

Location-Aware Pilot Allocation in Multi-Cell Multi-User Massive MIMO Networks

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Abstract—We propose a location-aware pilot allocation algorithm for a massive multiple-input multiple-output (MIMO) network with high-mobility users, where the wireless channels are subject to Rician fading. Pilot allocation in massive MIMO is a hard combinatorial problem and depends on the locations of users. As such, it is highly complex to achieve the optimal pilot allocation in real-time for a network with high-mobility users. Against this background, we propose a low-complexity pilot allocation algorithm, which exploits the behavior of line-of-sight (LOS) interference among the users and allocate the same pilot sequence to the users with small LOS interference. Our examination demonstrates that our proposed algorithm significantly outperforms the existing algorithms, even with localization errors. Specifically, for the system considered in this work, our proposed algorithm provides up to 37.26% improvement in sum spectral efficiency (SE) and improves the sum SE of the worst interference-affected users by up to 2.57 bits/sec/Hz, as compared to the existing algorithms.

Index Terms—Pilot contamination, pilot allocation, location-aware communication, massive MIMO.

I. INTRODUCTION

Massive multiple-input multiple-output (MIMO) is considered as a key technology for the fifth generation networks, since it offers an increased data rate and improved spectral efficiency (SE). However, challenges such as interference due to pilot contamination prevent us from achieving the full benefit offered by massive MIMO [1], [2]. Pilot contamination affects the performance of massive MIMO even when the number of antennas at the base station (BS) is very large. Consequently, pilot contamination is a widely studied problem in massive MIMO. The existing studies on pilot contamination can be classified into five broad categories: 1) protocol based [1]; 2) precoding based [2]; 3) angle-of-arrival (AoA) based [4]; 4) blind [5]; and 5) pilot design methods [6].

Recently, an increasing attention has been paid to utilize the location information of users for mitigating pilot contamination. The users' locations can be estimated or requested from the users directly by the BS and then the location information

can be leveraged to allocate pilot sequences in the network such that pilot contamination is minimized (e.g., [3], [4], [7]). We highlight that the existing location-aware pilot allocation algorithms only consider a simple channel model [3], [7], [8] that may not be generalized enough to depict certain practical channel conditions, such as the channels containing both line-of-sight (LOS) and non-line-of-sight (NLOS) components. In some cases, a LOS channel component may exist between BSs and users [4]. In order to deal with the pilot allocation problem under LOS conditions or when both LOS and NLOS conditions exist, we consider Rician fading channels in this work. Most existing studies in location-aware pilot allocation algorithms assume that the AoAs of all the users are strictly non-overlapping [3], [7], [8], which is hard to justify in some practical scenarios. We relax this assumption and demonstrate that the location information is beneficial for pilot allocation, even when the AoAs of interfering users are overlapping. Furthermore, different from existing studies, we assume that the pilot sequences used in a cell are not orthogonal. As such, our system model incorporates both the inter-cell and the intra-cell pilot contamination. The work [4] presented the pilot allocation in a single-cell network. Different from [4], we consider a more general multi-cell network, which encompasses the single-cell network as a special case. Moreover, in this work we derive the multi-cell LOS interference expression that is valid for an arbitrary number of BS antennas. Furthermore, in this work we perform a thorough comparison between the proposed algorithm and several existing algorithms under varying network conditions. We highlight that the derivation and the comparison were not presented in [4]. Throughout this paper, we define the LOS interference as the interference caused by the LOS components in the channels.

In this correspondence, we propose a low-complexity pilot allocation algorithm suitable for a network with high-mobility users. Our examination shows that the proposed algorithm improves the sum SE of the network as compared to the existing algorithms, even when the locations of the users suffer from estimation errors.

II. SYSTEM MODEL

We consider an L -cell massive MIMO network as illustrated in Fig. 1. In each cell, a BS equipped with M antennas communicates with N single-antenna users. We denote the BS in the i -th cell as BS_i and the j -th user in the i -th cell as U_{ij} . Additionally, we denote the location of U_{ij} as (d_{ij}, θ_{ij}) , where d_{ij} is the distance from U_{ij} to BS_i and θ_{ij} is the AoA of U_{ij} at BS_i . We represent the small-scale propagation factor between U_{ij} and the BS_l as h_{ijl} . We assume that h_{ijl}

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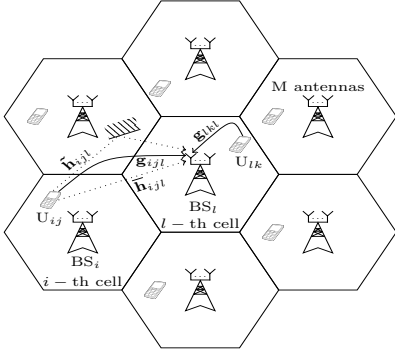


