}\boldsymbol{A}\boldsymbol{g}_{j}\boldsymbol{g}_{j}^{\dagger}\boldsymbol{A}^{\dagger}\boldsymbol{h}_{k} + \boldsymbol{h}_{k}^{\dagger}\boldsymbol{A}\boldsymbol{U}\boldsymbol{A}^{\dagger}\boldsymbol{h}_{k} + \sigma^{2}}\right)$$
(9)

where g_k is the kth column of G. The backhaul capacity of the *n*th BS in (12b) is written as

$$B_n(\boldsymbol{G}, \boldsymbol{U}) = \log\left(1 + \frac{1}{u_n} \boldsymbol{e}_n^{\dagger} \boldsymbol{G} \boldsymbol{G}^{\dagger} \boldsymbol{e}_n\right), \quad n \in \mathcal{I}_N \quad (10)$$

where e_n is the *n*th column of the *N*-dimensional identity matrix. The power constraint of the *n*th BS is written as

$$P_n(\boldsymbol{G}, \boldsymbol{A}, \boldsymbol{U}) = |a_n|^2 \left(\boldsymbol{e}_n^{\dagger} \boldsymbol{G} \boldsymbol{G}^{\dagger} \boldsymbol{e}_n + u_n \right), \quad n \in \mathcal{I}_N.$$
(11)

¹The bounded uncertainty is widely adopted in the literature [13–15]. In the case that the distribution of the channel uncertainty has a long tail, the region characterized by (5) can also be interpreted as a confidence interval, i.e., $\Pr(|h_{kn} - \hat{h}_{kn}|) \ge \alpha_0$, where α_0 is a constant close to 1.

3. SUM RATE MAXIMIZATION WITH PEFECT CSI

Assume that perfect CSI is available at the cloud. Then, problem (8) reduces to

$$\underset{\boldsymbol{G},\boldsymbol{A},\boldsymbol{U}}{\text{maximize}} \qquad \sum_{k \in \mathcal{I}_K} \varpi_k R_k(\boldsymbol{G},\boldsymbol{A},\boldsymbol{U},\boldsymbol{H}) \qquad (12a)$$

subject to
$$B_n(\boldsymbol{G}, u_n) \leq C_n, \quad n \in \mathcal{I}_N$$
 (12b)

$$P_n(\boldsymbol{G}, a_n, u_n) \le P_0, \ n \in \mathcal{I}_N$$
 (12c)

This problem is nonconvex and hence difficult to solve. Therefore, we propose a method to convert problem (12) into an equivalent form. With this conversion, the equivalent problem can be approximately solved by an iterative algorithm, in each step of which a convex problem is solved.

We refer to the Blahut-Arimoto algorithm [16] to convert (12a). Then, the rate in (9) can be redefined as

$$R_k = \mathbb{E}_{s_k, y_k} \log \frac{p(s_k|y_k)}{p(s_k)}, \qquad k \in \mathcal{I}_K$$
(13)

where $p(s_k)$ is the distribution of s_k given by $p(s_k) = \frac{1}{\pi} \exp\{-|s_k|^2\}$. With Bayes' rule, the *a posteriori* Gaussian distribution $p(s_k|y_k)$ can be written as

$$p(s_k|y_k) = \frac{1}{\pi\Sigma_k} \exp\left\{-\frac{1}{\Sigma_k} \left|s_k - \omega_k y_k\right|^2\right\}$$
(14)

where ω_k and Σ_k are auxiliary variables; the *a posteriori* mean is $\mathbb{E}[s_k|y_k] = \omega_k y_k$ and the *a posteriori* variable is $\mathcal{C}_{s_k s_k|y_k} = \Sigma_k$. From [17], the auxiliary variables are calculated by

$$\omega_k = \mathcal{C}_{s_k y_k} \mathcal{C}_{y_k y_k}^{-1} \tag{15}$$

$$\Sigma_k = \mathcal{C}_{s_k s_k} - \mathcal{C}_{s_k y_k} \mathcal{C}_{y_k y_k}^{-1} \mathcal{C}_{y_k s_k}$$
(16)

where the involved covariances are calculated by

$$\mathcal{C}_{y_k s_k} = \boldsymbol{h}_k^{\dagger} \boldsymbol{A} \boldsymbol{g}_k \tag{17}$$

$$\mathcal{C}_{y_k y_k} = \boldsymbol{h}_k^{\dagger} \boldsymbol{A} (\boldsymbol{G} \boldsymbol{G}^{\dagger} + \boldsymbol{U}) \boldsymbol{A}^{\dagger} \boldsymbol{h}_k + \sigma^2$$
(18)

and $C_{s_k s_k} = 1$. Plugging $p(s_k)$ and (14) into (13), the alternative form of the rate in (13) becomes

