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Abstract—This letter focuses on the pilot contamination problem in the uplink and downlink of cell-free massive multiple-input multiple-output networks with different degrees of cooperation between access points. The optimum minimum mean square error processing can take advantage of large-scale fading coefficients for canceling the interference of pilot-sharing user-equipments and thus achieves asymptotically unbounded capacity. However, it is computationally demanding and can only be implemented in a fully centralized network. Here, sub-optimal schemes are derived that provide unbounded capacity with linear-growing complexity and using only local channel estimates but global channel statistics. This makes them suited for both centralized and distributed networks. In this latter case, the best performance is achieved with a generalized maximum ratio combiner that maximizes a capacity bound based on channel statistics only.

Index Terms—Cell-free massive MIMO, pilot contamination, uplink combining, downlink precoding, reduced-complexity minimum mean square error, generalized maximum ratio.

I. INTRODUCTION

The interference generated by user equipments (UEs) that transmit the same pilot sequence for channel acquisition is known as pilot contamination [1], [2]. This interference not only reduces the estimation quality but also makes the channel estimates statistically dependent. This latter effect makes it particularly hard to mitigate the interference (known as coherent interference) between these UEs. Although existing in most networks, this problem has a greater impact on those where the large number of UEs requires a high pilot-reuse factor. This was the case of cellular massive multiple-input multiple-output (mMIMO) networks [1], [2] and has been inherited by the new cell-free (CF) mMIMO, but to a larger extent due to the CF implementation [3], [4]. In the beyond 5G era, CF mMIMO is seen as a promising solution to provide uniform service for massive Machine Type Communicantions (mMTC) and Ultra-Reliable Low-Latency Communications (URLLC). The scheme can be implemented either in a centralized or a distributed fashion since only local channel estimates are required, in addition to global channel statistics. An alternative, yet optimal, scheme is also proposed by using a more conservative capacity bound that depends only on statistical channel knowledge and provides an achievable rate when channel state information (CSI) is not available for final data detection. This is the case of a decentralized network in which the channels are estimated at the APs while data detection is performed at the central processing unit (CPU). These combiners are built based on the linear independence experienced by the global covariance matrices and the asymptotic behavior for a large number of APs, though they are valid under a finite regime. Neither of these processing schemes are constrained by pilot contamination and both show linear-growth complexity. Thanks to the uplink (UL)-downlink (DL) duality [7], precoding schemes can be obtained for the DL segment. These schemes are also valid if a user-centric approach is taken (e.g., [7], [8]).

Notation: The superscripts $^\top$, $^*$ and $^H$ denote transpose, conjugate, and Hermitian transpose, respectively. We use $C^\mathbb{R}$ to denote the circularly symmetric complex Gaussian distribution with zero mean and covariance matrix $\mathbf{R}$. The expected value of a random variable $x$ is denoted by $\mathbb{E}[x]$, while diag denotes the main diagonal components of a matrix. We use $a \asymp b$ to denote $a - b \sim_{\text{as}} 0$ almost surely for two (random) sequences $a_n, b_n$.

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II. NETWORK MODEL

We consider a CF mMIMO network with $M$ single-antenna APs. The APs serve jointly $K$ single-antenna UEs, and are connected via fronthaul links to a CPU. The standard time division duplex (TDD) protocol of cellular mMIMO is used [7, Sec. 2.3.2], where the $\tau$, available channel uses are employed
The estimates and estimation errors \( \hat{h}_{\text{mk}} = h_{\text{mk}} - \bar{h}_{\text{mk}} \) are independent random variables distributed as \( h_{\text{mk}} \sim \mathcal{CN}(0, \tau_{\text{mk}}) \) with \( \tau_{\text{mk}} = \frac{\beta_{\text{mk}}}{\gamma_{\text{mk}}} \) and \( \bar{h}_{\text{mk}} \sim \mathcal{CN}(0, \tau_{\text{mk}}) \) with \( \tau_{\text{mk}} = \beta_{\text{mk}} - \gamma_{\text{mk}} \). The interference generated by the pilot-sharing UEs in (3) is known as pilot contamination, e.g., [9]. To perform coherent processing at multiple APs, knowledge of \( h_{\text{ue}} \) is necessary. This is obtained as \( \hat{h}_{\text{ue}} = \hat{h}_1, \ldots, \hat{h}_{\text{ue}} \mathbb{1} \sim \mathcal{CM} \) and is distributed as \( h_{\text{ue}} \sim \mathcal{CN}(0, \Gamma_L) \) with \( \Gamma_L = R_L \Psi^{-1} R_L \) and \( \Psi = \text{diag}(\gamma_1, \ldots, \gamma_{14}) \) leading to \( \Gamma_L = \text{diag}(\gamma_1, \ldots, \gamma_{14}) \).