Fig. 1. A multi-cell massive MIMO network with Rician fading channels.

is subject to Rician fading. Consequently, \mathbf{h}_{ijl} consists of a LOS component denoted as $\bar{\mathbf{h}}_{ijl}$ and a Rayleigh distributed NLOS component denoted as $\tilde{\mathbf{h}}_{ijl}$, where $\tilde{\mathbf{h}}_{ijl} \sim \mathcal{CN}(\mathbf{0}, \mathbf{I}_M)$. We assume that the uplink channel between U_{ij} and BS_l is affected by large-scale propagation effects denoted as α_{ijl} . As such, the uplink channel from U_{ij} to BS_l is written as

$$\mathbf{g}_{ijl} = \sqrt{\alpha_{ijl}} \left(\sqrt{\frac{K_{ijl}}{1 + K_{ijl}}} \bar{\mathbf{h}}_{ijl} + \sqrt{\frac{1}{1 + K_{ijl}}} \tilde{\mathbf{h}}_{ijl} \right), \quad (1)$$

where K_{ijl} is the K -factor of U_{ij} at BS_l . We assume that the BSs are equipped with uniform linear antenna arrays. As such, $\bar{\mathbf{h}}_{ijl}$ depends on the location of U_{ij} and is expressed as

$$\bar{\mathbf{h}}_{ijl} = [1, e^{-j(\frac{2\pi r}{\lambda})\sin(\theta_{ij})}, \dots, e^{-j(M-1)(\frac{2\pi r}{\lambda})\sin(\theta_{ij})}]^T, \quad (2)$$

where r is the distance between two antennas and λ is the wavelength. We assume that $r = \frac{\lambda}{2}$, which is a widely adopted assumption [4]. The uplink channels between all the users in the i -th cell and BS_l are represented as $\mathbf{G}_{il} = \mathbf{H}_{il} \mathbf{D}_{il}^{\frac{1}{2}}$, where

$$\mathbf{H}_{il} = \bar{\mathbf{H}}_{il} [\boldsymbol{\Omega}_{il} (\boldsymbol{\Omega}_{il} + \mathbf{I}_N)^{-1}]^{\frac{1}{2}} + \tilde{\mathbf{H}}_{il} [(\boldsymbol{\Omega}_{il} + \mathbf{I}_N)^{-1}]^{\frac{1}{2}}, \quad (3)$$

with $\bar{\mathbf{H}}_{il} = [\bar{\mathbf{h}}_{i1l}, \dots, \bar{\mathbf{h}}_{iNl}]$, $\tilde{\mathbf{H}}_{il} = [\tilde{\mathbf{h}}_{i1l}, \dots, \tilde{\mathbf{h}}_{iNl}]$, $\boldsymbol{\Omega}_{il} = \text{diag}[K_{i1l}, \dots, K_{iNl}]$, and $\mathbf{D}_{il} = \text{diag}[\alpha_{i1l}, \dots, \alpha_{iNl}]$.

In this work, we consider the uplink transmission from the users to the BSs, which consists of two phases, i.e., uplink channel estimation and uplink data transmission.

A. Uplink Channel Estimation

In the uplink channel estimation phase, users from all the cells transmit their pre-assigned pilot sequences to the BSs. We assume that the length of the pilot sequence is ℓ . As such, only ℓ orthogonal pilot sequences are available in the massive MIMO network. The pilot sequence assigned to U_{ij} is represented as $\boldsymbol{\eta}_{ij}$. Accordingly, the pilot sequences assigned to all the users in the i -th cell are represented as $\boldsymbol{\Lambda}_i = [\boldsymbol{\eta}_{i1}, \boldsymbol{\eta}_{i2}, \dots, \boldsymbol{\eta}_{iN}]^T$. We assume that the pilot sequences are transmitted with unit power. The received matrix at BS_l in the uplink pilot transmission phase is given by

$$\mathbf{Y}_l = \mathbf{G}_{ll} \boldsymbol{\Lambda}_l + \sum_{i=1, i \neq l}^L \mathbf{G}_{il} \boldsymbol{\Lambda}_i + \mathbf{Z}, \quad (4)$$

where \mathbf{Z} is the Gaussian noise matrix at the BS_l and the distribution of each independent element in \mathbf{Z} follows $\mathcal{CN}(0, \sigma_z^2)$. We assume that BS_l only knows the estimated location of