$$\sum_{k \in \mathcal{I}_{K}} \varpi_{k} R_{k}$$

$$= \max_{\{\omega_{k}\}, \{\Sigma_{k}\}} - \operatorname{Tr} \left[\log e W \Sigma^{-1} \left(\Omega H^{\dagger} A G G^{\mathrm{H}} A^{\dagger} H \Omega^{\dagger} -2 \mathcal{R} \{ \Omega H^{\dagger} A G \} + I + \Omega H^{\dagger} A U A^{\dagger} H \Omega^{\dagger} + \Omega V \Omega^{\dagger} \right) \right]$$

$$+ \sum_{k \in \mathcal{I}_{K}} \varpi_{k} (\log e - \log \Sigma_{k})$$
(19)

where $\boldsymbol{W} = \text{diag}\{\varpi_1, \dots, \varpi_K\}, \boldsymbol{\Omega} = \text{diag}\{\omega_1, \dots, \omega_K\},$ $\boldsymbol{\Sigma} = \text{diag}\{\Sigma_1, \Sigma_2, \dots, \Sigma_K\}, \boldsymbol{V} = \text{diag}\{\sigma_1^2, \sigma_2^2, \dots, \sigma_K^2\},$ and *e* is the base of the natural logarithm.

We develop an iterative algorithm as follows. The optimization of G or A when fixing other variables is convex, and it can be solved by various existing tools, such as CVX [18]. The optimization of U when fixing other variables reduces to a linear programming. For fixed (G, A, U), the optimal Ω and Σ are given by (15) and (16), respectively. In a nutshell, the overall iterative algorithm is summarized as Algorithm 1.

Algorithm 1.

1: Init: $A = A_0$, $U = U_0$, $\Omega = \Omega_0$, $\Sigma = \Sigma_0$;

2: while the objective improves larger than a threshold δ do

3: Compute G by solving a reduced convex problem;

- 4: Compute *A* by solving a reduced convex problem;
- 5: Compute U by solving a linear programing;
- 6: Compute Ω and Σ using (15) and (16), respectively;

7: end while

4. ADAPTIVE CSI ACQUISITION APPROACH

We propose an adaptive CSI acquisition approach for a location-aware C-RAN. First, a lemma is provided to bound the performance loss due to channel uncertainty.

Lemma 1 For the uncertainty model in (5), given (G, A, U), a lower bound of the rate of the kth MS is written as

$$R_{k}^{w} = \log(1 + \frac{(|\hat{\boldsymbol{h}}_{k}^{\dagger}\boldsymbol{A}\boldsymbol{g}_{k}| - \|\boldsymbol{\varepsilon}_{k}\|)^{2}}{\sum_{j \neq k}(|\hat{\boldsymbol{h}}_{k}^{\dagger}\boldsymbol{A}\boldsymbol{g}_{j}| + \|\boldsymbol{\varepsilon}_{k}\|)^{2} + (|\hat{\boldsymbol{h}}_{k}| + \boldsymbol{\varepsilon}_{k})^{\mathrm{T}}\boldsymbol{A}\boldsymbol{U}\boldsymbol{A}^{\dagger}(|\hat{\boldsymbol{h}}_{k}| + \boldsymbol{\varepsilon}_{k}) + \sigma^{2}}\right) (20)$$

where $\boldsymbol{\varepsilon}_k \triangleq [\varepsilon_{k1}, \varepsilon_{k2} \dots, \varepsilon_{kN}]^{\mathrm{T}}, k \in \mathcal{I}_K.$

This lemma can be readily proved using the result in the author's previous paper [19]. Then, we determine a lower bound of (8) and use it as the metric in the adapative approach.

Proposition 1 *The sum rate achieved by the optimal solution of* (21) *is a lower bound to that of the original problem* (8)

$$\max_{\mathcal{T}} \max_{k \in \mathcal{I}_{K}} \tau_{k} \sum_{k \in \mathcal{I}_{K}} \overline{\omega}_{k} R_{k}^{w}(\hat{\mathcal{V}}, \hat{H}, \varepsilon_{k}) \quad (21a)$$

where \hat{H} is the nominal channel retrieved from location or estimated by pilots, and the operator $\hat{\mathcal{V}} = (\hat{G}, \hat{A}, \hat{U})$ is calculated by Algorithm 1 with \hat{H} .

Then, the proposed adaptive scheme is as follows.

Algorithm 2.