### III. UPLINK SIGNAL COMBINING

We address now the UL combining for both centralized and distributed processing. The optimal MMSE scheme is set as the upper benchmark that our proposals will be compared to. In the centralized scenario, each AP acts only as a relay that forwards its received signals to the CPU, which performs both channel estimation and data detection. Assuming error-free fronthaul links, the joint UL data signal \( y_{\text{mk}} \) available at the CPU is mathematically equivalent to the signal model of a single-cell system where the correlated fading \( h_{\text{mk}} \) has a diagonal spatial covariance matrix. At the CPU, the UE \( k \) data signal estimate is obtained as \( \hat{s}_{\text{mk}} = v_{\text{mk}}^{\text{UL}} y_{\text{mk}} \) where \( v_{\text{mk}} \in \mathbb{C}^M \) is the centralized combiner.

With MMSE channel estimation, an achievable spectral efficiency (SE) of UE \( k \) is

\[
\text{SE}_{\text{UL}}^k = \frac{1}{p_k} \log_2 \left( 1 + \text{SINR}_{\text{UL}}^k \right)
\]

where the expectation is with respect to channel realizations and the effective signal-to-interference-plus-noise ratio (SINR) is [7, Sec. 5.1.1]

\[
\text{SINR}_{\text{UL}}^k = \frac{|v_{\text{mk}}^{\text{UL}} h_{\text{mk}}|^2}{\sum_{i=1}^K |v_{\text{mi}}^{\text{UL}} h_{\text{mi}} + Z_i|^2} v_k
\]

with \( Z = \text{diag}(z_1, \ldots, z_K) \) being diagonal with elements \( z_m = \sum_{k=1}^K \tau_{mk} + \frac{1}{p_k} \).

This SE is valid for any combiner \( v_k \) but requires the channel estimates \( \hat{h}_{\text{mk}} \) and estimation errors \( \bar{h}_{\text{mk}} = [h_1, \ldots, h_M]^T \) to be independent. This condition is satisfied with the MMSE channel estimator. An alternative bound that can be applied along with any channel estimator is the so-called use-and-then-forget (UatF).\(^1\) This yields \( \text{SE}_{\text{UL}}^k \) smaller than \( \text{SE}_{\text{UL}}^k \) since it relies on a simplified implementation in which the channel estimates are not used at the CPU for signal detection.

Regarding the distributed network model, the MMSE channel estimates are computed locally at the APs and are used to obtain local estimates of UE data. This approach is more suitable for those use cases where low-latency is crucial. Let \( v_{\text{mk}} \in \mathbb{C}^M \) denote the local coefficient that AP \( m \) uses for UE \( k \). Then, the UE \( m \) local data signal estimate is \( \tilde{s}_{\text{mk}} = v_{\text{mk}}^{\text{UatF}} y_{\text{mk}} \), with \( y_{\text{mk}} \) the UL signal at AP \( m \). Any coefficient \( v_{\text{mk}} \) can be adopted. Unlike a fully centralized network, however, AP \( m \) can only use its own local channel estimates for the design of \( v_{\text{mk}} \). The local estimates \( \{v_{\text{mk}}^{\text{UatF}} : m = 1, \ldots, M \} \) are then sent to the CPU for final decoding. We assume that the final estimate \( \tilde{s}_{\text{mk}} \) is computed by averaging the local estimates, i.e., \( \tilde{s}_{\text{mk}} = \sum_{m=1}^M v_{\text{mk}}^{\text{UatF}} y_{\text{mk}} \). In a distributed network, the CPU does not have knowledge of channel estimates and thus only the statistics can be utilized to estimate \( s_{\text{mk}}^{\text{UatF}} \). Since \( \text{SE}_{\text{UL}}^k \) does not rely on channel estimates, it can be used to compute an achievable SE in a distributed network [7, Sec. 5.2.1].