each user, i.e., $(\hat{d}_{ij}, \hat{\theta}_{ij})$. As such, the estimates of the LOS components in (4) are known at BS_l . Next, we compute the received matrix corresponding to the NLOS component by subtracting the LOS components from \mathbf{Y}_l , i.e., $\hat{\mathbf{Y}}_l = \mathbf{Y}_l - \hat{\mathbf{Y}}_l$, where $\hat{\mathbf{Y}}_l = \sum_{i=1}^L \hat{\mathbf{H}}_{il} \hat{\mathbf{D}}_{il}^{\frac{1}{2}} [\hat{\boldsymbol{\Omega}}_{il} (\hat{\boldsymbol{\Omega}}_{il} + \mathbf{I}_N)^{-1}]^{\frac{1}{2}} \boldsymbol{\Lambda}_i$, $\hat{\mathbf{D}}_{il} = \text{diag}[\hat{\alpha}_{i1l}, \dots, \hat{\alpha}_{iNl}]$, $\hat{\mathbf{H}}_{il} = [\hat{\mathbf{h}}_{i1l}, \dots, \hat{\mathbf{h}}_{iNl}]$, $\hat{\boldsymbol{\Omega}}_{il} = \text{diag}[\hat{K}_{i1l}, \dots, \hat{K}_{iNl}]$. We assume that $\hat{\mathbf{h}}_{ijl}$ is obtained from (2) using $\hat{\theta}_{ij}$ and we obtain $\hat{\alpha}_{i1l}$ and \hat{K}_{i1l} based on the estimated distance \hat{d}_{ij} . Accordingly, $\hat{\mathbf{Y}}_l$ is obtained from (4) as

$$\hat{\mathbf{Y}}_l = \tilde{\mathbf{H}}_{ll} [(\boldsymbol{\Omega}_{ll} + \mathbf{I}_N)^{-1}]^{\frac{1}{2}} \mathbf{D}_{ll}^{\frac{1}{2}} \boldsymbol{\Lambda}_l + \sum_{i=1, i \neq l}^L \tilde{\mathbf{H}}_{il} [(\boldsymbol{\Omega}_{il} + \mathbf{I}_N)^{-1}]^{\frac{1}{2}} \mathbf{D}_{il}^{\frac{1}{2}} \boldsymbol{\Lambda}_i + \sum_{i=1}^L \xi_{il} + \mathbf{Z}, \quad (5)$$

where $\xi_{il} = \bar{\mathbf{H}}_{il} \mathbf{D}_{il}^{\frac{1}{2}} [\boldsymbol{\Omega}_{il} (\boldsymbol{\Omega}_{il} + \mathbf{I}_N)^{-1}]^{\frac{1}{2}} \boldsymbol{\Lambda}_i - \hat{\mathbf{H}}_{il} \hat{\mathbf{D}}_{il}^{\frac{1}{2}} [\hat{\boldsymbol{\Omega}}_{il} (\hat{\boldsymbol{\Omega}}_{il} + \mathbf{I}_N)^{-1}]^{\frac{1}{2}} \boldsymbol{\Lambda}_i$. We highlight that ξ_{il} appears in (5) due to localization errors. If the locations of users are precisely known, we have $\xi_{il} = 0$ and the received matrix corresponding to the LOS component is completely removed from (4). In other words, without localization error the AoA of each user does not affect the channel estimation.

We assume that the BS_l obtains the least-square (LS) channel estimates from (5) as

$$\hat{\mathbf{G}}_{ll} = \tilde{\mathbf{Y}}_l \boldsymbol{\Lambda}_l^H = \tilde{\mathbf{H}}_{ll} [(\boldsymbol{\Omega}_{ll} + \mathbf{I}_N)^{-1}]^{\frac{1}{2}} \mathbf{D}_{ll}^{\frac{1}{2}} \mathbf{R}_{ll} + \sum_{i=1, i \neq l}^L \tilde{\mathbf{H}}_{il} [(\boldsymbol{\Omega}_{il} + \mathbf{I}_N)^{-1}]^{\frac{1}{2}} \mathbf{D}_{il}^{\frac{1}{2}} \mathbf{R}_{il} + \bar{\mathbf{Z}}, \quad (6)$$

where $\mathbf{R}_{il} = \boldsymbol{\Lambda}_i \boldsymbol{\Lambda}_i^H$, and $\bar{\mathbf{Z}} = \sum_{i=1}^L \xi_{il} \boldsymbol{\Lambda}_i^H + \mathbf{Z} \boldsymbol{\Lambda}_l^H$.

Remark 1: From (6), we note that the channel estimate $\hat{\mathbf{G}}_{ll}$ suffers from intra-cell pilot contamination when $\mathbf{R}_{ll} \neq \mathbf{I}_N$. Additionally, we note that the channel estimates suffer from inter-cell pilot contamination when the same pilot sequences are repeated throughout the network. Specifically, when $\mathbf{R}_{il} \neq \mathbf{0}_N$ the channel estimates suffer from inter-cell pilot contamination. In real-world telecommunication networks, it is not possible to assign orthogonal pilot sequences to all the users in the network. As such, it is reasonable to assume that $\mathbf{R}_{il} \neq \mathbf{0}_N$ and inter-cell pilot contamination always exists.