- 1: Once getting location information of the MSs, retrieve CSI knowledge, i.e., the nominal channel \hat{H} and channel uncertainty parameter ε_k at this location;
- 2: Calculate the operator $\hat{\mathcal{V}}$ using Algorithm 1;
- 3: Calculate $R_k^{\mathrm{w}}(\hat{\mathcal{V}}, \hat{\boldsymbol{H}}, \boldsymbol{\varepsilon}_k), k \in \mathcal{I}_K$, by (20);
- 4: Arrange the MSs from $\Delta R_k = R_k^{w}(\hat{\mathcal{V}}, \hat{H}, \epsilon_c(\bar{p}_k, \cdot)) R_k^{w}(\hat{\mathcal{V}}, \hat{H}, \epsilon_\ell(\bar{p}_k, \cdot))$ in descending order $\pi_1, \pi_2, \dots, \pi_K$;
- 5: Set $\mathcal{T} = \emptyset$ and start linear search from MS π_1 . If ΔR_{π_k} is greater than $\frac{\tau_c \tau_\ell}{1 \tau_c + \tau_\ell} \left(1 \sum_{k \in \mathcal{I}_K} \tau_k\right) \sum_{k \in \mathcal{I}_K} \varpi_k \cdot R_k^{w}(\hat{\boldsymbol{G}}, \hat{\boldsymbol{A}}, \hat{\boldsymbol{U}}, \hat{\boldsymbol{H}}, \boldsymbol{\varepsilon}_k)$, let $\pi_k \in \mathcal{T}$; otherwise, let $\pi_k \notin \mathcal{T}$ and stop the search.



Fig. 1. Sum rate is evaluated w.r.t. SNR for the proposed scheme. Let N = K = 4, $\epsilon_c = 0$, and $\epsilon_\ell = 0.2$.

5. SIMULATION

We evaluate sum rate performance of a downlink C-RAN with respect to different parameter settings, including backhaul capacity limit and number of MSs. Two existing schemes in the literature are also evaluated as benchmarks [12, 13]. In addition, we also consider two other baselines, namely, the location-assisted scheme ($\mathcal{T} = \emptyset$) and the pilot-based scheme ($\mathcal{T} = \mathcal{I}_K$). In the simulation, we simply set W = I, $\tau_{\ell} = 0$ and $\tau_c = 0.0476$, which is a typical RS overhead associated with 3GPP for single antenna port [20].

Fig. 1 plots the performance of various schemes versus SNR. We can see that the proposed adaptive scheme achieves better performance than all baselines. The location-assisted scheme performs better than the pilot-based scheme in low SNR; while in high SNR, the pilot-based scheme performs better than the former. The proposed algorithm outperforms both schemes as it dynamically adjusts the CSI acquisition method according to channel knowledge. By comparing the three subfigures in Fig. 1, we can see that the location-assisted scheme is better than the pilot-based scheme in scenarios with smaller backhaul capacity or low SNR. This is because with tight backhaul limit or low SNR, the quantization noise U or the channel noise σ^2 is high. One can see that the location-assisted scheme performs better in a large nuisance case.

In Fig. 2, we evaluate the sum rate performance for the cases of 4, 6 and 8 MSs. Since the total overhead cost of the pilot-based scheme scales with the number of MSs, the location-assisted scheme becomes more preferable as the number of MSs increases. This observation indicates that the location awareness particularly benefits dense networks.

Finally, we evaluate the computational complexity of the proposed iterative scheme and compare it with the schemes in [12, 13]. Table 1 shows that the complexity of the proposed scheme is lower than that of the other schemes. This



Fig. 2. Sum rate is evaluated w.r.t. SNR for the proposed scheme. Let $C_n = 10$, $n \in \mathcal{I}_N$, $\epsilon_c = 0$, and $\epsilon_\ell = 0.2$.

 Table 1. Computational complexity and time consumption

| 1 | 1 | 2 | 1 |
|------------|---------------------------|------------------------------|----------------|
| | worst-case | 1 iteration / overall (sec.) | |
| | complexity | N = K = 4 | N = K = 6 |
| WMMSE [12] | $\mathcal{O}(N^{3.5}K^4)$ | 2.15 / 7.30 | 2.61 / 9.04 |
| MM [13] | $\mathcal{O}(N^8K^2)$ | 5.29 / 14.51 | 8.52 / 36.04 |
| Our scheme | $\mathcal{O}(N^{3.5}K^3)$ | 0.75/5.67 | 1.21 / 7.00 |

is because the scheme in [13] solves a semidefinite programming problem, whereas the proposed algorithm solves an second-order cone programming (SOCP) problem. Although the scheme in [12] also solves a SOCP problem, the proposed scheme has fewer constraints, and thus lower norm dimension. Table 1 also provides time consumption of each iteration of the optimization involved in the three schemes and the overall time consumption. The trend of time computation is consistent with the complexity evaluation of the three schemes and confirms that the proposed scheme has lower complexity than the other two existing schemes.

6. CONCLUSION

A location-aware adaptive scheme is proposed to maximize the weighted sum rate of a downlink C-RAN. By exploiting location awareness, part of the channel information can be estimated based on the location information, which avoids overhead signaling deployed for channel estimation. We show that the location-assisted scheme complements the conventional pilot-based channel acquisition methods in various scenarios, e.g., scenarios with low SNR, small backhaul capacity limit, large number of MSs, and inaccurate pilot-based channel estimation. Furthermore, the proposed location-aware adaptive scheme has lower complexity and better sum rate when compared to the existing schemes. The ramification of this paper reveals that location awareness is a new perspective to improve the performance of dense networks.

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