#### A. MMSE Combining

As in cellular mMIMO [5], [9], the SINR in (4) is a generalized Rayleigh quotient with respect to \( v_k \) and thus is maximized by the MMSE combining vector, i.e.,

\[
v_k = v_k = \sum_{k=1}^K \tilde{h}_k n_k + Z \tilde{h}_k.
\]

\(^1\)The name comes from the fact that the channel estimates are used for computing receive combining vectors and then effectively forgotten before signal detection takes place.
We will now analyze the asymptotic behavior of $\text{SE}^c_\text{MMSE}$ with the MMSE as $M \rightarrow \infty$. We assume that the global covariance matrices $\{R_k : k = 1, \ldots, K\}$ are asymptotically linearly independent, as analytically defined in [2]. This assumption is fairly realistic since each entry of $R_k$ is subject to a different channel gain. This is a key difference between the CF architecture and traditional single-cell mMIMO systems that allows CF systems to achieve unbounded capacity even with single-antenna APs. Under this condition, and building on [2, Th. 1], the next proposition follows.

**Proposition 1.** If MMSE combining is used and $\{R_k : k = 1, \ldots, K\}$ are asymptotically linearly independent, then $\text{SE}^c_\text{MMSE}$ increases unboundedly as $M \rightarrow \infty$.

**Proof:** It follows easily from [2, App. B] since the centralized case is basically a single-cell mMIMO network with diagonal spatial correlation matrices.

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**B. Reduced-Complexity MMSE Combining**

Although the MMSE combining vector $\hat{v}_k$ is optimal and achieves unbounded capacity (as in cellular mMIMO), it requires to compute the $M \times M$ matrix inverse in (7) in every coherence block, which may be too computationally demanding when the network size is large. Note this translates into a computational complexity that grows with $M^3$. To overcome this issue, we follow the same approach in [6], and consider the asymptotic regime. However, in contrast to a distributed cellular mMIMO network, we consider the asymptotic regime in CF mMIMO systems to be achieved by letting $M \rightarrow \infty$. This consideration invalidates the straightforward use of those derivations available in [6] in a CF scenario. Nevertheless, as shown in the Appendix, we can propose an alternative combiner $v_k = v_{\text{RC-MMSE}} = \left[\hat{v}_k, \ldots, \hat{v}_M\right]^T$ with $\hat{v}_{\text{RC-MMSE}}$ given by

$$v_{\text{RC-MMSE}} = \frac{1}{\sum_{i=1}^{M} \sum_{j=1}^{K} \beta_{mi} \beta_{nj}} \sum_{i=1}^{K} \beta_{mi} \hat{y}_{ni},$$

where $\hat{y}_{ni}$ is the $(n, i)$th element of the matrix $E\left\{y\right\}$. The entries of $E\left\{y\right\}$ are given by

$$[E\left\{y\right\}]_{ji} = 1 \sum_{m=1}^{M} \sum_{n=1}^{N} \frac{\beta_{mi} \beta_{nj}}{\sum_{k=1}^{M} \beta_{mk} \beta_{nk}} \left(\sum_{k=1}^{K} \gamma_{nk} + \frac{\beta_{nj}}{\rho^n}\right) \left(\sum_{k=1}^{K} \gamma_{mk} + \frac{\beta_{mi}}{\rho^m}\right),$$

where $\gamma_{nk}$ is the $(n, k)$th element of the matrices $E\left\{\gamma\right\}$. The entries of $E\left\{\gamma\right\}$ are given by

$$[E\left\{\gamma\right\}]_{ij} = 1 \sum_{m=1}^{M} \sum_{n=1}^{N} \frac{\beta_{mi} \beta_{nj}}{\sum_{k=1}^{M} \beta_{mk} \beta_{nk}} \left(\sum_{k=1}^{K} \gamma_{nk} + \frac{\beta_{nj}}{\rho^n}\right) \left(\sum_{k=1}^{K} \gamma_{mk} + \frac{\beta_{mi}}{\rho^m}\right).$$