B. Uplink Data Transmission and Spectral Efficiency

During the uplink data transmission, each user in a cell transmits uplink data symbols to the same-cell BSs. The BS_l multiplies the received vector \mathbf{y}_l with the zero-forcing (ZF) matrix \mathbf{W}_l to decode the symbols transmitted by the same-cell users. Accordingly, using the use-and-then-forget bound, the signal received from U_{lk} after detection is written as [11]

$$\mathbf{w}_{lk}^H \mathbf{y}_l = \mathbb{E}\{\mathbf{w}_{lk}^H \mathbf{g}_{lkl}\} x_{lk} + (\mathbf{w}_{lk}^H \mathbf{g}_{lkl} - \mathbb{E}\{\mathbf{w}_{lk}^H \mathbf{g}_{lkl}\}) x_{lk} + \sum_{i=1}^L \sum_{j=1, (i,j) \neq (l,k)}^N \mathbf{w}_{lk}^H \mathbf{g}_{ijl} x_{ij} + \mathbf{w}_{lk}^H \mathbf{n}_l / \sqrt{\rho}, \quad (7)$$

where \mathbf{w}_{lk} is the k -th column of the ZF detection matrix \mathbf{W}_l , x_{ij} is the symbol transmitted by U_{ij} , \mathbf{n}_l is the Gaussian noise at BS_l , and ρ is the signal-to-noise ratio. The uplink SE for U_{lk} is given as $\text{SE}_{lk} = (1 - \ell/\ell_c) \log_2(1 + \varrho_{lk})$, where ℓ_c is the channel uses in a coherence block [11], and ϱ_{lk} is the signal-to-interference-plus-noise ratio (SINR) given by

$$\varrho_{lk} = \frac{|\mathbb{E}\{\mathbf{w}_{lk}^H \mathbf{g}_{lkl}\}|^2}{\sum_{i=1}^L \sum_{j=1}^N \mathbb{E}[|\mathbf{w}_{lk}^H \mathbf{g}_{ijl}|^2] - |\mathbb{E}\{\mathbf{w}_{lk}^H \mathbf{g}_{lkl}\}|^2 + \frac{1}{\rho} \mathbb{E}\{\|\mathbf{w}_{lk}\|^2\}}. \quad (8)$$

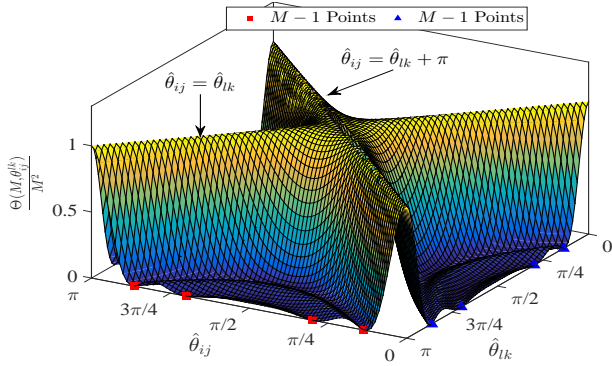


Fig. 2. AoA-dependent part of the LOS interference versus the AoAs.

We note that the product of linear detection vector and the channel, i.e., $\mathbf{w}_{lk}^H \mathbf{g}_{ijl}$, is important in determining q_{lk} . We next present the proposed pilot allocation algorithm that aims at reducing the interference caused by $\mathbf{w}_{lk}^H \mathbf{g}_{ijl}$ based on the estimated locations of the users.

III. LOCATION-AWARE PILOT ALLOCATION

In this section, we present our low-complexity location-aware pilot allocation algorithm. The algorithm requires the knowledge about the large-scale fading, AoAs, and K -factors to perform pilot allocation. Specifically, we first derive the expression for the LOS interference based on the estimated locations of the users. Then, the pilot sequences are allocated to the users sequentially to minimize the LOS interference.

A. LOS Interference

We derive the expression for the LOS interference between two users in the network in the following theorem.

Theorem 1: The LOS interference between \mathbf{U}_{ij} and \mathbf{U}_{lk} based on their estimated locations is given as

$$\delta_{ij}^{lk} = \underbrace{\frac{\hat{\alpha}_{ijl} K_{ijl} (1 + K_{lkl})}{\hat{\alpha}_{lkl} K_{lkl} (1 + K_{ijl})}}_{\text{part 1}} \underbrace{\frac{|\Theta(M, \hat{\theta}_{ij}^{lk})|^2}{M^2}}_{\text{part 2}}, \quad (9)$$

where

$$|\Theta(M, \hat{\theta}_{ij}^{lk})|^2 = \begin{cases} M^2 & \hat{\theta}_{ij}^{lk} = 0, \\ \frac{\sin^2(M\hat{\theta}_{ij}^{lk}/2)}{\sin^2(\hat{\theta}_{ij}^{lk}/2)} & -2\pi < \hat{\theta}_{ij}^{lk} < 2\pi \text{ and } \hat{\theta}_{ij}^{lk} \neq 0. \end{cases} \quad (10)$$

Proof: The proof is provided in Appendix A. ■

We note that the LOS interference given in (9) consists of two parts. Specifically, *part 1* is distance-dependent and *part 2* is AoA-dependent. We note that *part 1* is the smallest when the \mathbf{U}_{ij} and \mathbf{U}_{lk} are the farthest apart from each other. Fig. 2 depicts *part 2* at different AoAs for \mathbf{U}_{ij} and \mathbf{U}_{lk} for $M = 5$. We obtain the following insights regarding AoA-dependent *part 2* from Fig. 2. The AoA-dependent *part 2* is

- maximum when the AoAs are overlapping, i.e., $\hat{\theta}_{ij} = \hat{\theta}_{lk}$.
- maximum when the AoAs differ by π , i.e., $\hat{\theta}_{ij} = \pi - \hat{\theta}_{lk}$.
- minimum for certain mutual AoAs for \mathbf{U}_{ij} and \mathbf{U}_{lk} .
- minimum for $M - 1$ possible values of $\hat{\theta}_{ij}$ or $\hat{\theta}_{lk}$.

We highlight that the observations on *part 1* and *part 2* can be utilized for pilot allocation. As such, the location information can be used to identify the users with the minimum LOS interference and assign the same pilot sequence to such users to improve the sum SE. We note that the LOS interference (9) is obtained for the LS estimator and the ZF detector. We also clarify that for different combination of estimators and detectors, the LOS interference exists and can be obtained in a similar way to obtaining (9).

Lemma 1: In massive MIMO networks when $M \rightarrow \infty$, we have $\delta_{ij}^{lk} \xrightarrow{a.s.} 0$ when $\hat{\theta}_{ij} \neq \hat{\theta}_{lk}$ and

$$\delta_{ij}^{lk} \xrightarrow{a.s.} \frac{\hat{\alpha}_{ijl} K_{ijl} (1 + K_{lkl})}{\hat{\alpha}_{lkl} K_{lkl} (1 + K_{ijl})} \text{ when } \hat{\theta}_{ij} = \hat{\theta}_{lk}. \quad (11)$$

Proof: The proof follows directly from the definition of $|\Theta(M, \hat{\theta}_{ij}^{lk})|^2$ in (10). When $\hat{\theta}_{ij}^{lk} \neq 0$, the minimum value of (10) is obtained, i.e., $|\Theta(M, \hat{\theta}_{ij}^{lk})|^2 = 0$, when $\hat{\theta}_{ij}^{lk} = 2b\pi/M$ with $b = \pm 1, \dots, \pm(M-1)$. Moreover, when $M \rightarrow \infty$, we find that $|\Theta(M, \hat{\theta}_{ij}^{lk})|^2 \xrightarrow{a.s.} 0$ for $\hat{\theta}_{ij}^{lk} \neq 0$. Substituting (10) into (9), we obtain (11), which completes the proof. ■

Remark 2: According to Lemma 1, when the number of antennas at BSs is large, the LOS interference is high only when the AoAs of the two interfering users are strictly overlapping. Additionally, increasing the number of antennas at BSs increases the possibility of having two users with the minimum LOS interference, because the LOS interference is minimum at $M - 1$ values of the mutual AoAs, as depicted in Fig. 2. This observation highlights the benefit of massive MIMO for the proposed location-aware pilot allocation algorithm.

Remark 3: The optimal solution for pilot allocation can be found by performing an exhaustive search to identify the pilot allocation that leads to the highest sum SE. However, this exhaustive search is of a high computational complexity, which makes it infeasible for the network with a large number of high-mobility users. For example, for a given N and ℓ , there are $L \times N^\ell$ possible pilot allocations to be searched in each cell. This motivates us to propose a low-complexity pilot allocation algorithm in the next subsection.

B. Pilot Allocation Algorithm

In this subsection, we detail the proposed low-complexity pilot sequence allocation algorithm, which results in reduced pilot contamination and improved sum SE. We note that the SINR expression in (8) depends on instantaneous channel realizations, which cannot be accurately obtained when the network suffers from pilot contamination [12]. Due to this limitation, we focus on minimizing the LOS interference given by (9) and allocate the same pilot sequence to the users with low LOS interferences.