Plugging (13) into $v_k = W_k \hat{v}_k$ yields $v_k = \hat{v}_k = \left[\hat{v}_1, \ldots, \hat{v}_M\right]^T$ with (thanks to the diagonal structure of matrices)

$$v_{\text{RC-MMSE}} = \frac{1}{\sum_{i=1}^{M} \sum_{j=1}^{K} \beta_{mi} \beta_{nj}} \sum_{i=1}^{K} \beta_{mi} \hat{y}_{ni}.$$

We refer to (15) as generalized maximum ratio (GMR) combining. As for MMSE, we can analyze its asymptotic behavior as $M \rightarrow \infty$. With [6], [10], the next proposition follows.

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2In practice, $M$ will not be infinite. Numerical results will show that (8) works well for practical numbers of APs.

3Though not shown here due to the lack of space, the RC-MMSE combiner outperforms the proposed local MMSE (L-MMSE) schemes in [1] under full pilot reuse.
Proposition 2. If GMR combining is used and \( \{ R_k : k = 1, \ldots, K \} \) are asymptotically linearly independent, then \( \text{SE}_{\text{UL}} \) increases unboundedly as \( M \to \infty \).

This proposition shows that GMR has the same scaling behavior of MMSE and RC-MMSE as \( M \to \infty \). As with RC-MMSE, this is achieved by using only the channel statistics. Moreover, GMR has the same complexity of RC-MMSE as it follows by plugging \( \hat{h}_{mk} \) into (15) to obtain

\[
\hat{x}_{mk} = \hat{x}_{mk} \left( \frac{1}{\sqrt{\rho}} \mathbf{v}^H \hat{h}_{mk} \right) (16)
\]

where

\[
\hat{x}_{mk} = \frac{1}{\left( \sum_{k=1}^{K} \beta_{mk} + \rho_k \right) \left( \sum_{k=1}^{K} \beta_{mk} + \rho_k \right)} \sum_{k=1}^{K} \alpha_{mk} \beta_{mk}. (17)
\]

The key difference with respect to RC-MMSE in (8) is the scaling factor \( \omega_{mk} \), which does not depend on the variances \( \{ \omega_{mk} : i = 1, \ldots, K \} \) of the channel estimation errors but on the large-scale fading coefficients \( \{ \beta_{mk} : k = 1, \ldots, K \} \). This is because (15) maximizes \( \text{SE}_{\text{UL}} \), which does not take into account the imperfection CSI in the decoding process. As RC-MMSE, GMR can also be used in a decentralized network. Whatmore, anytime a distributed scenario with global statistics knowledge is considered, GMR should be used since it is the optimal scheme for MR-based processing.

IV. DOWNLINK SIGNAL PRECODING

We now consider the DL and design the precoding schemes for centralized and decentralized networks. As in the UL, the most advanced DL implementation is a fully centralized operation, where the AP only acts as relays that transmit signals generated by the CPU. A distributed operation is also possible in the DL where the CPU encodes the DL data signals \( \{ w_k : k = 1, \ldots, K \} \) and sends them to the AP, which selects the precoding coefficients on the basis of local estimates. This is the key difference between the two operation modes in the DL. The information available at the UE for signal detection is the same with both implementations. Since there are no DL pilots, in both cases UEs have no knowledge of channel estimates and must rely on statistics. An achievable SE can be computed for the two operation modes by using the channel hardening bound. This yields \( \text{SE}_{\text{DL}} \) as \( 2 \log_2 (1 + \text{SINR}_{\text{DL}}) \) with [7, Sec. 6.1.1]

\[
\text{SINR}_{\text{DL}} = \frac{\mathbb{E} \left\{ |h_{mk}^2 w_{mk}|^2 \right\}}{\sum_{i=1}^{K} \mathbb{E} \left\{ |h_{mk}^2 w_{mk}|^2 \right\} + \frac{1}{\rho_k}}. (18)
\]

As seen, \( \text{SE}_{\text{DL}} \) depends on the precoding vectors \( \{ w_i : i = 1, \ldots, K \} \) of all UEs. This stands in contrast to the UL SE and makes optimal precoding design hard. A common heuristic approach relies on the UL-DL duality [7, Sec. 6.1.2], which holds between the UL bound and hardening bound. Motivated by this duality, we select the DL precoding vectors as \( w_k = \frac{1}{\sqrt{\mathbb{E} \left\{ |h_{mk}^2 w_{mk}|^2 \right\}}} \). Precoding vectors can be chosen on the basis of RC-MMSE or GMR for either centralized or distributed networks. On the other hand, the MMSE precoder can only be used with a centralized implementation.