We next present the step-by-step algorithm for pilot sequence allocation. We first assign pilot sequences to the center cell and then to the neighboring cells.

1) *Divide the cell into tiers:* The BS divides the cell area into $n = \text{ceil}(N/\ell)$ tiers based on the estimated distance \hat{d}_{lk} as

$$\underbrace{\{\hat{d}_{l1}, \dots, \hat{d}_{l\ell}\}}_{\text{tier 1}} \underbrace{\{\hat{d}_{l(\ell+1)}, \dots, \hat{d}_{l(2\ell)}\}}_{\text{tier 2}} \dots \underbrace{\{\hat{d}_{l((n-1)\ell+1)}, \dots, \hat{d}_{lN}\}}_{\text{tier } n}, \quad (12)$$

where each of the first $n - 1$ tiers consists of ℓ users while there are no more than ℓ users in the tier n .

2) *Assign pilots in tier 1*: We next assign the orthogonal pilot sequences to the ℓ users in the tier 1, i.e., the tier closest to the BS. The rationale behind assigning orthogonal pilot sequences to the users in tier 1 is to reduce the pilot contamination. Specifically, the interference power from the users that are assigned the same pilot sequence depends on the large-scale channel coefficient, i.e., α_{ijl} . As such, if two users close to a BS are assigned the same pilot sequence, the interference is large, which results in an increased pilot contamination. This observation can also be validated from the distance-dependent *part 1* in (9).

3) *Assign pilots in tier 2*: We compute δ_{ij}^{ik} using (9) between U_{ij} in the tier 1 and the ℓ users in the tier 2. We highlight that we first assign pilot to the user closest to the BS. We assign the same pilot sequence as U_{ij} in tier 1 to the user U_{ik} in tier 2 with minimum δ_{ij}^{ik} . If K_{ijl} or K_{lkl} are zero, we only used *part 2* in (9). We repeat this process for the $\ell - 1$ remaining users in tier 2.

4) *Assign pilots in remaining tiers*: We compute the LOS interference δ_{ij}^{ik} between U_{ik} in tier n and U_{ij} in tier o , where $o \in \{1, \dots, n - 1\}$ and U_{ij} in tier o has been assigned the same pilot sequence. We then compute the average of the LOS interference and assign the same pilot sequence to U_{ik} with the minimum average LOS interference. If the tier n has less than ℓ users, some pilot sequences are not used in tier n .

5) *Assign pilots in remaining cells*: After completing pilot allocation for the center cell, we repeat Step 1 to Step 4 for pilot sequence allocation in neighboring cells. In Step 5, we consider all the LOS interference between a tier in the target cell and all the tiers in cells where the pilot sequence allocation has already been carried out, and then compute the average LOS interference and assign pilot sequences accordingly.

The algorithm returns a vector \mathbf{s} , where the l -th element of \mathbf{s} denotes the pilot allocation for the users in the l -th cell.

IV. NUMERICAL RESULTS AND ANALYSIS

In this section, we demonstrate the benefits of the proposed pilot allocation algorithm with random pilot allocation [9], the greedy iterative algorithm [10], and sector-based [13] as benchmarks. Random pilot allocation is the most widely adopted pilot allocation algorithm in massive MIMO [3], [4], [6]. In random pilot allocation, the BS allocates the pilots to all the users in a cell randomly. Greedy iterative algorithm [10] iteratively refines the sum rate by first identifying the user with the lowest rate and then searching a pilot sequence for the user which minimizes the interference. Sector-based algorithm divides the cell-area in sectors and all users in a sector are assigned the same pilot [13]. The system settings adopted in this section are summarized in Table I. All the results are obtained for an average of 10,000 Monte Carlo simulations.

Fig. 3(a) depicts the sum SE in the center cell for the proposed pilot allocation, random pilot allocation, and greedy

TABLE I
SIMULATION PARAMETERS

Number of cells L	2
Number of users per cell N	36
Cell radius d_{BS}	400 m
User distance from the BS d_{lk}	U [100 m, 400 m]
User AoA θ_{lk}	U [0, 2Δ]
Large-scale propagation constant α_{lk}	$(d_{lk}/d_{BS})^v$, where $v = 3.76$
Length of pilot sequence ℓ	12
Channel uses in coherence interval ℓ_c	196
SNR ρ	10 dB

iterative algorithm¹. We assume that the K factors for all the users are the same. The results are obtained using (8) for an average of 10,000 random user locations, where the user locations are accurately known to the BSs. By randomizing user locations we simulate high-mobility scenarios, where the locations of users change for each coherence interval. The advantage of the proposed pilot allocation algorithm is clearly observed from Fig. 3(a), where for $M = 200$ and $K = 0$ dB the proposed pilot allocation algorithm provides 22.73% and 37.26% improvement in sum SE as compared to the random pilot allocation and greedy iterative approach, respectively. Importantly, we observe that the performance improvement increases with K , which is due to the fact that the LOS interference dominates the total interference when K is large and our proposed algorithm is to minimize the LOS interference. We also observe that the performance improvement increases with M , which can be explained by our *Lemma 1* and demonstrates the benefit of massive MIMO. We observe that the greedy iterative algorithm achieves a lower sum SE than the random pilot allocation algorithm when K is small. This is due to the fact that in high-mobility scenarios, the user with low SINR may have a different location and channel conditions in the next iteration. This makes the greedy iterative algorithm more suitable for low-mobility scenarios.

In Fig. 3(b), we compare the performance of the users worst affected by interference. As such, the sum SE of such users is low. We compare the cumulative distribution function (CDF) of five users with minimum sum SE for the three pilot allocation algorithms. We set $M = 100$, $K = 10$ dB, and assume that the locations of users are accurately known to the BSs. Our proposed algorithm outperforms the random pilot allocation and greedy iterative algorithm by 1.56 bit/sec/Hz and 2.57 bit/sec/Hz, respectively.

In Fig. 3(c), we examine the performance of the proposed algorithm subject to localization errors. The location estimate has an error variance of σ_{error}^2 , where the location error is uniformly distributed. We clarify that certain location-based schemes may be more sensitive to the errors in AoA than to the errors in distance. However, in this simulation, we consider the errors in both distance and AoA. In the simulations, we use the K -factor as defined in 3GPP TR25.996 model. Accordingly, we define K_{ijl} (dB) = $13 - 0.03\hat{d}_{ijl}$, where \hat{d}_{ijl}

¹We note that there are $L \times N^\ell$ unique pilot allocations in the massive MIMO network, which leads to that identifying the optimal pilot allocation is of a high computational complexity. For a small scale scenario with $N = 4$, $\ell = 2$, and $L = 1$, we have found that the proposed pilot allocation algorithm achieves between 67.7% to 76.6% of the sum SE achieved by the optimal pilot allocation algorithm, but with a significantly lower computational complexity.

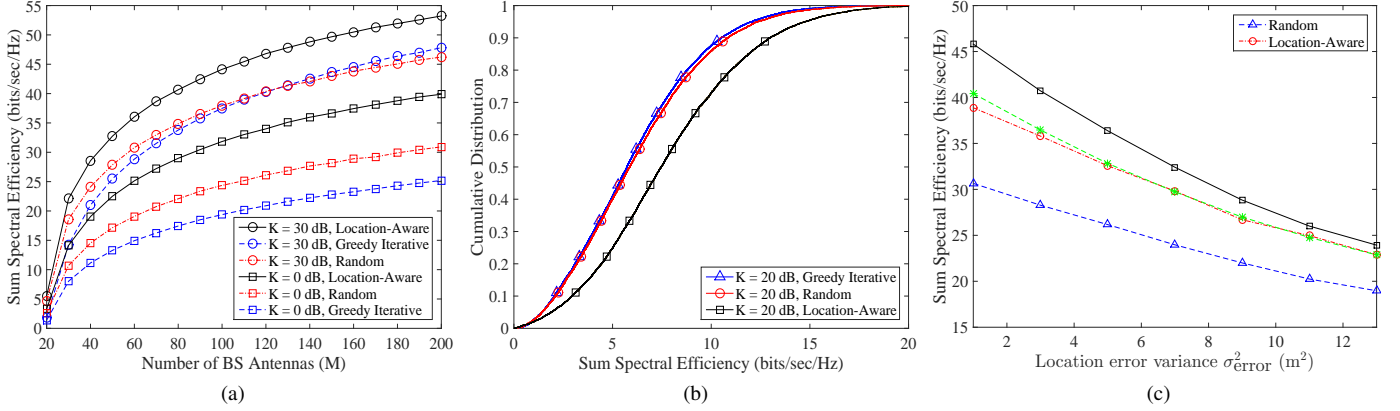


Fig. 3. Numerical results illustrating the advantages of the proposed location-aware algorithm. (a) The sum SE versus the number of BS antennas, (b) The CDF of the sum SE for $M = 100$, (c) The sum SE versus location error variance for the proposed location-aware algorithm and the three existing algorithms.