V. PERFORMANCE ANALYSIS

Up next the system performance is shown for the proposed schemes. The simulation parameters are reported in Table I. APs will be randomly deployed within a square coverage area of side \( D \). The large-scale fading coefficients are computed as

\[
\beta_{mk}[\text{dB}] = -35.3 + 10 \log_2 (d_{mk}) + \chi_{mk} - \sigma_m^2, (19)
\]

where \( \alpha \) is the path loss exponent, \( d_{mk} \) is the distance between AP \( m \) and UE \( k \), \( \chi_{mk} \sim \mathcal{N}(0, \sigma_m^2) \) is the shadow fading component and \( \sigma_m^2 \) the noise variance.

The cumulative distribution function (CDF) for the UL average SE per UE is shown in Fig. 1a. The number of
APs is set to $M = 100$ and $K = 20$ randomly distributed UEs are dropped with $D = 250$ m. Both centralized and distributed versions of the RC-MMSE and GMR combiners are considered. As upper and lower benchmarks, the centralized and distributed MR combiners are also presented. This latter scheme is computed by letting the entries of $v$ be $v_{n,k} = b_{n,k}$. Regarding centralized schemes, the proposed RC-MMSE scheme nearly matches the optimal combiner. This proves this new scheme is a very suitable alternative to lowering the required computational resources with little performance loss under severe pilot contamination. On the other side, the GMR shows a considerable gap. We can notably point out that for low SNR both RC-MMSE and GMR match the asymptotic bound considerably underestimates its performance. Lastly, the GMR shows the same asymptotic behavior, though the UatF shows a considerable gap. We can notably point out that for low SNR both RC-MMSE and GMR match the asymptotic bound considerably underestimates its performance. Lastly, the GMR shows the same asymptotic behavior, though the UatF shows a considerable gap.

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Fig. 2: Average UL SE per UE for $K = 5$.

VI. CONCLUSIONS

This letter focused on pilot decontamination in CF MIMO. Building on linear independence of correlation matrices, the RC-MMSE combining was proposed as an alternative to centralized MMSE that almost matches the optimal performance and is asymptotically optimal. This scheme turns out to be a more than fitting approach for centralized computationally-limited networks. The GMR alternative scheme was also derived showing the same asymptotic behavior but maximizing the UaF. This approach is the upper-bound of MR-based CF networks. Both schemes are valid for a finite number of APs and have linear increasing complexity (in contrast to the optimal MMSE). By the UL-DL duality, the same performance can be achieved in DL where the GMR alternative serves as an optimal approach for MR-based precoders.

APPENDIX

We define $H = [h_1, ..., h_K] \in \mathbb{C}^{M \times K}$ and use the matrix inversion lemma to get $v$ (after dividing and multiplying by $M$)

$$v_k \doteq \frac{1}{M} Z^{-1} \left( \frac{1}{M} H v v^H + \frac{1}{M} I_K \right)^{-1} v_k$$

(20)

from which $\hat{v}_{nk}$ is obtained as (by neglecting the factor $1/M$, since it does not affect the SINR in (4))

$$\hat{v}_{nk} \doteq \frac{1}{m} e_k^H e_k \left( \frac{1}{M} H v v^H + \frac{1}{M} I_K \right)^{-1} v_k$$

(21)

with $h_{nk} = [h_{n1}, ..., h_{nk}] \in \mathbb{C}^K$. By exploiting the fact that, as $M \rightarrow \infty$,

$$\frac{1}{M} H v v^H = \frac{1}{M} h_{nk} v_{nk}^H + \frac{1}{M} \Psi^{-1} \mathcal{R} v_{nk}$$

the combiner $\hat{v}_{nk}$ defined in (8) follows.

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