is the estimated distance between U_{ij} and BS_l . Furthermore, we assume that the probability of LOS decreases linearly as the distance between users and BSs increases. We highlight that the proposed algorithm still significantly outperforms the other two pilot allocation algorithms when the locations of the users suffer from estimation errors. We note that the sum SE decreases when σ_{error}^2 increases. For example, when σ_{error}^2 increases from 0 m^2 to 15 m^2 , the sum SE for the proposed algorithm decreases from 28.08 bit/sec/Hz to 24.59 bit/sec/Hz , which amounts to a reduction of 12.43% in the sum SE. However, the proposed pilot allocation algorithm provides an improvement of 10.46%, 12.10%, and 30.55% in the sum SE, respectively, as compared with sector-based allocation, random allocation, and greedy allocation when $\sigma_{\text{error}}^2 = 3 \text{ m}^2$.

V. CONCLUSION

We proposed a low-complexity location-aware pilot allocation algorithm for a massive MIMO network with high-mobility users. The algorithm exploited the behavior of LOS interference between users for pilot sequence allocation. Comparison with existing algorithms demonstrated the advantages of our proposed algorithm in terms of achieving a higher sum SE. In addition, the proposed algorithm is beneficial for the users that are worst-affected by interference and outperforms existing algorithms in the presence of localization errors.

APPENDIX A

From (8), we note that $\mathbf{w}_{lk}^H \mathbf{g}_{ijl}$ is important in determining q_{lk} . The vector \mathbf{w}_{lk}^H is based on channel estimates. For example, we have $\mathbf{w}_{lk} = \hat{\mathbf{g}}_{lkl}^H / \hat{\mathbf{g}}_{lkl}^H \hat{\mathbf{g}}_{lkl}$ for ZF detection. Consequently, we compute $\hat{\mathbf{g}}_{lkl}^H \mathbf{g}_{ijl}$ and obtain

$$\hat{\mathbf{g}}_{lkl}^H \mathbf{g}_{ijl} = \hat{\mathbf{g}}_{lkl}^H \bar{\mathbf{g}}_{ijl} + \hat{\mathbf{g}}_{lkl}^H \tilde{\mathbf{g}}_{ijl} + \hat{\mathbf{g}}_{lkl}^H \bar{\mathbf{g}}_{ijl} + \hat{\mathbf{g}}_{lkl}^H \tilde{\mathbf{g}}_{ijl}. \quad (13)$$

We highlight that (13) cannot be computed unless the locations of users and channel estimates are known to the BS. However, assuming that the BSs have estimated user locations ($\hat{d}_{ij}, \hat{\theta}_{ij}$), we calculate an estimate for the first term, i.e., the pure LOS term in (13), as

$$\hat{\mathbf{g}}_{lkl}^H \hat{\mathbf{g}}_{ijl} = \left(\frac{\hat{\alpha}_{lkl} \hat{\alpha}_{ijl} K_{lkl} K_{ijl}}{(1 + K_{lkl})(1 + K_{ijl})} \right)^{\frac{1}{2}} \Theta(M, \hat{\theta}_{ij}^{lk}), \quad (14)$$

where we have defined $\hat{\theta}_{ij}^{lk} = \pi[\sin(\hat{\theta}_{ij}) - \sin(\hat{\theta}_{lk})]$ and $\Theta(M, \hat{\theta}_{ij}^{lk}) = \sin(M\hat{\theta}_{ij}^{lk}/2) / \sin(\hat{\theta}_{ij}^{lk}/2) e^{j\hat{\theta}_{ij}^{lk}(M-1)/2}$. We highlight

that $\hat{\mathbf{g}}_{lkl}^H \hat{\mathbf{g}}_{lkl}$ is a special case of (14) when $i = l$ and $j = k$. Utilizing this observation we obtain $\hat{\mathbf{g}}_{lkl}^H \hat{\mathbf{g}}_{lkl} = M\hat{\alpha}_{lkl} K_{lkl} / (1 + K_{lkl})$. Normalizing (14) by $\hat{\mathbf{g}}_{lkl}^H \hat{\mathbf{g}}_{lkl}$, we obtain the expression for the LOS interference as

$$\delta_{ij}^{lk} = \frac{\hat{\alpha}_{ijl} K_{ijl} (1 + K_{lkl})}{\hat{\alpha}_{lkl} K_{lkl} (1 + K_{ijl})} \frac{|\Theta(M, \hat{\theta}_{ij}^{lk})|^2}{M^2}, \quad (15)$$

where $\delta_{ij}^{lk} = |\hat{\mathbf{g}}_{lkl}^H \hat{\mathbf{g}}_{ijl} / \hat{\mathbf{g}}_{lkl}^H \hat{\mathbf{g}}_{lkl}|^2$ represents the LOS interference between U_{ij} and U_{lk} .

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